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Econometrical issues in measuring the greenium: Evidence from corporate bonds issued in euros

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A B S T R A C T

With the world on course to breach the 1.5°C threshold within five years, it is now or never to avert the climate disaster. Scholars have recently studied green bonds as they offer a promising solution for financing the energy transition. They revealed that issuing green bonds comes with pricing advantages, known as the green bond premium or greenium. This thesis estimates the greenium for euro-denominated corporate bonds using novel loose and strict Coarsened Exact Matching (CEM) algorithms. The loose CEM discovered a significant 12.99 basis points (bps) greenium. The greenium became insignificant, however, when loose CEM matched issuers to control for unobservable issuer heterogeneities, although a highly significant 16.20 bps greenium persisted for utilities. Furthermore, the strict CEM found a significant 14.76 bps greenium. Greenium significance persisted when strict CEM matched issuers, and the greenium's size even doubled to 29.83 bps. Exploring K2K CEMs, this thesis revealed that K2K discards relevant bonds and estimates the greenium inconsistently. In addition to providing novel empiric evidence, this research demonstrates that the applied method materially affects results. This paper, therefore, intends to initiate a discussion on how to best estimate the greenium and interpret prior scholars' heterogeneous results.

A R T I C L E I N F O

JEL Classification: G12, Q01, Q2, Q54

Keywords: Climate bond pricing; Greenium; Econometrical issues; Coarsened Exact Matching

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Rens Eggink
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1 Introduction

Climate change poses an existential threat to biodiversity and human lives, and time is running out to mitigate its destruction. Half of the species in biodiversity hotspots immediately risk extinction due to climate change, and 3.6 billion people risk exposure to extreme heat, wildfires, humidity, food insecurity and flooding (Abay et al., 2022; IPCC, 2022; Vasconcelos et al., 2022).

Corporates must invest at least 46 trillion USD in green projects, equivalent to over 50 times the annual GDP of the Netherlands, to achieve the required decrease in greenhouse gas emissions (CBS, 2020; Sherwood et al., 2020). Unlike firms issuing conventional bonds, firms that issue green bonds commit to investing the raised capital towards projects that mitigate climate change (ICMA, 2021).

Green bonds are a relatively novel financial asset and gained traction after introducing the Green Bond Principles in 2014 (Chen & Zhao, 2021). Bonds are green if issuers use the proceeds to partly or wholly finance or refinance green projects (ICMA, 2021). Green bonds are a promising instrument for financing these investments, and deals are gaining significance. For example, in May 2022, TenneT TSO raised 3.85 billion euros with the most prominent corporate green bond sale in history to fund the greening of the Dutch and German electricity grids (Bloomberg, 2022).

As Schmitz and Schrader (2015) state in their literature review, firms can be motivated by profit maximisation or social preferences to engage in Corporate Social Responsibility (CSR) practices. From the perspective of capital providers, there are several reasons investors engage in CSR, which could manifest through purchasing green bonds. First, investors in fixed-income instruments might perceive green bonds as less risky. For instance, climate bonds might be less risky because the adherent projects face less strict regulations, and the market has more growth to capture. Furthermore, there is little probability of projects ending up as “stranded assets”, which could be the case for the carbon-intense sector (Byrd & Cooperman, 2018). These characteristics, therefore, might make green bonds an attractive investment for investors interested in mitigating their portfolio’s climate risk. Second, Zhou and Cui (2021) argue that socially responsible investors prefer to allocate capital to firms that perform well on ESG terms as they provide a positive environmental impact. Finally, investors might choose to invest in green bonds thanks to the additional transparency and disclosure that green bonds offer (Flammer, 2021).

Flammer (2021) researched the perspective of green bond issuers and identified the green bond puzzle. The phenomenon of firms issuing green bonds is arguably a puzzle because issuing corporate green bonds comes with additional disclosure requirements, costs and restrictions on asset allocation. Therefore, an alternative strategy might be issuing regular bonds and allocating funds to sustainable assets. In this light, firms that retrieve financing from traditional bonds can invest in more diverse projects to maximise shareholder value than firms that rely mainly on green bond financing.

Flammer (2021) offers potential motivations for firms to issue green bonds to solve the green bond puzzle. First, green bonds signal a firm's environmental commitment. Green bonds require firms to earmark their investments toward green causes. Earmarking allows the firm that issues the green bond to signal their commitment to allocating their capital towards green projects and improving their ESG performance. The signal that a firm is committed to green corporate practices alleviates information asymmetry as holders of conventional bonds see less disclosure regarding the firm's climate commitment (Hsueh, 2019).

Second, green bond issuance potentially helps firms obtain a better reputation for environmental performance and support greenwashing. Greenwashing means that a firm deceitfully claims to commit to ESG goals. Issuing green bonds could enhance the issuer's reputation by signalling environmentally strong performance without concrete actions to improve their actual climate performance. However, Xu et al. (2022) report that second-party opinions on ESG performance could mitigate the greenwashing risk. However, green bonds with a second-party opinion carry a higher greenium. The amplified greenium signals that investors value the credibility of the green bond's societal impact and avoid greenwashing by investing in green bonds with positive ESG ratings (Bour, 2019).

Despite evidence linking green bonds to enhanced ESG performance and reduced ecological footprints, the green bond market's full potential has yet to be unlocked (Bhutta et al., 2022; Fatica & Panzica, 2021). Moreover, the participation of firms in green bond issuances is not self-evident as they have additional issuance costs and restrict firm asset allocation strategy (Flammer, 2021). However, the green bond premium encourages firms to issue green bonds (Hsueh, 2019). The greenium reflects pricing differences between green and conventional bonds and exists when bonds with green labels have lower yields than identical conventional bonds. It is called a premium because the investors pay an implicit premium on the green bonds relative to the regular bonds. However, it is unclear whether the green bond premium exists and if issuing green bonds comes with pecuniary advantages. As a result, this study investigates the green bond premium empirically and seeks to answer the following research question:

Do corporate bonds issued in euros exhibit a green bond premium?

Flammer (2021) investigated the greenium globally and reported different greeniums per currency. As Harrison (2022) highlights that the euro currency dominates the green bond market, this study estimates the greenium for euro-denominated corporate bonds.

The findings of previous researchers on the greenium might be outdated because the risk premia of bonds tend to vary over time (Campbell et al., 2020). A time-varying green bond premium argues in favour of revisiting the green bond premium because past findings might not be extrapolatable to the future. Besides time-varying bond premiums, differences between research methods likely caused differences in reported greeniums (Cortellini & Panetta, 2021). Consistent with previous literature, this study estimates the green bond premium using a two-step approach. The first step matches green to conventional bonds, and the second estimates the green bond premium using regression analysis.

Matching links green bonds to conventional bonds that are identical to the green bonds except for the green label, creating an artificially controlled experiment, with the green label serving as treatment. Matching aims to increase the balance between the matched bonds. A sufficient balance between the matched bonds is essential. Ideally, the similarity between the matched green and conventional bonds is perfect. If there is a perfect balance between the matched bonds, the coefficient of the treatment variable, which is the green bond dummy, reflects an unbiased value for the green bond premium (Iacus et al., 2012). This thesis uses the relatively novel coarsened exact matching method of Iacus et al. (2012). The CEM was initially used by Löffler et al. (2021) to generate green and conventional bond matches before estimating the green bond premium.

The second step estimates the green bond premium using a regression with robust standard errors. In the regression, a green bond dummy is a treatment variable, while liquidity is a control variable. The second step runs a loose and strict CEM, further specified in Table 6.

The most important findings of this thesis are as follows. The loose CEM yields a significant 12.99 bps greenium. However, the greenium becomes insignificant when issuer level matching is applied but reappears as significant for utilities. Finally, the greenium's significance persists for the strict CEM if issuer level matching is applied, resulting in an estimated 29.83 basis points greenium for the overall sample.

Furthermore, the thesis explores K2K CEM algorithms. However, the K2K is not used in the second-step greenium estimation because the matching procedure discards many bonds. At the same time, the covariate balance is not improved. Also, issuer-level fixed effects models are explored to control unobserved factors such as reputation or risk of default.

Various societal stakeholders benefit from the knowledge gained by this study. First, investors learn that green bonds trade at lower yields than conventional peers, although they do not offer additional collateral. However, the higher probability of a green bond being ECB or REPO eligible may justify this pricing difference. Moreover, these informal benefits of already issued green bonds could increase over time. For example, central banks may incorporate the green label when assessing central bank stress tests or ECB haircuts. Aside from these economic benefits, green bonds allow investors to contribute to the investments needed to combat the climate crisis.

Issuers of euro-denominated corporate bonds may become aware that it is potentially attractive to start issuing green bonds, as this thesis finds a significant greenium. In addition, issuers might become aware of the better market access that green bonds offer, as signalled by the persistence of green bonds issued throughout challenging market conditions.

Furthermore, regulators might consider whether climate risk is appropriately priced by market participants given the size of the discovered premium in this thesis. Previous research suggests that climate risk is systematic, perhaps necessitating a higher greenium. In addition, a higher greenium could be encouraged by improved external conditions such as enhanced access to ECB asset purchasing programmes or tax discounts.

Finally, this research compares methodological approaches. The most concrete contribution is that this thesis discovers that the K2K CEM might be unsuitable for small datasets due to the large number of observations it discards. In addition, the thesis discovered that the CEM's specifications could significantly impact the estimated greenium's significance. However, it may depend on the size and other characteristics of the sample to determine which CEM is best suited, leaving room for future researchers to choose which CEM to employ. Finally, since results differ significantly across research methods, this paper intends to start a discussion on how to best estimate the greenium and interpret the results of previous papers.

This thesis is organised as follows. Section 2 motivates the hypothesis using the existing literature, section 3 describes the two-step methodology, and section 4 presents the results. Finally, section 5 concludes and suggests future research directions.

2 Hypothesis development

Green bonds may provide a pricing advantage, making them more appealing to issue. There is a "pricing benefit" if corporate green bonds yield lower than equivalent conventional bonds. (Flammer, 2021). Firms may join the green bond market to benefit from reduced borrowing costs. Social investors might be willing to accept lower investment returns in exchange for environmental impact and fewer risks of climate hazards (Bhutta et al., 2022).

However, the research on green bonds is mixed on whether or not such a premium exists. Several empirical studies have found negative greeniums, meaning that green bond yields are higher than conventional ones. For example, Karpf and Mandel (2017) report a negative greenium for US municipal bonds. Furthermore, according to Magnanelli and Izzo (2017), investors perceive green bonds are riskier than traditional bonds and demand greater expected returns, resulting in green bond discounts. However, the conclusions of Magnanelli and Izzo (2017) may be deemed out of date given the rapid pace of developments in climate bonds.

According to Bhutta et al. (2022), investors in climate bonds do not receive more collateral or seniority than conventional bondholders. Therefore, a profit-maximizing investor would disregard the bond's green label, and the label should not impact bond pricing. Consequently, green bonds should theoretically provide the same rate of return as their conventional equivalents.

Larcker and Watts (2019) discovered that similar green and non-green bond yields do not significantly differ. Instead, they only detect a positive greenium for firms with a low probability of greenwashing. Greenwashing refers to a project with a green label while not being environmentally friendly (Otek et al. (2021). Lau et al. (2022) corroborate Reed et al. (2017), who found no difference in conventional and green bonds pricing. They explain the absence of any greenium by investors fearing greenwashing. In other words, due to the knowledge asymmetry between issuers and investors, investors have little faith in the stated impact of green bonds. According to Xu et al. (2022), fear of greenwashing stems from companies' self-labelling of green bonds. They investigate the Chinese bond market and discover that only the issuances allocated entirely to green assets earn a greenium.

Larcker and Watts (2019) do not detect a greenium when they precisely match pairs of green and non-green bonds based on issuer, long-term issuer ratings, and duration, establishing a matched sample of equivalent to or nearly similar pairs. However, they exclusively examine the U.S. municipal bond market. Therefore, their findings cannot be applied directly to euro corporate bonds.

No substantial yield differences exist between climate and comparable non-climate bonds, according to Flammer (2021). Therefore, she hypothesises that companies may issue green bonds to demonstrate their commitment to environmental protection over financial benefit. Furthermore, firms may reduce their carbon footprint and enhance ESG ratings by issuing green bonds, making themselves more appealing to climate-conscious investors.

In addition, a substantial body of research supports the greenium. According to Matikainen (2017), financial institutions have historically been biassed toward carbon-intensive industries. Green bonds could play a crucial role in reducing this carbon bias. According to Monk and Perkins (2020), non-monetary considerations and increased awareness are helping to lessen investors' carbon bias. Non-financial factors and a desire to reduce carbon bias result in an oversubscription of green bond issuance, which may cause green bond yields to decrease and produce the greenium. Oversubscription suggests that demand exceeds supply for a particular green bond offering. Carbon bias occurs when financial institutions make disproportionate investments in carbon-intensive industries.

Harrison et al. (2020) indicate that the costs connected with the additional non-financial disclosure have led to a shortage of green bonds. As a result, issuers of debt instruments desire compensation for the higher costs connected with green issuances. Thus, lower yields on green bonds compensate for higher issue costs. In addition, Harrison et al. (2020) observed a lack of eligible projects to participate in the issue of green bonds. As a result, green bond prices may rise due to scarcity, creating a greenium.

According to Harrison et al. (2020), green bond yields are between 24 and 36 basis points lower than conventional bond yields. They defend this position by asserting that green bonds contain low information asymmetry. In other words, the additional information revealed regarding the green projects associated with the green bonds indicates a reduced environmental risk. Therefore, investors may be willing to accept lower yields due to the signalled reduction in climate risk. Moreover, Harrison (2022) discovers a significant greenium for euro-denominated bonds. Finally, Löffler et al. (2021) find a significant greenium using CEM algorithms.

Researching the greenium is relevant because, according to the research reviewed, corporations require reliable information on the height of the greenium before issuing green bonds. This information asymmetry is worrisome as green bonds can contribute significantly to fighting the climate crisis. As indicated by the cited research, there is theoretical and empirical disagreement in the green bond literature over the existence and magnitude of greenium. However, papers with methodologies close to this paper do find a greenium. For example, both the paper of Löffler et al. (2021) that uses CEM and the research of Harrison (2022) into euro-denominated bonds point to the existence of the greenium. Therefore, the following hypothesis is proposed:

H_1: The greenium exists for corporate bonds issued in euros.

3 Methodology

There are two elements to the analysis. First, green and non-green bonds are matched using coarsened exact matching (CEM). Then a regression estimates the green bond premium.

3.1 Data

Consistent with Löffler et al. (2021), the data is cross-sectional and has one observation in time observed on March 30, 2022, per actively traded bond. However, the data has a time dimension because bonds are issued in different years.

TABLE 1
FILTERS APPLIED TO EIKON DATA.

Action	***Bond types filtered for***	***No. of bonds left after filtering***
Open Eikon fixed income database	Active bonds (automatic filter).	929559
Remove	Securities not classified as bonds.	740582
Remove	Non-corporate debt securities.	619654
Remove	Bonds with no credit rating.	311753
Remove	Bonds issued privately.	288435
Remove	Bonds without fixed coupons.	129955
Remove	Issued prior to 2014.	116326
Remove	Bonds not denoted in euros.	19553
Remove	Bonds smaller than 500 mln USD.	3315
Export dataset to MS Excel	No additional filters were added.	3315
Remove	Bonds with a one-year maturity.	3305
Remove	Bonds of which the credit rating has been withdrawn.	2891

Table 1 shows the filtering steps in Eikon and Excel. Eikon's initial search only included actively traded bonds or bonds that had not yet matured. Initially, the dataset covered all fixed-income groups. Hence, only bonds are included in the initial filtering step. Next, bonds without a long-term credit rating are removed, as ratings are a significant yield driver (Agliardi & Agliardi, 2021). Then, privately placed bonds are removed since their pricing data might be outdated. Consistent with past scholarly work, the dataset exclusively contains fixed coupon bonds (Antoniuk & Leirvik, 2021; Cortellini & Panetta, 2021; Lichtenberger et al., 2022). The sample is then restricted to bonds issued between January 1, 2014, and April 1, 2022, because the Green Bond Principles launched on January 1, 2014 (Bhutta et al., 2021).

Additionally, the dataset excludes bonds denominated in currencies other than the euro because the euro dominates the market for green bonds (Harrison, 2022). In addition, to boost the sample's liquidity, bonds with outstanding amounts of less than USD 500 million are excluded, consistent with Harrison (2022) but not with Löffler et al. (2021). This size filter does include USD-denominated bonds. However, it refers to the outstanding debt's size, which Eikon measures in

USD. Next, bonds maturing in a year are excluded as they are too thinly traded for secondary market analysis. Next, bonds with withdrawn credit ratings are removed (Agliardi & Agliardi, 2021). The terminal dataset contains 2891 bonds, of which 219 are climate bonds and 2672 regular bonds.

TABLE 2

SUMMARY STATISTICS OF THE CLEAN SAMPLE.

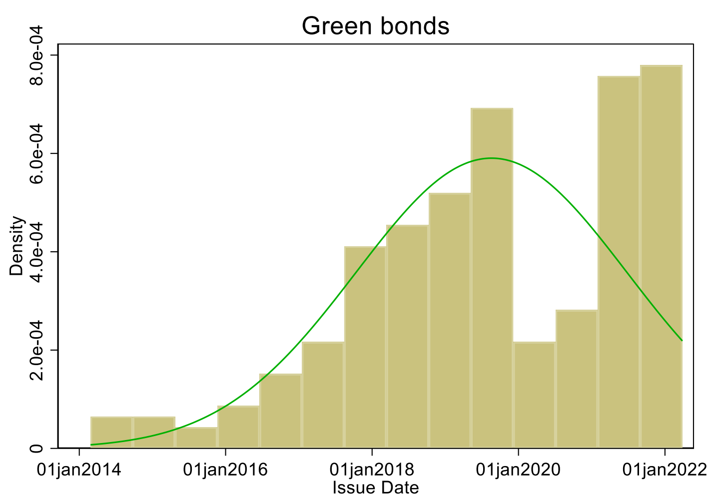
Green bonds					
Variables	Obs	Average	Std Dev	Min	Max
Coupon in per cent	219	0.750	0.662	0.000	3.500
Yield to maturity in per cent	219	1.277	0.820	-0.458	3.928
Duration to maturity in years	219	4.078	2.792	0.097	17.488
Tenor in years	219	6.881	2.888	3	20
USD outstanding in millions	219	655.290	181.667	549.052	1427.536
USD issued in millions	219	656.355	182.310	549.052	1427.536
Regular bonds					
Variables	Obs	Average	Std Dev	Min	Max
Coupon in per cent	2672	1.089	0.978	0.000	7.750
Yield to maturity in per cent	2672	1.268	1.212	-8.706	18.335
Duration to maturity in years	2672	3.455	2.622	0.003	24.653
Tenor in years	2672	7.392	2.945	2	30
USD outstanding in millions	2672	906.758	445.811	501.880	6588.628
USD issued in millions	2672	914.581	458.311	505.1281	6588.628

Note: The provided summary statistics pertain to the clean dataset divided into green and regular bonds.

Table 2 describes the sample's summary statistics. Note that the average outstanding amounts of conventional bonds are higher than green bonds. This gap may exist because green bonds are asset-linked and firms have limited numbers of qualifying green projects (Flammer, 2021).

FIGURE 1

NEW ISSUANCES OF GREEN CORPORATE BONDS THAT ARE ISSUED IN EUROS.



Moreover, the discovery in Figure 1 that green bond issuances have recovered after COVID-19 might explain why green bond durations are slightly longer than ordinary bonds. The quick recovery of green bond issuances may also signal enhanced market access for green bond issuers. For example, TenneT TSO's recent jumbo green bond issuance shows green bond issuers' extraordinary capital market access in challenging market conditions. However, it is not evident that the improved market access is only attributable to the green label. The relatively favourable credit ratings of a green bond investment, as shown in Figure 6, may partly explain the issuers' speedy return to the capital market. Figure 2 shows that conventional bond issuances decreased during COVID-19, suggesting increasing risk aversion among investors and a preference for keeping cash or risk-free assets rather than conventional bonds. Furthermore, conventional bond issuances have not yet rebounded to pre-corona levels.

FIGURE 2

NEW ISSUANCES OF CONVENTIONAL CORPORATE BONDS THAT ARE ISSUED IN EUROS.

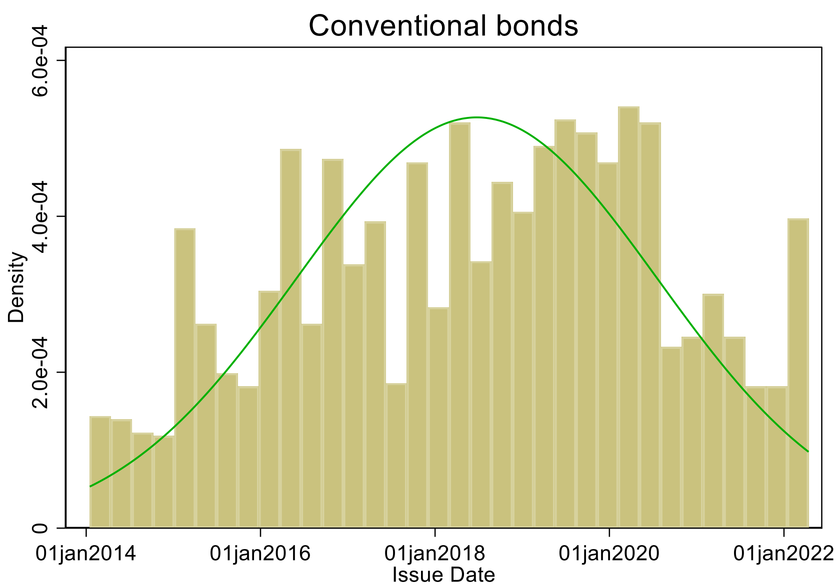


Figure 3 demonstrates that utilities have issued more than one in five green bonds but only one in 45 conventional bonds. Green bonds are asset-linked. Therefore the material character of utility balance sheets, explained by ambitious CAPEX programmes, likely explains utilities' overrepresentation in green bond issues. This overrepresentation is not likely to reverse soon due to heavy investments by utilities in the energy transition, the connection of clean energy sources to the grid and grid extension due to increased electricity consumption. To illustrate, Dutch utility TenneT TSO will grow its CAPEX programme significantly in the coming years.

FIGURE 3

COMPOSITION OF INDUSTRIES BETWEEN GREEN AND CONVENTIONAL BONDS.

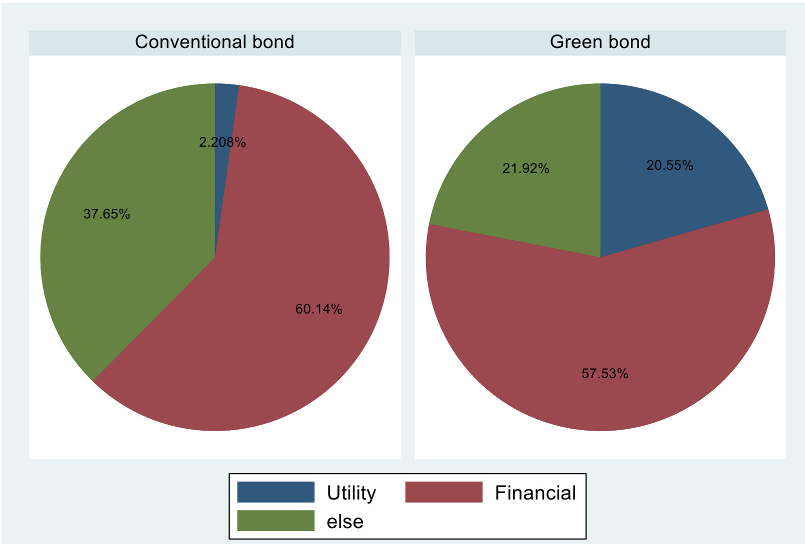


Figure 5 shows that green bonds still only compose 7.6 per cent of the market for bonds denominated in euros. This small percentage corroborates that the green bond market is still nascent, even though recent growth has been spectacular.

3.2 Step 1: Matching the sample

The first step, matching, is suitable for analysing cross-sectional observational data that contains both a treatment and a control group (Iacus et al., 2012). Matching pairs two identical observations except for one variable of interest. In this study, matching refers to pairing green bonds with similar conventional bonds. The primary objective is obtaining an optimal balance among the treatment and control groups. The only difference should ideally be the green label.

If pairs are perfectly matched, it is unnecessary to include additional control variables in the regression to estimate the greenium. According to Iacus et al. (2012), the only difference between the treatment and control groups in terms of independent variables should be the treatment or the green bond dummy. In other words, only the treatment variable should affect the dependent variable, yield at maturity. However, accurately matching treatment and control groups based on observational data is challenging (Iacus et al., 2012).

Unlike this thesis that only uses CEM, Gianfrate and Peri (2019) used propensity score matching (PSM) to pair regular to green bonds. However, PSM can aggravate imbalances and bias between treatment and control groups (Iacus et al., 2012). Increasing disparities between the two groups are troublesome because the covariates that the PSM method seeks to match are becoming progressively divergent. However, the objective of matching is to pair a green bond with a conventional bond based on similar qualities or covariates. Therefore, more different covariates indicate that the PSM technique achieves the reverse of what it intends. In addition, the PSM algorithm includes assumptions that are only valid for the averages of multiple samples. Furthermore, it is unattainable to test the PSM method's underlying sample assumptions (Iacus et al., 2012). According to Iacus et al. (2012), the PSM method is a popular matching method due to researchers' lack of experience with matching methods and unawareness of the PSM's worrisome robustness (Iacus et al., 2012).

3.2.1 Motivation for applying the CEM algorithm

Iacus et al. (2012) introduced the Monotonic Imbalance Bounding matching approaches, one of which was the Coarsened Exact Matching (CEM) method. The CEM is particularly effective for cross-sectional samples. This thesis implements CEM since it is statistically more robust than propensity score matching or PSM in several ways (Guo et al., 2020).

First, in contrast to PSM, CEM makes no assumptions about the control and treatment groups. Using 5000 simulated samples, Iacus et al. (2012) discovered that, in contrast to PSM, CEM never worsens the balance between pairs. Second, CEM is preferable even when all PSM assumptions are met. As a result, CEM reduces the dependence on the second step's regression model specification, which is advantageous because the green dummy coefficient likelier captures the greenium accurately (Ho et al., 2007). Thus a potentially flawed second-step regression model causes less harm. Third, while matching treatment and control groups perfectly on each explanatory variable is unattainable, CEM always reduces biases.

CEM effectively decreases imbalances between treatment and control groups because it allows for exact matching (King et al., 2011). Exact matching means that the CEM will only accept a match if the matching criterion is identical for the green and conventional bond (Iacus et al., 2012).

Furthermore, CEM rejects fewer matched pairs than competing methods. Discarding occurs when a matching algorithm cannot find a suitable pair due to significant covariable differences. This CEM characteristic is advantageous because, unlike Löffler et al. (2021), who take a global perspective, this dataset contains relatively few observations due to its emphasis on a single currency. Moreover, this thesis applies stringent inclusion criteria to ensure liquidity and reliable recent pricing data.

Another advantage of CEM is that it handles the sample's correlational nature well (Iacus et al., 2012). Handling correlation is essential for this sample because credit ratings and coupons tend to correlate. This correlation can be interpreted as that bond investors demand higher coupons to compensate for the increased default risk signalled by poor credit ratings (Berk et al., 2013).

Finally, CEM produces the multivariate L1 statistic representing the harmony between the two groups. This statistic is essential because it reflects how precisely the samples are matched and permits a comparison of the balance generated by matching across studies.

To conclude the consideration between PSM and CEM, King et al. (2011) provide evidence that PSM can increase the imbalance between matched pairs. In contrast, CEM never increases the imbalance between pairs thanks to exact matching, as Iacus et al. (2012) demonstrated with their simulated samples. The reviewed literature indicates that CEM provides more robust results than PSM and that the CEM performs well for samples with a correlation nature and limited numbers of observations. Therefore this thesis only applies CEM to generate pairs of green and conventional bonds.

3.2.2 Applying CEM algorithm

The CEM algorithm operates as follows. Before matching, CEM coarsens or codes the covariates of each bond. Then, after coding, CEM applies an algorithm to match and pair the green and conventional bonds. After forming the pairs, the algorithm decodes the data. The coded data is then dispensed, and the matched pairs with decoded covariates are kept.

Additionally, the CEM can coarsen variables of interest into multiple categories. For instance, the variable reflecting bond seniority comprises ten distinct categories, which CEM aggregates into two subgroups, secured and unsecured. Secured indicates that a security is asset-backed.

The asset serving as collateral reduces the bond's default risk and yield, all else being equal (Berk et al., 2013).

The CEM algorithm in this study matches green to conventional bonds on the following criteria, namely 1. issuer, 2. sector, 3. country, 4. long-term credit rating, 5. issue year, 6. tenor, 7. seniority, 8. amount outstanding, 9. coupon, 10. callability, 11. REPO qualification, and 12. ECB qualification.

The matching criteria applied by previous authors are enhanced in several ways. For instance, unlike Löffler et al. (2021), this paper matches bonds on ECB and REPO qualifications and controls for outstanding amounts. These matching criteria improve the criteria of prior research because Table 2 indicates that the average size of conventional bond issuances is 140 per cent of the average size of climate bond issuances. In addition, Figure 10 and Figure 11 indicate that green bonds are more often REPO and ECB eligible.

In addition to the limited number of matching criteria, Löffler et al. (2021) included bonds whose credit rating has been withdrawn. According to Agliardi and Agliardi (2021), credit ratings significantly determine bond yields. Including bonds with withdrawn credit ratings is worrisome because it could lead to, for instance, the pairing of an AAA-rated bond with a junk bond. This pairing is problematic because Figure 6 demonstrates that conventional bonds are four times more likely than green bonds to receive a junk credit rating. The second-step regression would measure the yield differential between safe and risky bonds instead of a greenium and bias the estimated greenium.

CEM can be conducted as the conventional CEM or the K2K CEM. The conventional CEM is relatively flexible compared to the K2K CEM. Flexible means that the conventional CEM can pair a specific green bond to multiple conventional bonds if the conventional bonds, as a group, are highly similar to the green bond (Iacus et al., 2012). The K2K CEM, on the other hand, applies 1:1 matching. 1:1 matching means that a green bond can only be matched to one other conventional bond.

It would be interesting to investigate which CEM is better suited for estimating the greenium for this dataset for two reasons. First, the dataset is relatively small due to the focus on one currency and the relatively strict data inclusion criteria. Therefore, it is relevant to investigate which CEM discards the fewest bonds. Discarding is relevant because discarding too many bonds might come at the disadvantage of losing information that might affect the second step's estimation of the greenium. Second, since perfectly matched samples allow obtaining the unbiased greenium, it is relevant to assess whether the conventional or K2K CEM achieves a higher balance between the pair's covariates.

3.3 Step 2: Greenium estimation

After the first step, matching, prior scholars employed regression analysis to estimate the premium on green bonds. Since matching cannot produce perfectly similar pairs, developing a suitable model via subsequent regression is essential. Therefore, Cortellini & Panetta (2021) proposed incorporating an independent variable into the regression to serve as a control variable to enhance the robustness of the estimated greenium. Following the recommendation of Boutabba and Rannou (2022), this thesis includes liquidity as a control variable in the second step's regression. According to Chen et al. (2020), controlling for liquidity is essential because liquidity affects corporate bond yields. Consequently, liquidity is measured by Equation (1), following Chen and Zhao (2021).

$$(1) \qquad Liquidity = \frac{ask - bid}{(bid + ask)/2}$$

Equation (2) represents the regression used to estimate the greenium. The yield to maturity reflects the dependent variable and the nominal annual return that a bondholder would earn when all the coupon payments have been made (Berk et al., 2013). The yield to maturity thus reflects the nominal annual return of the bondholder if the bond does not default. A green bond dummy indicates 0 for conventional bonds and 1 for green bonds. As the green bond dummy is regressed against the yield to maturity, the coefficient of the dummy reflects the estimated greenium. A negative coefficient for the green bond dummy corresponds to a green bond premium. In contrast, a positive coefficient signals a discount. The regression estimates the greenium with robust standard errors.

$$(2) \qquad Yield\ to\ maturity = \alpha + \beta_1 GBdummy + \beta_2 Liquidity + \epsilon$$

In the second step of estimating the greenium, Löffler et al. (2021) used a fixed effects regression on the issuer level to account for unobservable characteristics, such as ESG risks of the issuer. However, applying fixed effects is a problematic approach for several reasons. Larcker and Watts (2020) compared the results of fixed effects regressions to samples matched perfectly on the covariates. To the detriment of the fixed effect approach, the estimated greenium by fixed effects differed from the greenium reflected by the exactly matched sample. According to Iacus et al. (2012), exactly matched samples produce unbiased results in the second step. Thus, the fixed effects regression results must be biased, as the estimated greenium of the fixed effects regression differs from the unbiased greenium indicated by the exactly matched sample. Given the large number of covariates that the strict CEM matches on in this thesis, one could argue that the CEM is incapable of producing precisely matched pairs. However, the following section provides even more crucial evidence why applying fixed effects is inappropriate for estimating the greenium, even if exact matching is not achieved.

Placebo bonds are traditional bonds issued by issuers of green bonds. Larcker and Watts (2020) applied fixed effects on placebo bonds to estimate the greenium and got spurious results. Larcker and Watts (2020) replicated the approach of Tolliver et al. (2019). The latter reported a greenium and confirmed its existence using fixed effects. However, Larcker and Watts (2020) substituted green bonds for placebo bonds in a fixed effects regression. They discovered that the fixed effects regression on the placebo bonds samples estimated roughly the same greenium. It is problematic if a regression estimates the same greenium for a placebo bond as for an actual green bond because the greenium aims to measure the difference between green and regular debt yields. However, fixed effects regressions signal a greenium for conventional bonds, which should, by definition, be impossible. The results of Larcker and Watts (2020) may suggest that the mere act of issuing green bonds reduces the yields on conventional bonds issued by green issuers. The halo effect is the phenomenon that issuing green bonds comes with enhanced overall capital market access (Basar & Krebbers, 2019).

Since this thesis aims to measure the effect of a green label on yields, fixed effects regressions are ineffective for measuring the greenium in the second step. Therefore, rather than applying fixed effects on the issuer level, this thesis's primary analysis matches bonds on issuers to account for unobservable issuer characteristics. Nevertheless, the thesis applies fixed effects as a robustness check to estimate the greenium to determine whether the different methodology affects results.

The two-step methodology applied in this thesis can be summarised as follows. First, this paper matches green and non-green bonds using CEM. Then, linear regressions estimate greeniums with robust standard errors and a green bond dummy as the treatment variable and liquidity as the control variable.

4 Results

The results chapter is structured as follows. Chapter 4.1 presents and interprets the matching outcomes and explores the alternative CEM setting, the K2K. Chapter 4.2 then estimates the greeniums and relates the findings to the hypothesis and results of previous authors.

4.1 Step 1: Matching outcomes

Table 3 provides the matching results of four conventional CEMs and their K2K peers. The only difference between the CEMs and their adherend K2K version is whether or not the K2K is applied. Recall that the K2K CEM matches 1:1, which means that each green bond is only paired to one conventional bond. In contrast, the regular CEM can pair a green bond to multiple conventional bonds that, when combined, pose a suitable match for a green bond.

CEMs (1a) and (1b) have relatively few matching criteria and are thus loose, while (2a) and (2b) are categorised as strict. The strict CEM applies the matching criteria described in chapter 3.2.2. In contrast, the loose CEM applies the matching criteria described in Table 6.

The parameters provided in Table 3 can be interpreted as follows. A value of 0 for the multivariate L1 distance indicates perfectly matched pairs, whereas a value of 1 indicates that the pairs are perfectly mismatched. The K2K CEM does not consistently yield a lower or higher multivariate L1 distance than the conventional peer CEM, even though Table 3 signals this. This inconsistency arises because the K2K produces a different balance each time the K2K is conducted on the same dataset. K2K produced different pair balances and L1 each time K2K was run. This discovery is relevant because the multivariate L1 distance shows how well the pairs' covariates are matched. Remember that covariates reflect bond characteristics such as ECB eligibility, the year of issuance or credit rating. As Figure 14 indicates, not only the first-step multivariate L1 distance is different each time the same K2K CEM is run. The second step's estimated greenium is also affected and yields inconsistent results.

Moreover, to the detriment of the K2K, the K2K always discards more green and conventional bonds relative to the conventional CEMs. Discarding is especially problematic given the relatively few observations in this dataset. Therefore, K2K CEMs do not suit smaller datasets because K2K discards additional bonds even though it does not increase balance. Furthermore, discarding is even more problematic if K2K systematically discards particular bond categories. Systemic discarding could create a bias in the second step of the greenium estimation due to correlated omitted observations.

Furthermore, perhaps against intuition, the additional matching criteria of the strict CEMs explain their relatively high multivariate L1 distances and thus lower balances than CEM (1a) and (1b) and their K2K counterparts. Remember that the K2K can only find one match for each green bond. Algorithm strictness and the challenge of finding appropriate matches could explain the relatively high L1 distance of CEM (2a) and (2b). However, the higher multivariate L1 distances of the strict CEMs are not a problem as CEM never increase imbalances (Iacus et al., 2012). Also, note that the strict CEMs discarded many bonds due to their additional criteria. For instance, note that K2K of CEM (2b) discards 98.24% of the conventional bonds, while the loosest CEM, CEM (1a), discards just 66.76% of the conventional bonds. All the CEMs discarded relatively many conventional bonds relative to green bonds. However, this is not surprising given that there are many conventional bonds in the sample, which still leaves sufficient conventional bonds to be matched to green peers.

The L1 statistic of all the CEMs is higher than the L statistic of 0.243 reported by Löffler et al. (2021). The larger sample size of Löffler et al. (2021) likely explains their lower L1 statistic (Iacus et al., 2012).

TABLE 3
MATCHING SUMMARY.

Matching criteria	*Loose*		*Loose+issuer*		*Strict*		*Strict+issuer*	
	(1a)	(1a) K2K	(1a)	(1a) K2K	(2a)	(2a) K2K	(2b)	(2b) K2K
No. matched CB	888	182	150	92	396	135	56	47
No. unmatched CB	1784	2490	2522	2580	2276	2537	2616	2625
No. matched GB	195	182	111	92	151	135	62	47
No. unmatched GB	24	37	108	127	68	84	157	172
% CBs discarded	66.76	93.19	94.38	96.55	85.18	94.94	97.90	98.24
% GBs discarded	10.96	16.89	49.31	57.99	31.05	38.35	71.69	78.53
Multivariate L1 D.	0.673	0.593	0.666	0.597	0.823	0.792	0.806	0.787
No. Strata	500	500	1379	1379	1031	1031	1746	1746
No. matched Strata	78	78	67	67	72	72	36	36

Note: Multivariate L1 distance indicates pair balance. GBs refer to green bonds, CBs to conventional bonds, D. refers to distance, and Strata refer to groups of matched bonds. All CEMs applied the Scott break method for imbalance, the standard Stata setting. The percentage of discarded green and conventional bonds is computed by dividing the number of unmatched green or conventional bonds respectively by the total number of green or conventional bonds.

Note that the 1:1 principle of the K2K results in K2K CEMs always having the same numbers of matched green and conventional bonds, unlike the conventional CEM. It is essential to acknowledge that the K2K CEMs discard relatively many bonds because the K2K algorithm only aims to find one match for each green bond. However, the conventional CEM algorithm finds multiple viable matches for each green bond. Conventional CEM hence discards less of this dataset's low number of observations. For instance, CEM (2b) has 32% more matched green bonds than its K2K peer.

The K2K will not be considered in the greenium estimation. It is ambiguous whether the K2K CEM improves the multivariate L1 distances, but, on the other hand, K2K significantly decreases the already low number of matched green bonds. Besides the worrisome fit of the K2K with this specific sample size, the K2K setting is not the standard Stata setting, making it unlikely for future researchers to use K2K. Therefore, the K2K is not preferred from a research comparability perspective, as researchers are likely to employ the conventional CEM.

4.2 Step 2: Greenium estimation

Panel A in Table 4 displays the estimated greenium for the entire period. The coefficient for the green label is negative for all the CEMs signalling a green bond premium. A negative green bond label coefficient should be interpreted as the green bonds, ex-post matching, have lower yields than their paired conventional bond.

Even though the sign of the green label is always negative, the greenium's significance differs per approach. For approach (1), the loose CEM, the greenium, becomes insignificant after matching bonds on the issuer level. Thus, the greenium loses significance when the loose CEM controls for issuer-specific characteristics such as CSR profile or insolvency risk. The green label coefficient of CEM (1b) that matched bonds on the issuer level indicates a less pronounced greenium relative to CEM (1a) that did not match issuers. This result can be interpreted as that issuer-specific characteristics might explain lower yields on green bonds if step 1 matches bonds on the loose CEM criteria.

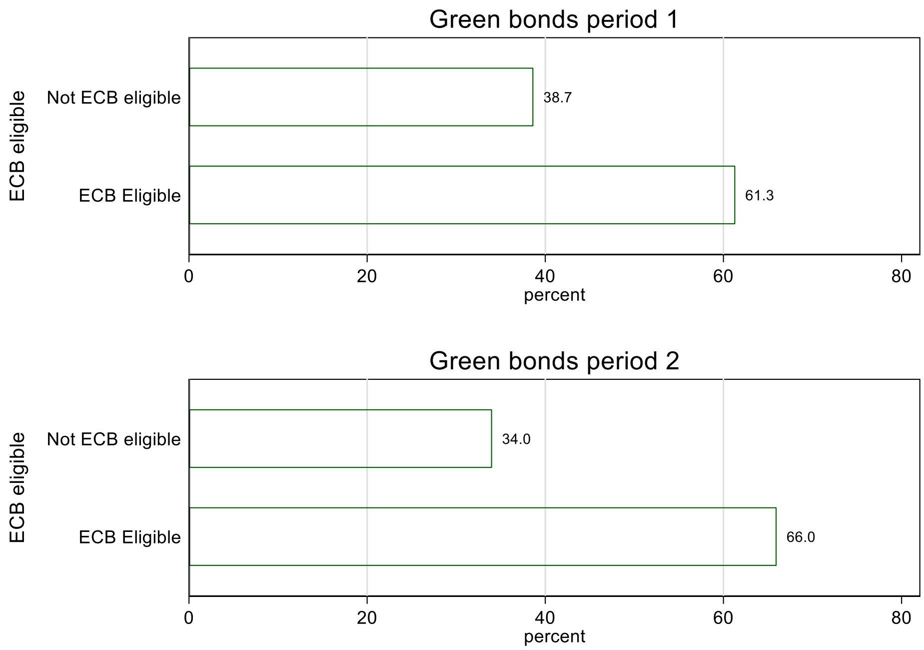
Surprisingly, the strict CEM (2) shows an entirely different result. The green label indicates a greenium for both the strict approach that matched issuers and did not match issuers. In contrast to the CEM (1) result, the greenium became more significant for the strict CEM that matched issuers. Also, the green label coefficient even doubles in size.

Result *(The effect of the green label on bond yields). Loose CEM discovers a significant 12.99 bps greenium. However, significance disappears when loose CEM matches on the issuer level, but significance persists for utilities. A significant greenium is found for strict matching, and the greenium persists when issuer matching is applied.*

Campbell et al. (2020) reported that the green bond premium potentially differs across issuance periods. Moreover, Löffler et al. (2021) discovered that the greenium was only significant for bonds issued after 2017. Therefore, this subchapter investigates potential differences in the green bond premium for two different issuance periods. The first period refers to bonds issued between 2014 and 2018 and reflects bonds issued after the Green Bond Principles initially emerged. The second period concerns bonds issued between 2019 and 2022 and reflects bonds issued after the European Commission's Sustainable Finance Action Plan. It is interesting to investigate these timespans as bonds issued right after the Principles emerged had relatively few rules regarding ESG disclosure, which might lead to a lower greenium. In contrast, green bonds issued after the European Commission's Sustainable Finance Action Plan might be subject to stricter regulation and may have a higher greenium. An additional motivation for specifically these periods is to ensure that both subsamples have sufficient numbers of bonds for the analysis.

FIGURE 4

ECB ELIGIBILITY OF GREEN BONDS OVER THE TWO ISSUANCE PERIODS.



Differences between issuing periods might arise because, for instance, the strict CEM matches bonds on ECB eligibility. In addition, there could be differences in bond characteristics between issuance periods. For instance, the ECB may have become more engaged concerning climate change over the recent years. Climate engagement might explain why green bonds issued in the second period are relatively often ECB eligible, as Figure 4 demonstrates. However, this should be interpreted cautiously as climate bonds are more likely to obtain investment-grade ratings, as Figure 6 demonstrates.

On the other hand, the ECB eligibility for conventional bonds did not materially change, as Figure 12 indicates. This difference implies that strict CEM includes different bonds than the loose CEM per period because the strict CEM matches bonds on ECB eligibility and other variables.

TABLE 4 GREENIUM ESTIMATIONS: CONVENTIONAL CEM AND FIXED EFFECTS MODELS.

Panel A: Greenium estimation for bonds issued between 2014 and 2022 (introduction of the Green bond Principles until today)						
Green Bond=1	-0.1299**	-0.1158	-0.1476*	-0.2983**	-0.0538	-0.0909
	(0.064)	(0.093)	(0.082)	(0.1441)	(0.0569)	(0.0677)
Liquidity	228.700***	203.192***	228.306***	144.353***	193.767***	250.170***
	(25.611)	(61.159)	(38.655)	(55.302)	(7.2507)	(7.4683)
Constant	0.810***	0.791***	0.784***	0.953***	0.7958***	0.6583***
	(0.067)	(0.155)	(0.101)	(0.162)	(0.0215)	(0. 0257)
Obs.	1,073	261	542	118	2873	2873
F	49.98	8.65	23.26	5.78	357.13	561.37
R^2	0.3665	0.3296	0.4368	0.2584	0.3317	0.3317
Panel B: Greeniums estimation for bonds issued between 2014 and 2018 (the first years after Green bond Principles emerged)						
Green Bond=1	-0.1424**	-0.0965	-0.1051*	-0.2015	-0.1724**	-0.2995
	(0.059)	(0.067)	(0.0580)	(0.1262)	(0.0867)	(0.1054)
Liquidity	309.671***	433.507***	469.939***	315.149***	247.619***	274.201
	(41.108)	(101.468)	(84.372)	(224.281)	(11.700)	(10.728)
Constant	0.335***	0.107	-0.028	-0.232	0.5105	0.4625
	(0.071)	(0.144)	(0.135)	(0.316)	(0.0283)	(0.0312)
Obs	456	98	185	43	1518	1518
F	31.62	14.30	26.00	3.91	229.62	334.49
R^2	0.4014	0.4514	0.5688	0.2179	0.3503	0.3499
Panel C: Greenium estimation for bonds issued between 2019 and 2022 (the period after European Commission's Sustainable Finance Action Plan)						
Green Bond=1	-0.1204**	-0.100	-0.1738*	-0.3055*	-0.0379	-0.1211
	(0.077)	(0.114)	(0.1019)	(0.1722)	(0.0600)	(0. 0850)
Liquidity	177.958***	115.512**	170.714***	83.620*	143.228***	209.787***
	(23.903)	(50.876)	(31.435)	(44.782)	(7.754)	(10.133)
Constant	1.132***	1.341***	1.192***	1.456***	1.1479***	0. 9580***
	(0.072)	(0.170)	(0.110)	(0.173)	(0. 0263)	(0.0401)
Obs.	617	163	357	75	1355	1355
F	33.69	3.65	21.12	3.21	171.21	214.83
R^2	0.288	0.1721	0.3698	0.1525	0.2817	0.2812
CEM type	(1a)	(1b)	(2a)	(2b)	(3)	(4)
CEM criteria	Loose	Loose + Issuer	Strict	Strict + Issuer	NO CEM	NO CEM
Fixed effects	NO	NO	NO	NO	YES (issuer-level)	YES (sector-level)

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. The dependent variable is yield to maturity. Table 6 and Table 7 explain approaches in detail. The green bond coefficient reflects percentages. For example, a -0.1039 green bond coefficient indicates a 10.39 basis points greenium.

Surprisingly, there are again remarkable differences between the methods. Loose CEM that does not match issuers sees the greenium shrink for bonds issued in the second period. The other CEMs amplify the greenium for bonds issued after the second period. Consistent with Löffler et al. (2021), most CEMs deliver the largest greenium for bonds issued in the second period. Moreover, for the strict CEM that matches issuers, the greenium is only significant for the second period, consistent with Löffler et al. (2021). Finally, a different pattern per period is found for model (3), which estimates the greenium by applying fixed effects on the issuer level. The greenium discovered by the fixed effects model is only significant for climate bonds issued in the first period.

Panel C in Table 4 displays estimated greeniums for the second period's issued bonds. Unlike the first period's results, the green bond label is insignificant for the issuer-level fixed effects approach. However, for the strict approach that matches the issuers, the second period's greenium is significant, unlike the first period.

The numbers of observations are strikingly lower for the strict CEMs relative to the loose CEMs. For instance, the strict CEM that additionally matches on issuers to account for unobservable issuer characteristics only has 118 observations relative to 261 observations of the loose CEM that also matches on the issuer. The fewer observations signal that the additional matching criteria discarded relatively many bonds. Surprisingly, the R^2 consistently drop when the CEM matches issuers. The R^2 implies that the strict approach fits better when there is no matching on the issuer level.

Furthermore, adding liquidity as a control variable was helpful to control for potentially omitted variables as liquidity was significant in the regression. The sign of the liquidity coefficient is positive in all the regressions and, therefore, consistent with Löffler et al. (2021). A positive coefficient implies that higher bid-ask spreads go along with higher yields. This relationship suggests that investors demand a liquidity premium and require higher expected returns on less liquid bonds.

Where Larcker and Watts (2020) find a 15-20 bps greenium, this thesis finds a greenium between 11 and 29 bps, depending on the approach's strictness. This difference might be explained by this thesis's exclusion of bonds with withdrawn credit ratings and strict data inclusion criteria concerning the bond size. Moreover, differences might arise due to their global approach, and this thesis focuses on bonds denominated in euros. Perhaps even more essential, CEM (2), this thesis's strict approach, matches bonds on additional characteristics and, therefore, likelier extracts the unbiased greenium. The greenium might be higher because the stricter CEM also accounts for ECB and REPO status, and Figure 10 and Figure 11 signal that climate bonds are more likely to obtain such beneficial qualifications.

TABLE 5

GREENIUM ESTIMATES PER SECTOR FOR LOOSE CEM MATCHING ON ISSUERS.

	Utilities	Financials	Other
Green label significant	YES***	NO	NO
Green Bond=1	-0.1620	-0.1123	-0.1096
	(0.010)	(0.109)	(0.266)
Observations	6	121	49
F	1433.41	4.90	0.51
R^2	0.9914	0.2669	0.0422
Control variable (=liquidity)	YES	YES	YES
Fixed Effects	NO	NO	NO
CEM criteria	Loose+issuer	Loose+issuer	Loose+issuer
CEM type	(1b)	(1b)	(1b)

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. CEM applied loose criteria (1b) specified in Table 6.

Table 5 explores if the insignificant greenium estimated by CEM (1b) differs per industry. For example, investors might view conventional utility bonds positively from an ESG perspective due to the central role of utilities in the energy transition. In this light, investors might instead purchase a more attractively priced conventional bond if they expect green utility bonds to be relatively expensive due to the greenium. The greenium of utilities could thus be relatively amplified because utilities tend to have positive ESG ratings. However, on the other hand, the halo effect might also drive yields of conventional bonds down because ESG ratings are given on the corporate level and not on the bond-specific level. In other words, the conventional bonds of utilities might be considered green, and the green label might matter less.

Surprisingly, Table 5 provides highly significant evidence that utilities earn a greenium, and investors might perceive these bonds as dark green. The green coefficient for financials and other sectors is insignificant, albeit the negative direction of the green label coefficient signals a greenium.

5 Conclusion

Gianfrate and Peri (2019) found a 17 bps greenium using PSM, while Löffler et al. (2021) discovered greeniums ranging from 16 to 24 basis points with PSM. However, propensity score matching (PSM) is susceptible to bias and pair imbalances (Guo et al., 2020; Iacus et al., 2012; King et al., 2011). The thesis, therefore, applied highly robust coarsened exact matching algorithms of Iacus et al. (2012) and estimated the green bond premium in two steps.

This thesis discovers that greenium size and significance depend on applied CEM criteria. In addition, estimated significant greeniums range from 12.99 to 29.83 basis points for the entire sample period, depending on CEM strictness. Furthermore, while the greenium is always significant for the strict CEM, the greenium loses significance if the loose CEM matches on issuer level. However, significance persisted for utilities in the loose CEM that matched bonds on issuers.

This thesis improved the data inclusion criteria of previous authors in several ways. Furthermore, unlike Löffler et al. (2021), this thesis excluded bonds whose long-term credit rating is withdrawn to prevent matching investment-grade to high-yield bonds, following the recommendation of Agliardi and Agliardi (2021). Furthermore, this thesis only included bonds with amounts outstanding higher than 500 million USD to ensure liquidity, following Harrison (2022). Note again that this size filter only refers to the outstanding debt's size, measured by Eikon in USD. Only euro-denominated bonds were included in this study.

A primary contribution lies in operationalising a stricter algorithm of the relatively novel coarsened exact matching method to estimate the greenium. As an extra contribution, this thesis improves the operationalisation of the CEM by Löffler et al. (2021) by using stricter matching criteria and identifying additional variables on which green and non-green bonds are matched. An additional methodological improvement is that this thesis explored issuer matching and did not include fixed effects in the primary regression, following the recommendation of Larcker and Watts (2020). Fixed effects, however, were still employed as a robustness check.

Tolliver et al. (2019) reported that identifying appropriate control variables to match the comparable green and non-green bonds is challenging. Therefore, the thesis added liquidity to control for potentially omitted variables in the regression that estimates the green bond premium. Liquidity was selected as a control variable because Boutabba and Rannou (2022) report that green bonds tend to be less liquid than conventional bonds and, therefore, might affect the greenium.

This paper has the following limitations. First, Iacus et al. (2012) indicate that the treatment coefficient provides an unbiased reflection of the treatment effect on the dependent variable. However, the CEM's multivariate L1 distance remained higher than 0 and higher than the L1 reported by Löffler et al. (2021). As a result, the CEM algorithm did not produce perfectly balanced matches, and the green label may not reflect an unbiased greenium estimate. However, Iacus et al. (2012) note that although CEM does not produce an L1 of 0, pair imbalances are still decreased.

However, liquidity was used as a control variable to mitigate a potential bias, and the strict CEM matched bonds on several novel characteristics. Moreover, it is questionable if adding more matching criteria made sense, given that CEM discards more bonds as the number of matching criteria increases.

In addition, CEM does not prioritise covariates criteria in matching. For instance, the credit rating is arguably essential for bond pricing, while REPO eligibility is a nice one to have.

Furthermore, because CEM algorithms had relatively few observations to choose from in the thesis, the relatively small sample size may have harmed the multivariate L1 distance or pair balance. However, the tiny sample size was purposefully chosen to estimate the greenium for the euro and corporates because the euro is the dominant currency globally. In addition, corporates play a critical role in the energy transition (Abay et al., 2022). Furthermore, the 500 million USD inclusion criterium discarded 83% of bonds. This strict criterium limits the study's external validity since the thesis estimated the greenium for large bonds. However, this was deemed a necessary inclusion criterium to ensure liquidity, which was especially relevant because the thesis estimated the greenium for the secondary market.

The matching algorithm with strict criteria rejected many bonds. Therefore, the stricter algorithm makes it more challenging for future researchers with fewer observations to obtain results that rely on a sufficient number of observations. Therefore, strict matching settings could be problematic for researchers who want to investigate the greenium for specific industries, issuance periods, or ESG labels.

Finally, this research only considers the secondary bond market. The dataset from Reuters Eikon did not contain bond yields at issuance, making it not feasible to investigate the greenium for the primary market. It could have been possible to compare the prices at issuance. However, because the number of bonds in the dataset is limited, the chance is still too small that two similar bonds in the dataset are issued on the same day. Same-day issuance is critical for internal validity because issue prices may depend on market conditions.

Fruitful avenues for future researchers are as follows. As Boutabba and Rannou (2022) observed, green bonds are identified as either green or regular. Ideally, however, it would be interesting to investigate if various ''shades of green'' carry different green bond premiums. For example, one possible proxy for greenness could be to investigate whether green bonds with a second-party opinion label have a different greenium than other green bonds. Therefore, an additional proxy for bond greenness in future research could be S&P green instrument evaluations or Sustainalytics ESG ratings. These ESG ratings could assist in assessing whether investors use green bonds to greenwash their investments. For example, suppose a green bond of an issuer with an unfavourable ESG rating nonetheless earns a greenium. In that case, investors may not desire to have a positive effect but have a green bond allocation.

Huynh et al. (2022) argue that investors should disregard the green label because they do not receive additional economic rights such as collateral or seniority. However, the green bonds that adhere to the EU green bond standard may benefit investors via tax breaks, enhanced REPO eligibility and better ECB haircuts. Moreover, as Figure 10 suggests, green bonds are already more frequently ECB eligible today. In this light, future researchers could investigate the halo effect, first coined by Basar and Krebbers (2019). The halo effect refers to the narrative that green issuers have better access to debt capital markets. For example, this effect could be measured by comparing oversubscriptions to conventional issues between issuers green and conventional issuers.

Furthermore, ESG ratings may become secondary credit ratings. ESG ratings may signal improved market access of green issuers, allowing them to continue issuing debt securities during market distress. In this light, a test of improved market access of green bond issuers could be to see if green issuers have better access during market turmoils or credit crunches. Investigating green issuers' market access during market uncertainties may be challenging given the insufficient data points. However, examining the COVID-19 period may be interesting. Figure 1 and Figure 2 indicate a decrease in bond issuances during COVID-19, signalling increased risk aversion among investors and a preference for holding cash rather than conventional bonds.

Moreover, it would be interesting to investigate if the European Union's green bond taxonomy affects the greenium. For example, market participants may examine bonds that adhere to the new taxonomy as greener than "regular" green bonds due to the additional disclosure. Thus the greenium on green bonds that adhere to the taxonomy may be amplified. In other words, bonds that follow the green taxonomy and the EU green bond standard may become ''gold-plated'' bond issuances and expand pricing differences. In addition, it might be interesting to investigate whether small bond issuers can comply with the increased regulations that may accompany the issuance of these gold-plated green bonds.

Finally, future scholars could investigate sustainability-linked bonds (SLBs) pricing. This suggestion, however, is only for several years ahead because, at the time of writing, there were insufficient SLBs issued to do an exhaustive analysis. Because, unlike green bonds, SLBs are not asset-linked, they may be appealing to companies whose investments are dominated by OPEX rather than CAPEX programmes. In addition, SLBs, unlike green bonds, are linked to KPIs such as greenhouse gas emission reductions relative to a specific base year. It will be interesting to look into pricing advantages because SLBs could be appealing to companies that still need to switch to clean energy, like fossil fuel producers. Finally, SLBs may appeal to investors because reducing greenhouse gas emissions stops planetary warming and not whether an investment is asset-linked. After all, SLB issuers have more room to improve their carbon footprints.

On the other hand, SLB issuing firms may still be relatively polluting. This adverse ESG profile could cause investors to see the conventional bonds as ''brown'' instead of conventional, creating an inverse halo effect. As a result, estimating the greenium for SLBs may be worthwhile because it is unclear which narrative will win.

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7 Appendix

FIGURE 5

THE PROPORTION OF GREEN AND CONVENTIONAL BONDS IN THE SAMPLE.

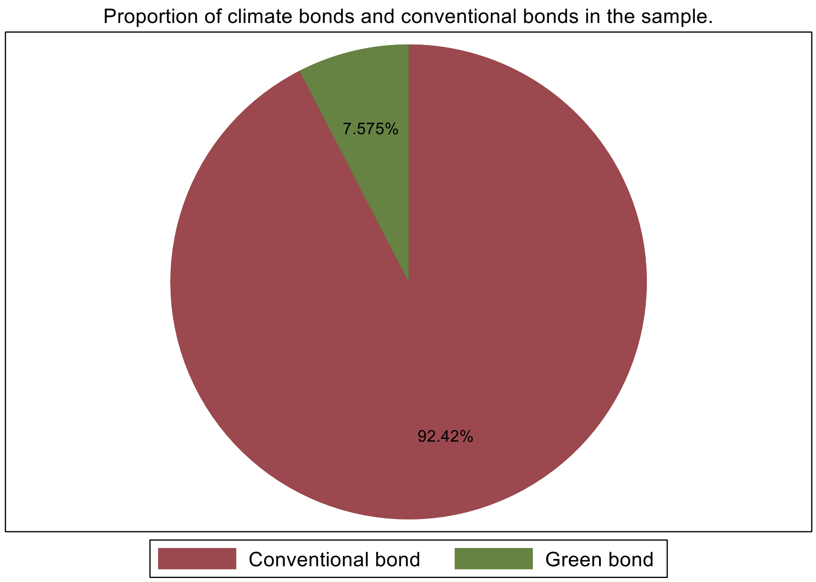


FIGURE 6

INVESTMENT-GRADE VERSUS JUNK GRADE FOR GREEN AND REGULAR BONDS.

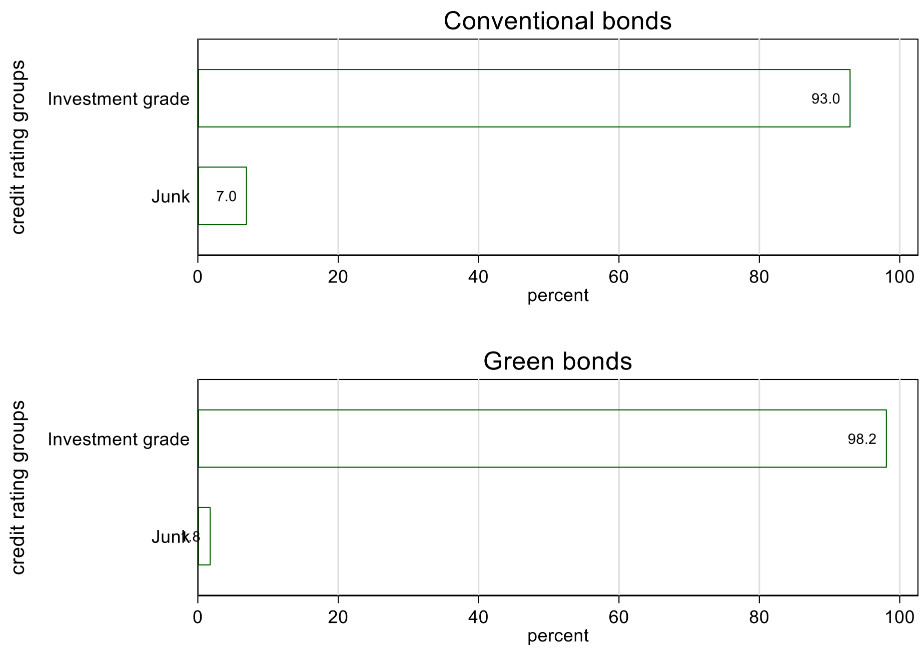


FIGURE 7

CREDIT RATINGS OF REGULAR AND CLIMATE DEBT SECURITIES.

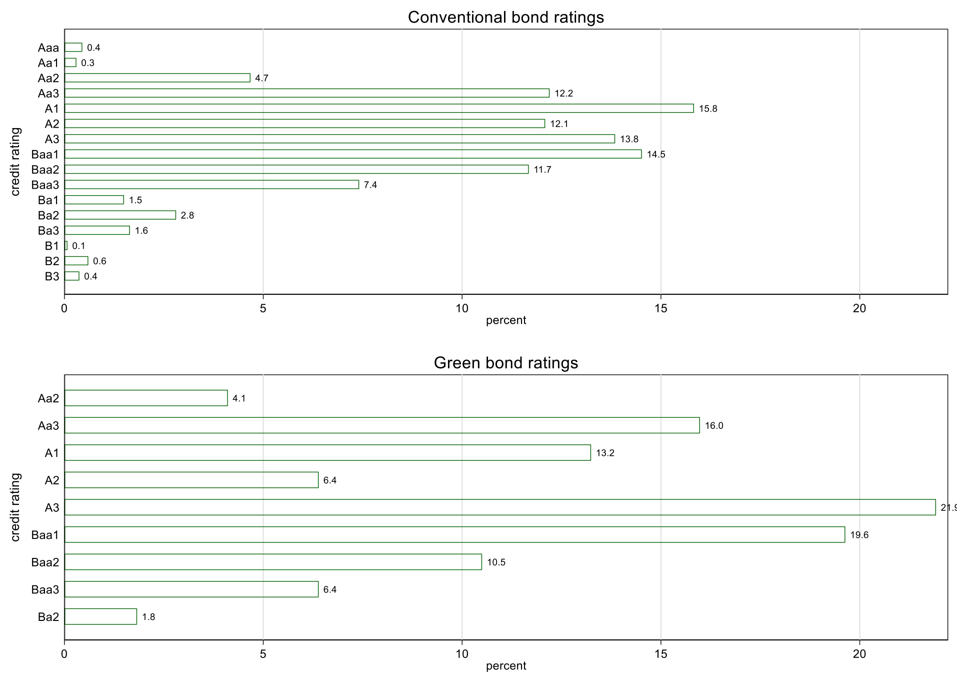


FIGURE 8

USE OF PROCEEDS OF GREEN BOND ISSUANCES.

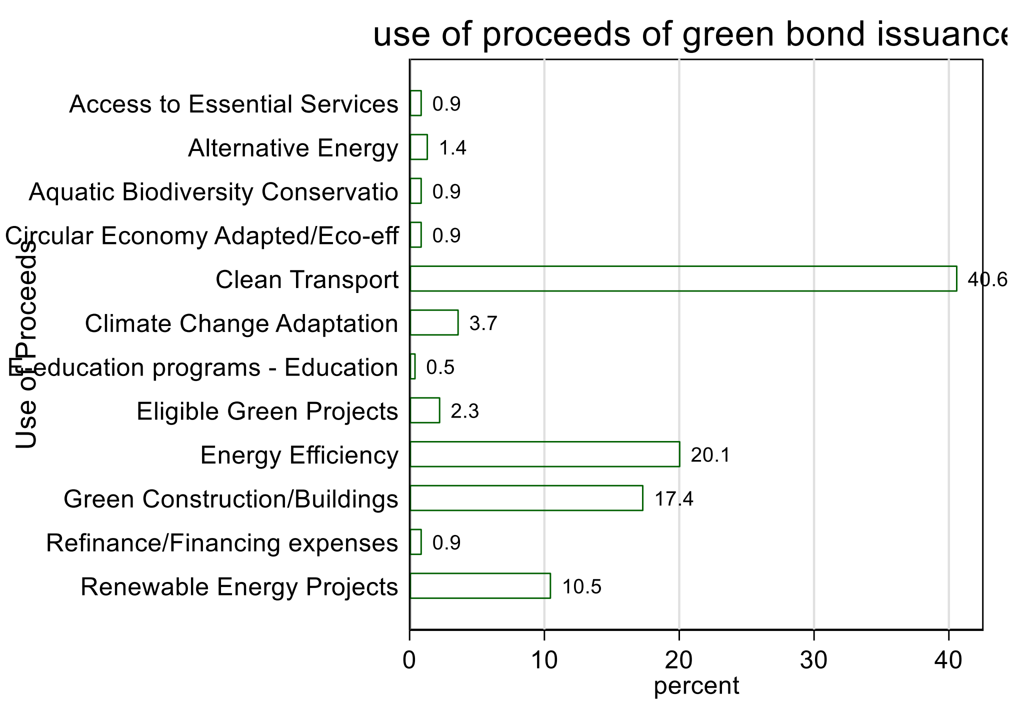


FIGURE 9

THE TENOR FOR CONVENTIONAL AND GREEN BONDS.

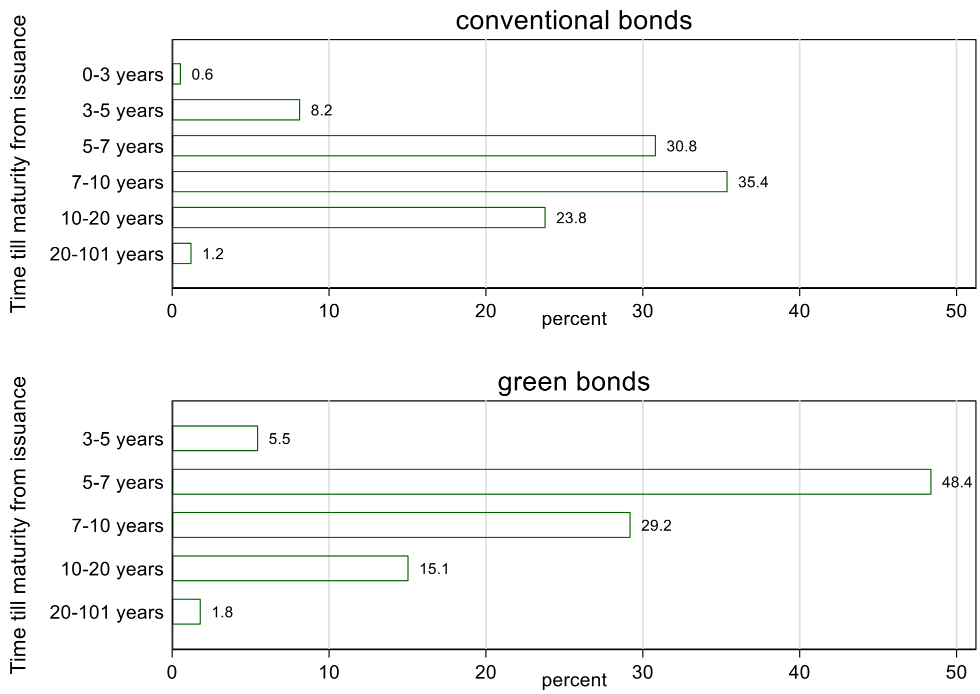


FIGURE 10

ECB QUALIFICATION FOR CONVENTIONAL AND GREEN BONDS.

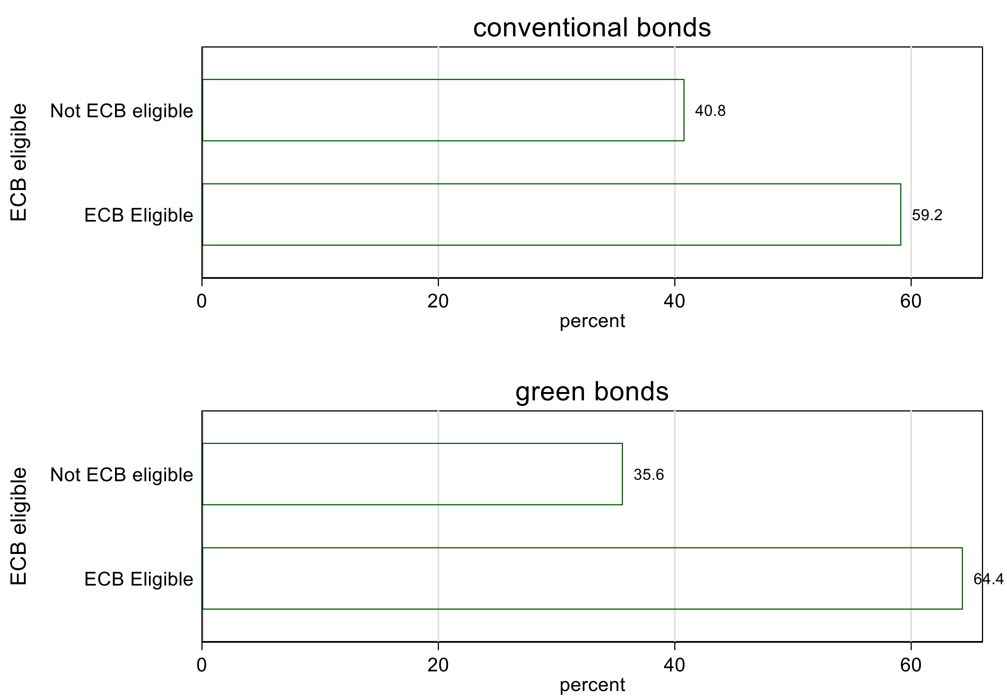
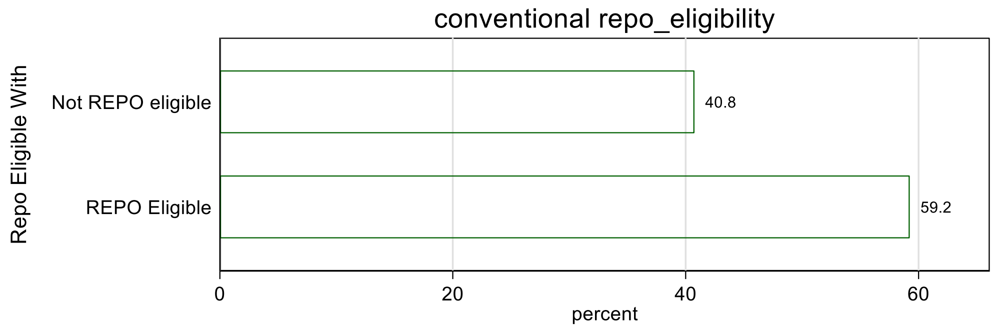


FIGURE 11

REPO ELIGIBILITY FOR CONVENTIONAL AND GREEN BONDS.



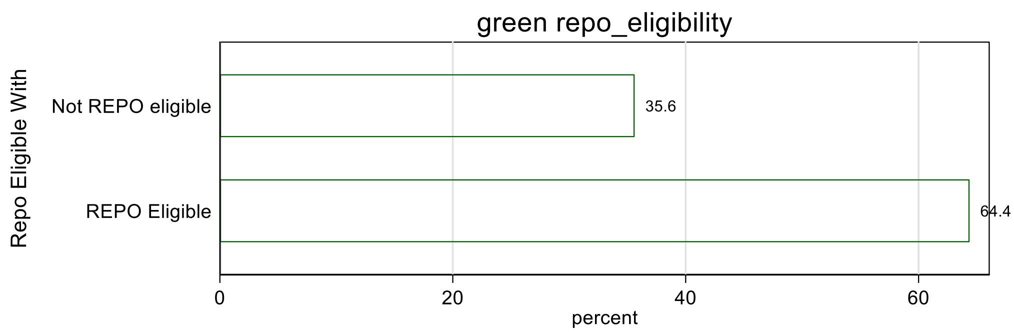


FIGURE 12

GREEN BOND ISSUER EXPERIENCE CONCERNING CLIMATE BOND ISSUES.

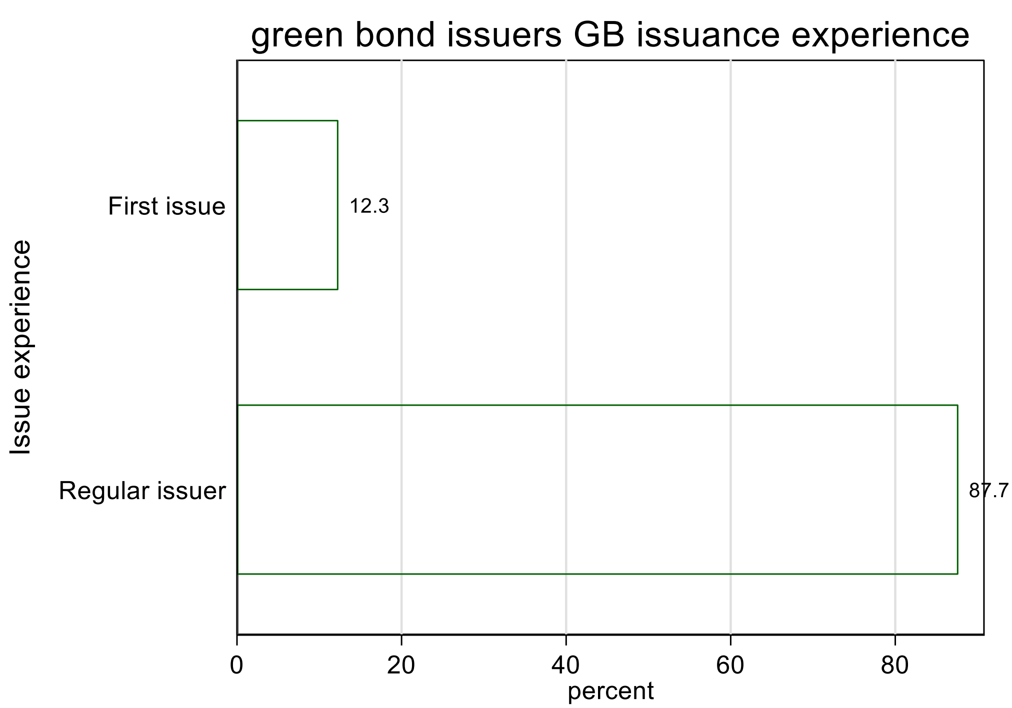


FIGURE 13

RELATION BETWEEN YIELD TO MATURITY AND CREDIT RATINGS FOR ALL BONDS IN THE SAMPLE.

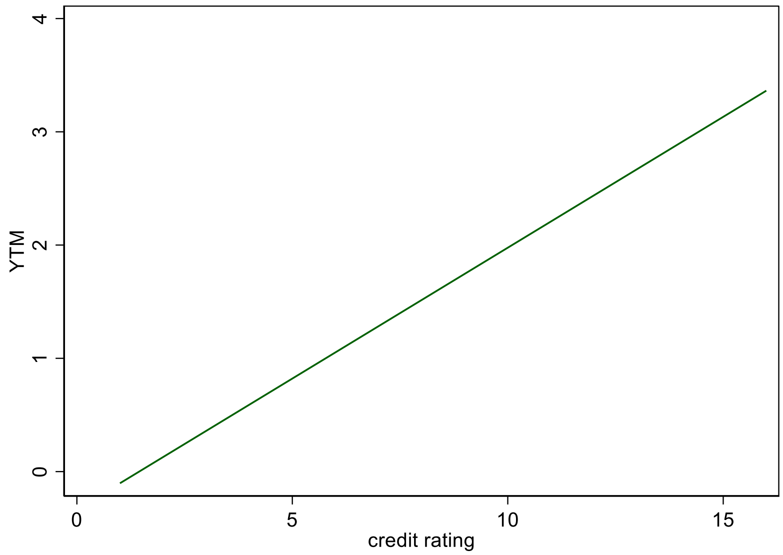
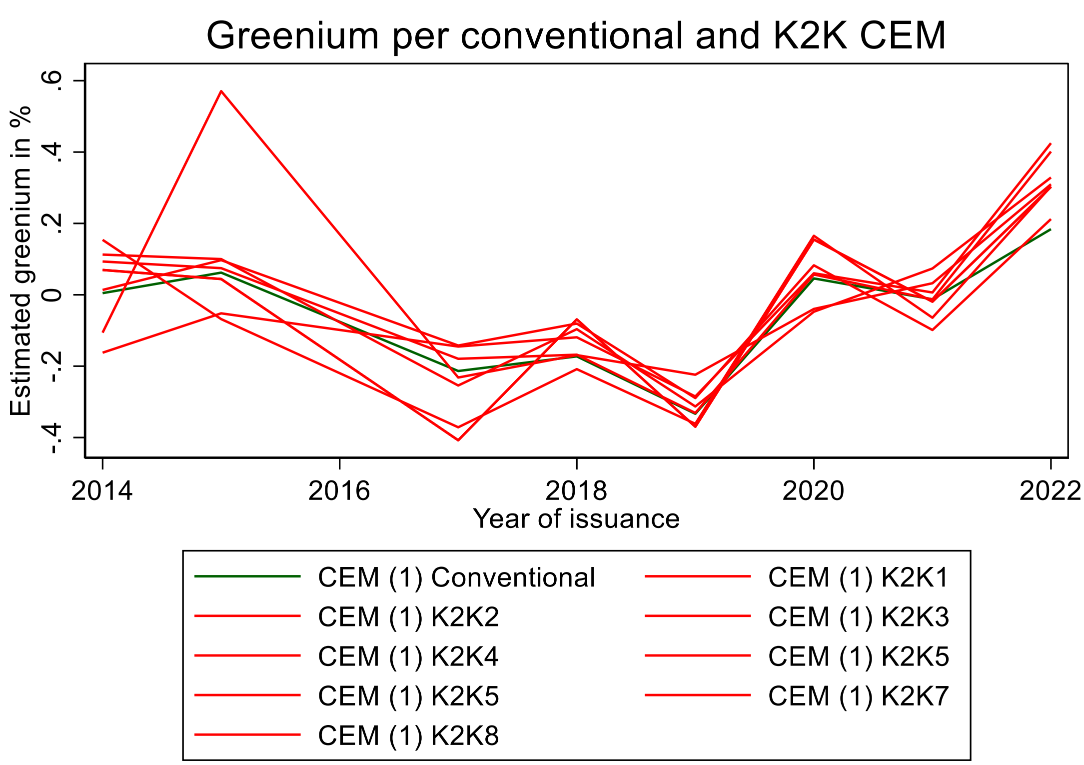


FIGURE 14

CEM (1) AND THE ESTIMATED GREENIUMS ESTIMATED BY THE K2K CEMS OF CEM (1).



Note: Each time Stata runs the same K2K, a different balance and adherend different greenium is estimated. These greeniums vary wildly. For instance, 2016 is left out of the figure because the K2K estimated a 900 bps greenium which is highly unrealistic. In addition, discarding of observations and extreme greenium estimates confirm that the conventional CEM is best suited for estimating the greenium.

TABLE 6

CEM MODELS OVERVIEW.

CEM type No.	(1a)	(1b)	(2a)	(2b)
CEM criteria	Loose	Loose+issuer	Strict	Strict+issuer
Matching on issuer	NO	YES	NO	YES
Regression type:	OLS	OLS	OLS	OLS

Note: The loose CEMs have the relatively loose matching criteria of the Löffler (2021) paper. Strict CEMs are relatively strict because they match additional bond characteristics constructed by this thesis. The loose CEM or the Löffler et al. (2021) CEM matches bonds on sector, issue year, tenor year, rating and seniority. The strict CEM matches on sector, country, issue year, tenor year, rating, seniority, amount outstanding, coupon, callability, REPO qualification and ECB qualification. Table 4 displays the estimated greeniums for the CEMs.

TABLE 7

FIXED EFFECTS MODELS.

Analysis No.	(3)	(4)
Issuer fixed effects	YES	NO
Sector fixed effects	NO	YES
Control variable liquidity	YES	YES
CEM	NO	NO

Note: Table 4 displays the estimated greeniums for the fixed effects models.

FIGURE 15

ECB ELIGIBILITY OF CONVENTIONAL BOND FOR THE TWO ISSUANCE PERIODS.