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Estimating the green bond premium and its determinants for EUR-denominated green bonds

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Abstract

This paper studies the existence and the determinants of the green bond premium in the European bond market, using a dataset of 4598 conventional and 311 green bonds from Bloomberg and Dealogic. Due to the large heterogeneity in methodologies, past evidence has produced widely varying results on the green bond premium. This research aimed to improve the methodological approach to estimate the existence and determinants of the green bond premium by using stricter criteria to match green and conventional bonds and comparing results of the relatively new coarsened exact matching (CEM) and more widely used propensity score matching (PSM) methods. The main result of this paper is that there is no green bond premium for the whole sample. However, green bonds do appear to be more expensive in the financial sector and in the period of 2014-2017.

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Compliance statements

Non-plagiarism statement

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1 Introduction

This paper studies the green bond premium for green bonds denominated in the euro currency. The paper aims to answer the following research question:

Does a green bond premium for EUR-denominated bonds exist and if so, what are the determinants of that premium?

Green bonds are fixed income securities that are similar to conventional bonds, except that their proceeds should be mainly used for green projects. Green bonds appeal to a wide range of investors because they combine standard financial characteristics with a specific use case, namely green projects. Green bonds thus offer issuers and investors both a low-risk financial instrument and an opportunity to reach their sustainability goals, making green bonds an effective instrument to stimulate capital flows to green investments (Bachelet, Becchetti, & Manfredonia, 2019). At first glance, conventional and green bonds are alike in fundamental characteristics and therefore there is no rationale for a difference in pricing (Slimane, Da Fonseca, & Mahtani, 2020). Despite this similarity, the German government issued one conventional and one green bond with identical characteristics (Löffler, Petreski, & Stephan, 2021). The green bond had a lower yield to maturity of 2 basis points (bps) in the secondary market, indicating investors were willing to pay more for the green bond[1]. This paper will thus investigate whether premium is paid on other bonds as well.

There is a need for critical research on the green bond premium as approximately 25 studies have empirically investigated whether a pricing difference between conventional and green bonds exists without conclusive results. It is necessary to find robust results for the pricing of green bonds for issuers, investors and policy makers. An efficient green bond market aligns the motives of these market participants and increases capital flows to green projects, accelerating the desired transition to greener economies and lower carbon emissions (Maltais & Nykvist, 2020).

To study this important topic, the heterogeneity in results on the green bond premium is worrisome. Authors in this field have used varying methods to study to create pairs of similar conventional and green bonds. Most articles conclude green bonds are either issued or traded at lower yields (hence, are more expensive). This strand of literature argues this is due to a mis-

[1] In bond pricing, lower yields ceteris paribus lead to a higher price

match of supply and demand. On the supply side, authors cite high costs and difficulty in finding eligible projects as a barrier (Hyun, Park, & Tian, 2020). On the demand side MacAskill, Roca, Liu, Stewart, and Sahin (2020) argued green bonds are in great demand which often results in oversubscription and thus higher prices. The demand for green bonds is attributed due to green mandates of institutional investors (Tang & Zhang, 2020) or non-pecuniary motives (Sze, Wan, & Wong, 2020). Another strand reports no difference in the pricing of conventional and green bonds, indicating investors are unwilling to forgo on profitable investments (Larcker & Watts, 2020). Few articles found a green bond discount. This strand argues investors only want to pay more for green bonds when the issuer has a credible reputation of ethically using the proceeds of the bond (Kapraun & Scheins, 2019). In numeric terms, the difference in yield estimates of these past articles ranges from -18 bps to +8 basis points (bps).[2] Larcker and Watts (2020) argued that the heterogeneity in results can be attributed to methodological misspecifications that led to biased results, mostly because of inadequately controlling for bond price determinants or comparing dissimilar conventional and green bonds. It appears the most important problem in studying the difference in yields between green and conventional bonds is to find adequate control variables or similar conventional and green bonds (Zerbib, 2019).

This paper builds on past studies of Gianfrate and Peri (2019), Larcker and Watts (2020) and Löffler et al. (2021) that use non-parametric matching methods such as the coarsened exact matching (CEM) methods and propensity score matching (PSM) methods to match the bonds and then estimate the yield differences. This research aims to review and improve the methodological approaches of these papers in two ways. Firstly, this paper uses the theoretically superior CEM matching method (King & Nielsen, 2019) to match conventional and green bonds[3]. Besides using an apparently more robust matching method (Löffler et al., 2021), this paper focuses on only one market. Past articles that studied multiple currencies at once showed the green bond premium varied widely across regions. Therefore, this research will focus on EUR-denominated bonds because more than half of green bonds are issued in the euro currency (I will present evi-

[2] For brevity, I will abbreviate green bond premium to 'greenium' hereafter. To be consistent with the past literature, the greenium is defined as the yield difference between a green and conventional bond. This will hold for most of the text. It will be clearly stated when the research refers to a difference in price. To be clear, this research will thus refer to the greenium as a negative difference in yield, or a positive difference in price. When a green bond has a positive difference in yield or a negative difference in price, I will refer to it as a green bond discount.

[3] PSM is used in more than 45,000 scholarly articles (King, Nielsen, Coberley, Pope, & Wells, 2011)

dence for this in figure 2). To adequately control for bond pricing determinants, this research also controls for eligibility of the European Central Bank (ECB) asset purchase program. Furthermore, this paper aims to extend the research on what drives the greenium by furthering research that investigated the effects of (i) the number of issues (Fatica, Panzica, & Rancan, 2020), (ii) ESG scores of the issuer (Kapraun & Scheins, 2019), iii) an external review (Hyun et al., 2020) and (Slimane et al., 2020), amongst others) and iv) differing use of proceeds (Russo, Mariani, & Caragnano, 2021). Using a sample of 4598 conventional and 311 green bonds, this paper finds no strong greenium for EUR-denominated bonds. However, this paper does present results that green bonds issued in the financial sector and that green bonds issued between 2014-2017 are more expensive. Furthermore, green bond specific characteristics also appear to have an effect on the yields of green bonds, except for the external review variable.

The paper is structured as follows. Section 2 describes the institutional setting of the green bond market and its developments. Section 3 critically reviews past empirical papers on the subject and synthesizes what authors in the field agree and do not agree on. Section 4 lays out the hypotheses this research will test to help answer the research question. Section 5 discusses the data retrieval process and compares the sample with similar papers. Section 6 describes the statistical methods I use to match the conventional and green bonds and how I analyse the green bond premium. Section 7 reports the results of the research. Section 8 summarizes the findings of the study, provides avenues for future research and lists limitations of this research.

2 Institutional setting

This section describes the institutional setting of the green bond market. It aims to provide an overview of the green bond market by discussing how a green bond is issued, the developments in growth and composition of the market and the important advancements in the market. Furthermore, this section investigates whether the heterogeneity in the results may be due to the specific institutional setting of green bonds.

2.1 Issuing a green bond

In essence, the process to issue a green bond is similar to issuing a conventional bond. Issuing a green bond requires additional reporting and, preferably, external verification (which will be discussed in section 2.4. An issuer should complete a green bond framework that complies with the commonly accepted guidelines of The Green Bond Principles (GBP) and Climate Bonds Initiatives (CBI). These two sets of guidelines are universally accepted (voluntary) standards that assist issuers in the process (Bachelet et al., 2019). A green bond framework is essentially a report that details for what projects the proceeds of the bond will be used. The proceeds of a green bond can be used for projects that i) invest in renewable energy, such as projects that invest solar, wind and hydro energy, ii) energy efficiency, such as projects that invest in green buildings, iii) agriculture and forestry, which includes reforestation and iv) other sustainability purposes, such as clean water management (Bachelet et al. (2019) & Gatti and Florio (2018)). Furthermore, it describes why the projects or other intended use cases comply with green definitions, how the issuer handles the proceeds and how it intends to report on the environmental impact to investors.[4].

Currently, there is no central institution that provides a green label to bonds. The founders of the Green Bond Principles (a group of large, multinational banks) decided that volume and recognition of green bonds was the first priority (Reed, Cort, & Yonavjak, 2019), concluding low entry barriers would allow the market to grow quickly and that the market as a whole would be able to discern between true green and non-green issuers. Still, issuers themselves label their bond as green (Cheong & Choi, 2020). Issuers are recommended to consult with specialized rating agencies (rating agencies and external verification procedure will be discussed

[4] Usually, an issuer is guided by an experienced bank when it first goes to the market (Maltais & Nykvist, 2020)

in subsectionrating) to ensure compliance with these standards, but this is not obligatory. The next subsection discusses the participants of the green bond market.

2.2 Market participants

This subsection sketches the market participants and their motives to enter the green bond market. The market can be categorized into three segments: issuers, investors and policy makers. Sze et al. (2020) note it is not necessary to invest in green projects through green bonds only. This begs the question what motivates these participants to participate in the market.

Starting with the issuers of green bonds, many entities issue green bonds, namely corporations, financial institutions but also sovereign, supranational and other agencies (SSA). Issuers have a strong financial motive to enter the green bond market, but there are non-financial motivations as well. By issuing a green bond, an issuer can improve its reputation, attract a broader investment base and with that improve their access to financial capital (Sze et al., 2020). An issuer improves its reputation as a sustainable entity, as going through the rigorous process of issuing a green bond sends a strong signal of commitment to sustainable business practices to the market. Furthermore, investors appreciate the additional transparency and disclosure an issuer provides by issuing green bonds (Kapraun & Scheins, 2019). Flammer (2020) argued green issuers attract long-term investors with an increase of 21% and issuing green bonds leads to positive stock announcement returns. Despite these financial incentives, issuing green bonds is not cheap due to the required additional reporting[5]. Aside from pure financial motives, Maltais and Nykvist (2020) argue issuers are incentivized by non-financial motives such as being able to offer new products to clients and creating internal synergies.

Secondly, the green bond market has attracted many types of investors. Investors are either motivated by seeking a traditional profit or seeking a sustainable and impactful investment (Deschryver & De Mariz, 2020). The main innovation of green bonds that attracts all types of investors is the ‘use of proceeds’ aspect, which provides quantitative information for investors to better support investment decisions. Dorfleitner, Utz, and Zhang (2021) state that investors are increasingly demanding projects that mitigate climate change due to the prolonged low-interest rates environment and because investors have become more aware of the risks of climate change

[5] Estimates vary between 0.1 and 0.6 bps, (Slimane et al., 2020)

[6] to the financial sector as a whole[7], incentivizing investors to hedge for this climate risk by investing in projects that combat climate change (Banga, 2019).

Thirdly, policy makers are motivated to engage with the green bond market as another way to guide the transition to less carbon emissions. Green bonds provide policy makers with an instrument to stimulate financial capital towards green projects more easily. Moreover, green bonds assist in implementing climate policies (Shishlov, Morel, & Cochran, 2016).

To summarize, green bonds appeal to both institutional and other investors as green bonds provide them with financial and non-financial benefits (Shishlov et al. (2016), (Deschryver & De Mariz, 2020)). Furthermore, policy makers can facilitate investments into green projects. Green bonds thus present a financial instrument that aligns the incentives of issuers, investors and policy makers (Maltais & Nykvist, 2020). However, as the market is still evolving, several problems remain that could hinder the growth of the market.

2.3 Market problems

This subsection describes the main problems of the green bond market. The main problems of the green bond market are greenwashing and a lack of supply

Greenwashing means that projects seem green and beneficial to the environment, but do not provide significant or any benefits in reality (Banga, 2019). Examples of this are the $6bn green bond issue of Mexico City Airport in 2016 to construct a new airport (Kapraun & Scheins, 2019) and a green bond issuance in China to repay bank loans (Deschryver & De Mariz, 2020), which did not benefit the environment in any way[8]. As we established in section 2.2, issuers have strong financial incentives to issue green bonds. Cheong and Choi (2020) note that the combination of i) financial benefits, ii) issuers themselves labelling their bonds as green and iii) compliance with guidelines still being voluntary (Kapraun & Scheins, 2019) are factors that contribute to greenwashing. Deschryver and De Mariz (2020) point that greenwashing is however not without risks for issuers nor investors[9]. Undersupply is another problem of the green bond

[6] Some reports state climate change could lead to severe losses in economic activity, as much as 10% of the U.S. economy by 2100. *https://nca2018.globalchange.gov/*

[7] Klomp (2014) for example found that large-scale natural disasters increase the likelihood of banks' default.

[8] The aviation industry is one of the most polluting industries (Kapraun & Scheins, 2019)

[9] Volkswagen suffered a severe reduction in the stock price following the news of having cheated with emission tests of their new engines in 2015

market. Deschryver and De Mariz (2020) state especially smaller issuers face multiple barriers before being able to issue a green bond. Firstly, issuers struggle to find eligible projects that also appeal to investors. Usually, projects should be larger than 300 million to be attractive financially. Secondly, the long and expensive process to issue a green bond also presents a barrier to issue a green bond. As a result, green bonds are often oversubscribed.

In sum, the main impediment to further growth and efficiency in the green bond market is the risk of greenwashing. Past authors collectively argue trust in the green label is paramount (Reed et al. (2019), Shishlov et al. (2016) and Dorfleitner et al. (2021)). Deschryver and De Mariz (2020) states the lack of a universal standard of what constitutes a green project is the root of the problem, leading to higher transaction costs and lower efficiency in the entire market. Until a global standard is in place, external rating agencies fulfil the role of reviewing whether green bonds are really green. I will discuss these rating agencies and external reviews in the next subsection.

2.4 External reviewers

This section briefly lays out what an external review is, what types there are and what entities perform such a review.

The GBPs list three types of external reviews, namely i) a second-party opinion (SPO), ii) a verification report and iii) a green rating. Firstly, specialized rating agencies such as Sustainalytics or Cicero (amongst others) provide SPOs attempt to provide an objective review of the compliance of the green bond framework of the issuing company with the GBP and the greenness of the bond.[10]. Berg, Koelbel, and Rigobon (2019) notes that because the rating agencies use different methodologies to review the frameworks, the ratings of the frameworks may differ per agency which may lead to confusion how green a framework actually is[11]. Secondly, large auditing firms such as EY and Deloitte prepare verification reports. These reports tend to solely focus on the compliance with the GBP (Dorfleitner et al., 2021), rather than also providing a qualitative re-

[10] The rating agencies use different methodologies to review the frameworks. Sustainalytics provides a thorough analysis of the framework, Cicero also provides a qualitative review and a scale of greenness. For example, a dark green evaluation reflects that a framework provides long-term, sustainable solutions instead of quick fixes.

[11] Berg et al. (2019) finds a correlation of 0.6 among ratings. The correlation of results of traditional rating agencies that review regular bonds is above 95%.

view like Cicero. Specialized firms are arguably better at gauging the environmental impact, so those are preferred over these firms. Thirdly, traditional rating agencies such as Fitch and S&P provide green ratings on a scale from one to five, but reviews are not very common. MacAskill et al. (2020) documents that the rate of externally reviewed bonds is increasing, which is a positive trend[12]. The next section discusses the growth of the market and reviews the drivers of that growth.

2.5 Market developments

This subsection aims to describe the development of the green bond market by discussing the growth of the market, changes in the composition of the market and developments in standardization and regulations.

2.5.1 Market growth

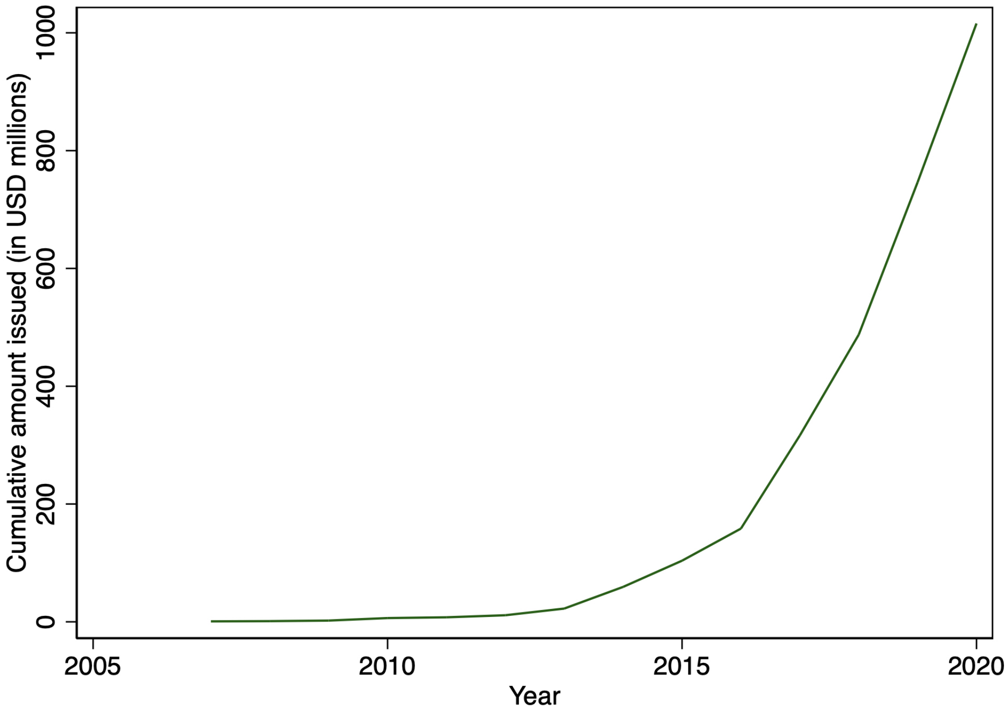
The first green bond was issued in 2007. Figure 1 shows the global cumulative growth over the years[13]. Currently, the green bond market exceeds $1trn in terms of amount issued and although it is still small compared to the regular bond market (Maltais & Nykvist, 2020), the market is no longer a niche segment anymore (Kapraun & Scheins, 2019). Several factors contributed to the growth of the market. Firstly, the introduction of standards such as the GBPs led to a better understanding of green bonds as an instrument. As discussed in subsection 2.3 more transparency was required to lure investors to the market. As we can see, issuance volume increased rapidly after the introduction of the Green Bond Principles in 2014 (Swinkels, 2021). As a result of increased understanding of the product and interest in the market, both issuers and investors recognized the potential of the green bond market (Maltais & Nykvist, 2020). Secondly, investors have become more aware of potential financial consequences of climate risk and therefore demanded more sustainable investments. Deschryver and De Mariz (2020) found European pension funds increased their presence in the market due to their investors' demands. Thirdly, Liaw (2020) states governmental support is another factor to market growth. The Paris Climate Agreement of 2015 is an example of this. The agreement urged investors to allocate more capital towards climate-oriented investments (Liaw, 2020). The next paragraph discusses

[12] In 2018, 83% of green bonds were externally reviewed, compared with 53% in 2014

[13] Data was manually collected from the CBI website: $https : //www.climatebonds.net/files/reports/cbi_sotm_2019_vol1_04d.pdf$

how the composition of the market changed.

Figure 1: Green bond market growth
This figure shows the cumulative issue amount of green bonds, globally

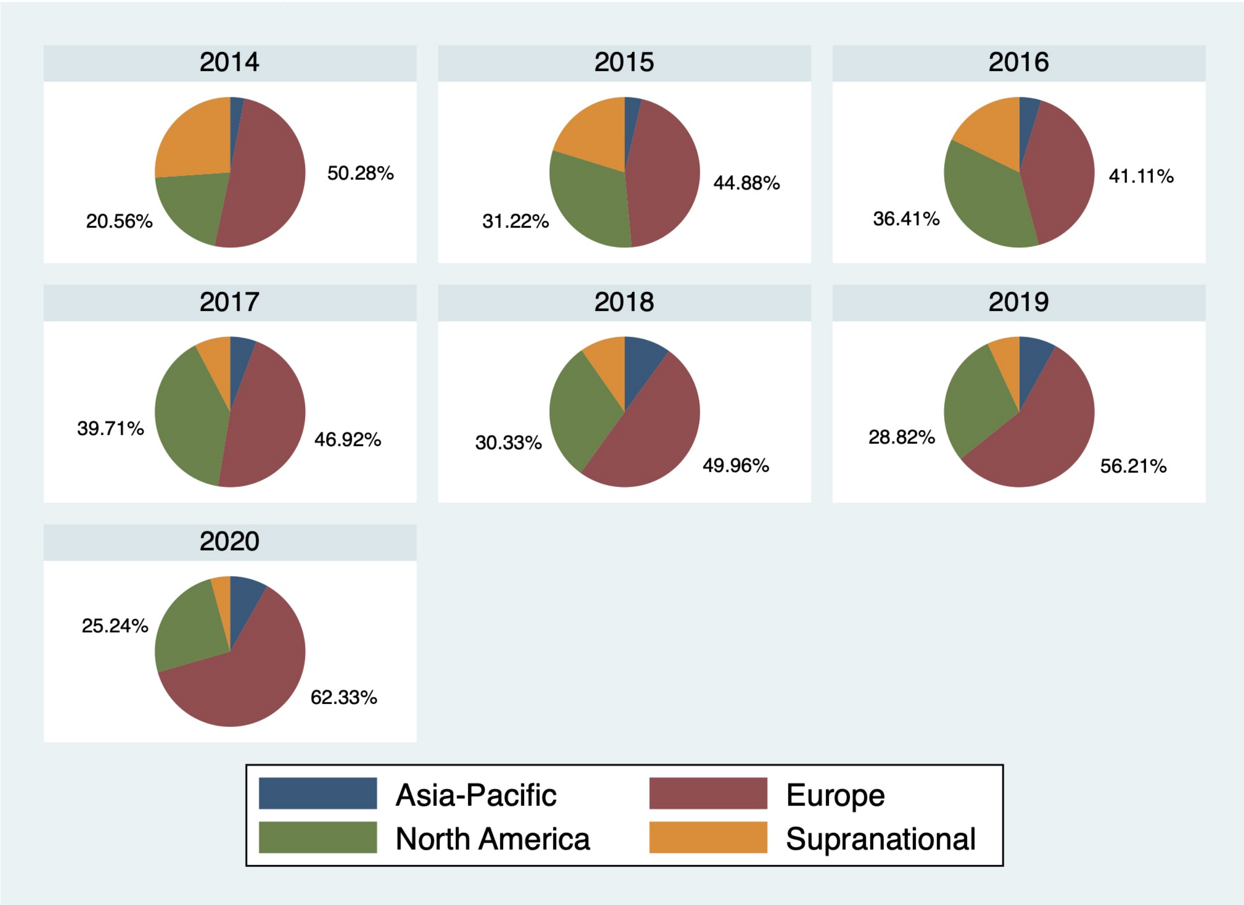


Swinkels (2021) reviewed how the composition of the market changed in terms of i) credit ratings, ii) currency, iii) sector and iv) tenor of the bonds. Firstly, the credit rating composition of the market has become more evenly distributed. In 2010, most of the bonds were rated AAA. Ratings are now distributed roughly similar from AAA to BBB. Gatti and Florio (2018) empirically found that with the introduction of the GBPs in 2014 issues with low credit ratings were also able to enter the market. Secondly, the euro currently is the dominant currency, with around 65% of issues being denominated in euros. Figure 2 shows that among the geographic regions where most green bonds are issued, a large part of green bonds are issued in Europe[14]. Thirdly, green bonds are now issued by all types of entities. Until 2013, only governmental agencies issued green bonds. In 2013, the private sector stepped into the green bond market. China entered the market in 2015 and France state was the first sovereign issuer in 2017. Globally, SSAs still issue the most green bonds with 30% of the market, whereas the other sectors issue roughly the rest of the green bonds. Lastly, Swinkels (2021) states the green bond market is maturing, as some

[14] Data was manually collected from the CBI website: $https://www.climatebonds.net/files/reports/cbi_sotm_2019_vol1_04d.pdf$

issuers now issue bonds with very long maturities. At the start of the market, maturities were relatively short, probably to satisfy investors who still viewed green bonds as risky securities. In sum, Swinkels (2021) showed the composition of the market has changed considerably over the last two decades. The next section zooms in on the latest regulatory advancement, the EU taxonomy.

Figure 2: Green bond issuances per region
This figure shows the volume of green bond issuances per region.



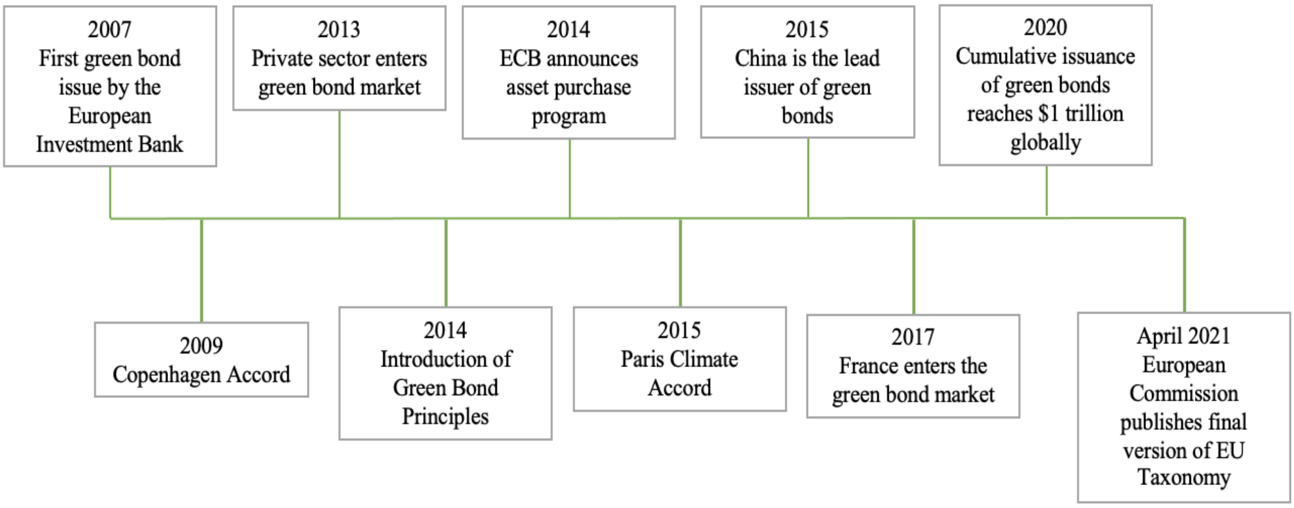
2.5.2 Political factors in the EU green bond market

As we established in section 2.3, the lack of a global standard impedes analysis for investors, which in turn impedes market efficiency and market growth. In 2018, the European Commission ordered a technical expert group (TEG) to address this problem by creating standardized definitions of sustainable investments (Schütze, Stede, Blauert, & Erdmann, 2020). As Reed et al. (2019) noted investors are able to more easily compare green with conventional bonds if the environmental performance of the bond is clearer. On April 21, 2021, the European commission published the final version of the EU taxonomy[15]. For issuers, the introduction of the EU taxonomy changes the process at the first step, namely determining what constitutes a green project. Compared to the GBPs, the EU taxonomy contains clearer definitions, but also stricter thresholds of what constitutes a green project. Therefore, projects that were eligible as a green project under the GBPs may not be considered 'green' under the EU taxonomy, potentially limiting the number of eligible projects further. However, the taxonomy has significant potential for globalizing the green bond market because it provides a comprehensive and detailed overview of what constitutes green projects. A consistent use of the taxonomy allows for better compatibility of issuers and projects, which may lead to lower greenwashing risk. Lower greenwashing risk may greatly increase investments in the green bond market as investors can make well-informed decisions.

Another development that had an impact on the green bond market was the ECB asset purchase program, initiated in 2014[16]. The goal of the program was to ensure price stability in the eurozone. The purchase program is an important factor in bond pricing. The program namely increases demand for bonds, which affects the yields and prices of the bonds. Bremus, Schütze, and Zaklan (2021) showed the purchase program negatively impacted the yields of green bonds, increasing prices. Therefore, it is important to take the effects of this program into consideration when investigating the greenium.

[15] $https : //ec.europa.eu/commission/presscorner/detail/en/IP_21_1804$
[16] https://www.ecb.europa.eu/mopo/implement/app/html/index.en.html

Figure 3: Timeline of events in the green bond market
This figure shows important events in the short history of the green bond market



2.6 Conclusion on institutional setting

This section provided an overview of the green bond market by showing the issuance process of green bond, reviewing the market participants and their motivations and discussing market developments. Figure 3 provides a summary of important events. In sum, issuing green bonds can be a tedious and complicated process. All types of issuers and investors have entered the green bond market, some with a traditional motivation to find a profitable investment, others are more motivated to invest responsibly. Maltais and Nykvist (2020) explains the growth of the green bond is due to the strong alignment of the incentives of investors, issuers and policy makers. The market has grown to over $1 trn in cumulative issues and will probably continue growing following the introduction of increased standardization. The next section will review how past articles have studied the greenium and summarize the results of these studies.

3 Literature review

This section reviews the existing literature and identifies gaps and inconsistencies in the literature. The review will show that the literature is currently inconclusive about the existence and the magnitude of the green bond premium. The section is structured as follows. Section 3.1 will explain the common methodological approaches the existing literature has employed and the different results these approaches produce. Section 3.2 discusses what potentially drives the differences in yield and prices by reviewing past evidence of green bond specific factors. Finally, I describe how this paper will fit into those methodological approaches and what the contributions of this paper are to the literature.

3.1 Overview of methodological approach to estimate the greenium

Table 1 shows an overview of papers on the green bond premium. As we can see, the methodological approach to discover the greenium indeed widely differs. In column 5, we can see that the existing literature predominantly uses regression models, but newer papers use treatment effects. In column 6 we can see many authors report a greenium, some papers report a green bond discount and some report no difference between conventional and green bonds.

Table 1: Summary of literature review

This table presents an overview of existing literature. The column "Data" describes how many green bonds are used for analysis. In the column "method", I describe the research methodology. FE stands for fixed effects, OLS for ordinary least squares, TE for treatment effects, RE for random effects. The final column displays the result on the yield differences. A negative sign indicates a greenium, a positive sign indicates a green bond discount.

Study	**Market**	**Scope**	**Data**	**Period**	**Method**	**Result on greenium (in bps)**
Bachelet et al. (2019)	Secondary	Global	89	2013 - 2017	OLS / FE	Mixed
Dorfleitner et al. (2021)	Primary & secondary	Global	250	2007 - 2020	OLS	No greenium
Fatica et al. (2020)	Primary	Global	1.397	2007 - 2018	FE	.-8 to 0 (depending on type of issuer)
Gianfrate and Peri (2019)	Primary & secondary	EUR	121 / 3,055	2013 - 2017	TE	Primary market: -15 to -19 Secondary market: -6 to -13
Hachenberg and Schiereck (2018)	Secondary	Global	63	2015 -2016	RE	-1
Hyun et al. (2020)	Secondary	Global	60	2010 - 2017	OLS / FE	Mixed
Immel, Hachenberg, Kiesel, and Schiereck (2021)	Secondary	Global	466	2007 - 2019	OLS	-8 to - 14
Kapraun and Scheins (2019)	Primary & secondary	Global	2,099 / 21,872	2009 - 2018	FE	Primary market: -15 Secondary market: +10
Larcker and Watts (2020)	Primary	USD	640	2013 - 2017	TE	No greenium
Löffler et al. (2021)	Primary & secondary	Global	1,928 / 186,685	2007 - 2019	FE	Primary market: -15 to -24 Secondary market: - 12 to - 15
Nanayakkara and Colombage (2019)	Secondary	Global	43	2016 - 2017	FE	-63
Preclaw and Bakshi (2015)	Primary	Global	N.A.	2014 - 2015	OLS	-16.7
Sheng, Zheng, and Zhong (2021)	Primary	CHN	418	2016 - 2018	TE	-7.8
Slimane et al. (2020)	Secondary	Global	532	2016 - 2020	FE	-2.17
Zerbib (2019)	Secondary	Global	135	2013 - 2017	FE	-1.8

Table 1 shows more authors conclude a greenium exists, but the magnitude is uncertain. Liaw (2020), Slimane et al. (2020) and Immel et al. (2021) conjectured the contrasting evidence is due to differences in methodologies. Broadly speaking, there are two methodological approaches that the existing literature has employed, namely regressions models and treatment effects. First, I will discuss the results of the papers that use regression models. Secondly, I will synthesize the papers that use treatment effects.

3.1.1 Results of OLS regression models

Preclaw and Bakshi (2015) studied the global primary green bond market and estimated a greenium of 16.7 bps (green bonds thus had a 16.7 bps lower yield on average), using an OLS model that controlled for average rating, option-adjusted duration, issuance amount and currency. The major concern with this early study was that a simple OLS model does not adequately control for invariant differences such as the type of issuer and coupon type for example. Without adequate control for these differences, it is uncertain that a greenium exists solely due to the effect of a green label. Immel et al. (2021) improved the methodology of Preclaw and Bakshi (2015) by using a more homogeneous dataset by applying rules of restriction to the dataset and also added the ESG score of the issuer as a control variable. They studied the global green bond market but focused on the secondary market and for a larger period. They found a less strong greenium, namely 8 to 14 bps. Bachelet et al. (2019) also focused on the issuer of the bonds, attempting to identify the yield difference between green and conventional bonds between institutional and private issuers and the effect of third-party verification. They used both OLS and fixed effects regression (this regression will be discussed in the following section) models in their research. Their OLS regression model produced a green bond discount of 4.7 bps. Hyun et al. (2020) performed a similar study as Bachelet et al. (2019) and reported a similar result, namely a green bond discount of 4.2 bps. Dorfleitner et al. (2021) used hybrid OLS regressions to estimate the greenium. They found no greenium for their sample. The results produced by OLS models are thus contradicting, as the yield differences ranged from -17 to +4 bps. Section 3.1.2 discusses the results from the segment within this strand of literature that use fixed effects models.

3.1.2 Results of fixed effects regression models

Table 1 shows fixed effects models are often employed to estimate the greenium as it can account for unobserved heterogeneity differences. Within this segment, most papers use yield spread as variable of interest (Zerbib (2019), Bachelet et al. (2019), Fatica et al. (2020) and Kapraun and Scheins (2019)), but some estimate the greenium through option-adjusted spread (Nanayakkara and Colombage (2019) and (Slimane et al., 2020)). These two segments will be discussed subsequently.

Zerbib (2019) used a global dataset and focused on the secondary market. He improved the methodological approach to estimate the greenium by introducing a matching approach to find comparable bond pairs. Specifically, he employed a model-free approach to match green bonds with almost identical characteristics, by requiring the currency, rating, bond structure, seniority, collateral and coupon type to be equal. He applied other rules for characteristics such as maturity and liquidity[17]. The result of his research was a greenium of 1.8 bps. Bachelet et al. (2019) followed Zerbib (2019) as they used a similar matching procedure. However, Bachelet et al. (2019) did not use a two-step regression method like Zerbib (2019) but used a fixed effects regression and estimated a green bond discount of 3.1 bps, which contrasts with the greenium of 1.8 bps of Zerbib (2019). Like Bachelet et al. (2019), Fatica et al. (2020) also focused on the differences between different types of issuers and the effect of third-party verification. They did not find a significant result for the overall sample but did large greeniums for supranational and non-financial issuers. Kapraun and Scheins (2019) studied the global primary and secondary markets, focusing on the differences of the greenium between different types of issuers. They found a greenium -15 bps for the primary market, but a green bond discount of 10 bps for the secondary market. Baker, Bergstresser, Serafeim, and Wurgler (2018) studied the US municipal green bond market and the patterns of ownership of green bonds. They estimated the greenium between 7.6 and 5.5 bps. As a reaction to this, Löffler et al. (2021) used other forms of matching methods, namely the propensity score matching (PSM) and coarsened exact matching (CEM) methods. I will discuss these methods in detail in section 6. Löffler et al. (2021) first matched the bonds and then used a fixed effects regression model. They reported a greenium between 20

[17] The rules included that (i) the maturity of the bond could not differ more than two years, (ii) issue size of a conventional bond could not be larger than four times the size of a green bond issue and (iii) the issue date of a conventional bond could not differ more than six years.

and 15 bps, depending on the matching method.

Nanayakkara and Colombage (2019) criticized the use of yield spread differences to compare credit spreads, stating option-adjusted spread is a better proxy for the credit spread of corporate bonds. Studying the global secondary market and focusing on corporate green and conventional corporate bonds, they found a strong greenium of 62.7 bps. Slimane et al. (2020) followed Nanayakkara and Colombage (2019) and defined the greenium as the difference between the OAS for green and conventional corporate bonds, estimating a much smaller greenium of 2.17 bps.

3.1.3 Results of other regression methodologies

Hachenberg and Schiereck (2018) used a random effects model. They combined the research of Nanayakkara and Colombage (2019) and Zerbib (2019), using a more comprehensive dataset than Nanayakkara and Colombage (2019) while using a roughly similar methodology as Zerbib (2019) and found a small greenium of 1 bps.

In sum, the results from the regression methods widely differ, both in variable of interest and in specification. For the primary market, yield differences from OLS models vary between a greenium of 17 bps and no difference. For the secondary market, past papers found yield differences between -11 and +4.3 bps for the secondary market. Authors that used fixed effects regression models found yield differences ranging from -19 bps to insignificant for the primary market and - 63 to + 10 bps for the secondary market. Larcker and Watts (2020) reacted on the strand of literature that used fixed effects regression models, arguing the greenium should be estimated through treatment effects. They conjectured fixed effects models could produce an artificial greenium if the controls (i.e. fixed effects) are not adequate. I will discuss the results of treatment effects in section 3.1.4.

3.1.4 Results of treatment effect estimations

This subsection explains more specifically what treatment effects are and their corresponding results for estimating the greenium. In short, estimating a treatment effect is analogous to studying the effect of a medicine. To do so, researchers give treatment to one group and a placebo to a control group and study the difference. In this setting, green bonds are bonds that receive 'treatment', namely a green label. Gianfrate and Peri (2019) studied yield spreads in the primary and secondary markets for EUR-denominated green bonds by using the propensity score matching (PSM) method. For the primary market they estimated the greenium to be between 15 to 19 bps and between 6 to 13 bps for the secondary market. Sheng et al. (2021) also used the PSM method to study the green bond premium in the primary market, focusing on Chinese green bonds. They reported a greenium of 7.8 bps, thus a less strong premium than Gianfrate and Peri (2019). Larcker and Watts (2020) studied the greenium in the US municipal primary bond market. They reproduced the study of Baker et al. (2018), showing that when they used a fixed effects regression model, they found a greenium. However, this was not the case when they estimated treatment effects. That finding strengthened their view that a fixed effects model does not lead to a valid result due to issuer-related omitted variables. In sum, similarly to the results of the regression models, the results from the strand of literature that employs treatment effects are ambiguous. However, it should be noted that there are only three papers that use treatment effects and all use different regions.

In short, the strand of literature that estimated treatment effects also produced widely varying results for the yield differences between green and conventional bonds, ranging from a greenium of 20 bps to no greenium. The next section examines what potentially drives the yield and pricing differences.

3.2 Determinants of the greenium

Section 3.1 discussed how past articles studied the greenium. This section advances the discussion on the greenium by discussing what the existing literature argues are the factors that drive the greenium. I split this into two segments, namely factors that can be attributed to bonds specifically and factors that can be attributed to the issuer.
Section 2 indicated there are various types of external reviews available.

3.2.1 Bond specific factors

The bond specific factors that I will discuss are factors that are debated most or specific to the green bond market, namely the (i) credit rating, (ii) liquidity, (iii) external review, (iv) and the use of proceeds.

Firstly, Slimane et al. (2020) and Zerbib (2019) empirically found a higher credit rating is associated with a higher greenium. MacAskill et al. (2020) summarizes that investment grade bonds trade at a greenium of 2 to 6 bps, whereas Slimane et al. (2020) and Zerbib (2019) show bonds that have a lower credit rating have smaller greeniums. Secondly, Febi, Schäfer, Stephan, and Sun (2018) established that it is important to control for liquidity in the green bond market. Slimane et al. (2020) further states that the green bond market as a whole is less liquid than the conventional bond market. These two groups of authors reported a negative relationship between liquidity and the greenium; more liquid green bonds carry a less negative greenium. Thirdly, authors that studied the relationship between the greenium and whether or not a green bond is externally reviewed, agree an external review leads to a more negative yield difference or stronger greenium. Moreover, Hyun et al. (2020) reports that the more critical the review, the stronger the premium.[18] The exact effect is disputed, however. Slimane et al. (2020) reports a modest greenium of 3 bps, whereas Fatica et al. (2020) reported a greenium of 70 bps. Fourthly, Zerbib (2019) indicated that future research should investigate whether the use of the proceeds had an effect on the greenium. Russo et al. (2021) followed this suggestion and argued they discovered a causal link between the use of proceeds and the yield to maturity of green bonds. They found that projects aimed at curbing pollution lowered yields the most, whereas projects that focused on projects like water management and biodiversity only benefited from reputational effects. On the other hand, Kapraun and Scheins (2019) found no significant relationships between the use of proceeds and the issue yield of green bonds. This subsection showed it is required to jointly investigate the yield differences with bond specific factors, as they appear to have an effect on the yields of green bonds. The next section reviews the factors that can be attributed to the issuers of the green bonds.

3.2.2 Issuer specific factors

The existing literature studied the impact of the following issuer-specific factors: (i) type of issuer, (ii) the effect of the first issue or issuing regularly and (iii) ESG scores.

Table 2 provides a summary of the papers that study the differences in green and conventional bond yields per issuer type. The table shows the recurring theme; varying estimates of the yield

[18] Hyun et al. (2020) showed that the more stringent CBI review leads to a higher greenium of 2 bps.

differences between green and conventional bonds.

Table 2: Greenium by issuer type

This table shows the variation of the yield differences by issuer type. A negative sign indicates a greenium, a positive sign indicates a green bond discount. The results are in basis points. SSA stands for sovereign, supranational and agency issuers.

Study	Financial	Non-financial corporations	SSA
Panel A: Primary market			
Fatica et al. (2020)	Insignificant	-22	-80
Gianfrate and Peri (2019)		-20	-14
Kapraun and Scheins (2019)		Insignificant	-5.4
Sheng et al. (2021)	-1.2	5.7	
Panel B: Secondary market			
Bachelet et al. (2019)		3	-3
Dorfleitner et al. (2021)	3		Insignificant
Hachenberg and Schiereck (2018)	-6		6
Kapraun and Scheins (2019)		Insignificant	-4.5
Slimane et al. (2020)	-1.2	-3.4	-2.2
Zerbib (2019)	-2.5		Insignificant

Secondly, from section 2 we know that issuers try to improve their reputation as credible issuers. Kapraun and Scheins (2019) argued an issuer can improve its reputation as a credible issuer if it is able to consistently keep its promises about the proceeds of green bonds. Building on research of Flammer (2020) who reported that stock prices react positively following a green bond announcement, Kapraun and Scheins (2019) found that the first issue of a green bond by an issuer was favourably received by the market with a greenium of 18 bps. Fatica et al. (2020) found a higher greenium of 44 bps for the whole sample at the first issue, but not for supranational and financial issuers. Thirdly, the ESG score of the issuer can be another way to portray its reputation. Hachenberg and Schiereck (2018) explained higher ESG scores signal that a company is often strongly externally monitored. Investors reward this by accepting lower yields. Immel et al. (2021) underscored this by stating every point increase (on a scale from one to ten) in ESG score was accompanied by a higher greenium of 6 bps. Slimane et al. (2020) furthered the research of Immel et al. (2021), reporting green bonds with a high ESG[19] score have a higher greenium.

[19] These are Amundi ESG ratings. These ratings are on a scale starting at F (lowest) to A (highest)

3.3 Conclusion on literature review

This section provided a review of the existing literature and showed many different results on the yield differences between green and conventional bonds. There are two strands of literature that attempt to estimate the greenium, namely one that employs regression models and the other that estimates treatment effects. The yield differences produced by regression models vary between -19 to 0 bps, similar to the yield differences from treatment effects which vary between -18 to 0 bps. The regression models for the secondary market show stronger discrepancies with estimates varying from a greenium of 62.7 to a green bond discount of 4.2 bps. Only two studies analysed the greenium in the secondary market with treatment effects with estimates varying from a greenium of 9.5 bps (Gianfrate & Peri, 2019) and no difference (Larcker & Watts, 2020). Overall, the results indicate either a small greenium or a small discount in the primary market. The reported results for the secondary market vary more widely, ranging from high greeniums to high green bond discounts.

To compare the results of the two strands of literature, it is imperative to compare the same regions and markets. As this research is focused on the European market, I will zoom in on results on that specific region. For the primary market, the regression model of (Kapraun & Scheins, 2019) produced a greenium of 8.7 bps. Gianfrate and Peri (2019) employed a treatment effect model, which estimated a higher greenium of 10 bps. In sum, treatment effects seem to produce a slightly more negative greenium for the European market. For the secondary market, Zerbib (2019) and Slimane et al. (2020) found a small greenium of around 2 bps, Kapraun and Scheins (2019) did not find a significantly negative result. Gianfrate and Peri (2019) found a greenium of 10 bps in their study.

Furthermore, the existing literature examined bond-specific variables such as credit ratings, issuer-specific variables such as ESG scores and variables unique to the green bond market, namely how often an issuer has issued a green bond, whether or not a green bond is externally reviewed and the use of proceeds of the green bonds. In sum, higher rated bonds tend to have a higher greenium. It seems that higher transparency leads to lower yields, since higher ESG scores (Slimane et al., 2020), external reviews (Hyun et al., 2020) and repeated issuance lead to a stronger greenium, bonds that are externally reviewed carry a more negative greenium and issuers that often more often also carry a more negative greenium (Fatica et al., 2020). Lastly, the yield difference also depends on the use of proceeds of a green bond (Russo et al., 2021).

To summarize, the existing literature agrees that green and conventional bonds should be closely matched on their characteristics (of which there are many) to obtain valid inferences. To find such pairs, green and conventional bonds should be matched on (observable) characteristics such as rating, issuer type or use of proceeds. Not controlling for this biases the results (Larcker & Watts, 2020)[20]. On the other hand, the existing literature is inconclusive on the existence, magnitude and determinants of the greenium, as the greenium appears to differ widely per issuer type, region, and other characteristics (Kapraun and Scheins (2019), Slimane et al. (2020), amongst others). Contrasting evidence thus seems to be a recurring theme in green bond pricing, requiring a deeper analysis of the available methodologies. Furthermore, I agree with Slimane et al. (2020) that research on the primary market is thin and requires more attention.

To finalize the literature review, I will discuss the position of this paper inside the existing literature and what this paper will add to the existing literature. This is summarized in figure 4. First, this research will aim to advance the methodological approaches of identifying the greenium in the spirit of Kapraun and Scheins (2019). I will attempt to improve the methodologies of Gianfrate and Peri (2019) (who use the PSM method to estimate treatment effects) and Löffler et al. (2021) (who use the CEM matching method before employing a fixed effects regression model). Specifically, this research aims to improve on the limitations of Gianfrate and Peri (2019) who do not control for liquidity [21] and Löffler et al. (2021) who use bonds without credit ratings which could impede proper matching of the bonds. Furthermore, this research will add another control variable to ensure proper matching of the bonds, namely the eligibility for the ECB asset purchase program.

[20] For example, Larcker and Watts (2020) showed that some issuers may be more likely to issue a green bond as their business is more exposed to climate risks than others.

[21] Zerbib (2019) explicitly points out that it is important to control for liquidity in the green bond market

Figure 4: Overview of position in current literature
This figure displays the position of this paper relative to similar papers

4 Hypothesis development

The previous section discussed the current state of the research on the existence and determinants of the greenium. This section summarizes those views into hypotheses to test for this research. This research investigates both the primary and secondary market, so each market deserves a separate discussion. This section is structured as follows. Firstly, I will formulate hypotheses on the greenium. Secondly, I will develop hypotheses on the effects of a credible reputation of the issuer of green bonds.

4.1 Hypotheses on the yield difference between green and conventional bonds

The first set of hypotheses is related to the greenium. At first glance, the only difference between conventional and green bonds is the use of proceeds and therefore no price difference needs to exist. However, possible reasons for this could be that i) demand exceeds supply (Sze et al., 2020), ii) investors want to pay for a socially and environmentally responsible investment (Zerbib, 2019) and iii) issuers need to receive compensation for the additional costs they incur for fulfilling all requirements (Hachenberg & Schiereck, 2018). As stated in section 3 and as can be seen in table 1, research on the primary market is thin and deserves more attention. For the primary market, a majority of papers reported a greenium, some papers found no significant relationship and no papers reported a green bond discount. The secondary market has received more attention, but also more varying results. Past articles have reported large negative greeniums, but also a positive estimate. As stated before, existing literature is not conclusive about the sign and magnitude of the greenium. However, most evidence points towards a greenium. From this, I formulate the first group of hypotheses.

$H1.1_0$: **There is no yield difference between green and conventional bonds in the primary market**

$H1.1_a$: **There is a negative yield difference between green and conventional bonds in the primary market**

$H1.2_0$: **There is no yield difference between green and conventional bonds in the secondary market**

$H1.2_a$: **There is a negative yield difference between green and conventional bonds in the secondary market**

4.2 Hypotheses on the effects of issuer type and reputation on green bond yields

The second set of hypotheses tests whether differences between types of issuers exist. Table 2 showed the estimates of the greenium vary widely per type of issuer. The results seem to be especially strong for non-financial corporations, with estimates as large as 22 bps for non-financial corporations, but also green bond discounts. Again, more research is required to find the true effect. I theorize the following about the effect of the type of the issuer on the yield on green bonds.

$H2.1_0$: **The greenium does not differ per issuer type on the primary market**

$H2.1_a$: **The greenium differs per issuer type on the primary market**

$H2.2_0$: **The greenium does not differ per issuer type on the secondary market**

$H2.2_a$: **The greenium differs per issuer type on the secondary market**

Thirdly, Kapraun and Scheins (2019) argued that issuers of green bonds enjoy reputational benefits. They theorized issuers improve their reputation as a credible and green issuer if they are able to successfully return to the market. Fatica et al. (2020) also studied this effect and agrees the more an issuer returns to the market, the higher the greenium becomes. As a result, the following hypotheses will test whether this holds for this dataset:

$H3.1_0$: **The greenium is not related with the number of issuances by the same issuer in the primary market**

$H3.1_a$: **The greenium is positively related with the number of issuances by the same issuer in the primary market**

$H3.2_0$: **The greenium is not related with the number of issuances by the same issuer in the secondary market**

$H3.2_a$: **The greenium is positively related with the number of issuances by the same issuer in the secondary market**

Moving on to the fourth set of hypotheses, Kapraun and Scheins (2019) argued investors tend to pay more for a green bond that is issued by a credible issuer. Specifically, Hachenberg and Schiereck (2018) stated issuers that have higher ESG scores are subject to more stringent external monitoring which tends to improve their credibility. Immel et al. (2021) and Slimane et al. (2020) found a higher ESG score relates to a more negative greenium. I summarize these findings into the following hypotheses:

$H4.1_0$: **The ESG score of an issuer has no effect on the greenium in the primary market**

$H4.1_a$: **The ESG score of an issuer increases the greenium in the primary market**

$H4.2_0$: **The ESG score of an issuer has no effect on the greenium in the secondary market**

$H4.2_a$: **The ESG score of an issuer increases the greenium in the secondary market**

4.3 Hypotheses on the effects of green bond specific variables on green bond yields

This subsection focuses on variables that are specific to green bonds. Many authors investigated the effect of an external review on the pricing of a green bond. Recall from subsection 2.4 that external reviews of green bonds are necessary to create trust in the market. Across the literature, authors estimated an external review lowered the yield for a green bond, hence an external review is associated with a pricing advantage for the issuer. Dorfleitner et al. (2021) reported investors accept greeniums of 3 to 8 bps if a bond is externally verified, whereas Kapraun and Scheins (2019) reported greeniums of 4 to 16 bps. Slimane et al. (2020) found an external review led to a slight greenium of 1.57 bps. Therefore, I hypothesize the following about the effect of an external review on the yields of green bonds:

$H5.1_0$: **An external review does not affect the greenium in the primary market**

$H5.1_a$: **An external review does affect the greenium in the primary market**

$H5.2_0$: **An external review does not affect the greenium in the secondary market**

$H5.2_a$: **An external review does affect the greenium in the secondary market**

Finally, Zerbib (2019) indicated future research could investigate whether the use of proceeds affected the green bond premium. Russo et al. (2021) found there was a significant effect. If the proceeds are used for projects associated with pollution control and eco-efficient products had lower yields, whereas projects that focused on sustainable water management led to higher yields. It therefore seems the use of proceeds have an effect on the yield of a green bond.

$H6.1_0$: **The yield at issuance of a green bond does not depend on the use of proceeds**

$H6.1_a$: **The yield at issuance of a green bond depends on the use of proceeds**

$H6.2_0$: **The yield to maturity of a green bond does not depend on the use of proceeds**

$H6.2_a$: **The yield to maturity of a green bond depends on the use of proceeds**

This section described the hypotheses this research will use to come up with an answer on the research question. The next section will describe the data that will be used to test these hypotheses.

5 Data

This section describes the data that will be used to test the hypotheses as described in the previous section. Firstly, section 5.1 explains the data retrieval process and describes the variables. Secondly, section 5.2 what transformations were necessary to analyse the data. Thirdly, section 5.3 discusses descriptive statistics of the final dataset and compares the bond and issuer characteristics with datasets of similar studies.

5.1 Data retrieval process

I use two databases for this research, namely Bloomberg and Dealogic. Firstly, I use Bloomberg to download pricing data on conventional and green bonds. The sample consists of bonds issued between 2014 until 2021[22]. The search strategy is summarized in table 3. In line with other research, I restrict the sample to securities with a fixed coupon, (Immel et al. (2021), Larcker and Watts (2020), Gianfrate and Peri (2019), Kapraun and Scheins (2019)). Then, I exclude all bonds that are not issued in the EUR-currency. To ensure a sample of liquid bonds, I only include bonds with an issue amount of 200 million, which is in line with Gianfrate and Peri (2019). In contrast with Löffler et al. (2021), but in line with Gianfrate and Peri (2019), I exclude bonds that have no rating to ensure a proper matching of the bonds. Lastly, I exclude bonds that are private placements. The raw sample consisted of 4,948 securities, of which have 331 a green label.

Table 3: Sample construction

This table shows the strategy employed for the Bloomberg database	
Total dataset as of 03/06/2021	2,793,625
Include: Bonds with a fixed coupon	1,633,118
Include: Bonds with an issuance volume above 200 million	124,940
Include: EUR-currency bonds	22,559
Exclude: Bonds without a credit rating	5,761
Include: Bonds with an issue date beyond 01/01/2014	5,027
Exclude: Bonds that are placed privately	4,984

22 Bloomberg started including green bonds in 2014 (MacAskill et al., 2020).

When I finished the search, I downloaded data on the main characteristics of the bonds and issuers necessary for the matching process. Secondly, I used the Dealogic database to obtain data on whether a green bond is externally reviewed[23]. Furthermore, Dealogic provides data on the main use of proceeds of the green bond. Table 11 provides a description of the variables.

5.2 Data transformations

The raw data required some transformations prior to analysis. To remove the possibility of potential pricing noise in the data, bonds with a speculative rating are not included in the final sample Gianfrate and Peri (2019). As we can observe in figure 6, only 1% of the bonds in the raw sample contain a speculative rating, which means it is unlikely this removal could change the results. Secondly, I transformed the maturity type variable from Bloomberg into a dummy variable to distinguish between bonds that have options and bonds that do not. Thirdly, I formed maturity groups following Swinkels (2021) for a better interpretation of the results. Fourthly, I generated groups for the variable ESG scores, following (Kapraun & Scheins, 2019). Furthermore, to include the effect of the total amount issued, I generated issue deciles following Löffler et al. (2021) and the natural logarithm of the total amount issued following (Kapraun & Scheins, 2019) and (Gianfrate & Peri, 2019). Lastly, to improve the methodology of Gianfrate and Peri (2019), I generated the bid-ask spread by subtracting the bid price from the ask price (Löffler et al., 2021).

5.3 Sample discussion

This subsection discusses descriptive statistics, detailed characteristics of the dataset and the representativeness of the sample. Table 4 shows green bonds have significantly lower coupons and are issued in lower total amounts. The variables of interest for this research, yield at issuance and yield to maturity, seem lower for green bonds, although the difference in means is not statistically significant.

[23] Bloomberg does not require green bonds to be externally verified: (https://www.icmagroup.org/assets/documents/Regulatory/Green-Bonds/Green-Bond-Databases-Summary-Document-190617.pdf)

Table 4: Descriptive statistics

This table provides descriptive statistics for the entire sample, split into conventional and green bonds. The symbol (*) indicates that the means of the specific variables are significantly different between conventional and green bonds. Coupon (%) is the annual interest payment; Time to maturity is the difference in years between the maturity date and the issue date; amount issued is measured in millions of euros; yield at issuance and yield to maturity are measured in percentages; Liquidity is the difference between ask and bid price.

Panel A: Conventional bond statistics						
Variable	Observations	Mean	Standard deviation	Maximum	Median	Minimum
Coupon	4598	1,333*	1.216	10.125	1.059	0.000
Time to maturity	4598	9.231	5.897	100.000	8.000	1.000
Amount issued	4598	1072,789*	1423.131	25113.540	750.000	201.000
Yield at issuance	979	1.993	1.467	10.125	1.676	-0.476
Price at issuance	2656	99.610	0.664	108.040	99.668	92.756
Yield to maturity	4553	0.369	1.079	8.907	0.082	-7.777
Liquidity	4563	0.356	0.314	7.300	0.292	0.000
Panel B: Green bond statistics						
Variable	Observations	Mean	Standard deviation	Maximum	Median	Minimum
Coupon	331	1,011*	1.043	8.500	0.830	0.000
Time to maturity	331	8.674	4.152	30.000	8.000	2.000
Amount issued	331	749,998*	594.070	6100.600	500.000	250.000
Yield at issuance	40	1.534	1.309	6.375	1.294	0.053
Price at issuance	170	99.543	0.767	103.407	99.625	97.330
Yield to maturity	331	0.325	0.969	8.605	0.066	-0.641
Liquidity	331	0.364	0.221	1.512	0.325	0.030

To ensure validity of the final results, it is important to compare the sample of this study with other studies and see if the sample is representative. To do this, I compare datasets of similar studies, namely those of Kapraun and Scheins (2019), Löffler et al. (2021) and Gianfrate and Peri (2019). The final dataset of this research contains observations on 4598 conventional and 331 green bonds. The dataset of (Gianfrate & Peri, 2019) comes closest to this paper, since they also study only EUR-currency bonds for the period of 2013 - 2017. The sample of Gianfrate and Peri (2019) is smaller due to the shorter time period studied, containing 3,055 conventional bonds of which 121 were labelled as green. The observations on the descriptive statistics differ from Kapraun and Scheins (2019), as their dataset consists of bonds that mature a year earlier on average and are issued in lower amounts (€620mln versus €1015mln in this dataset. When looking at other similar studies, Kapraun and Scheins (2019) studies 21,872 conventional and 2,099 green globally issued bonds. Their descriptive statistics indicate green bonds in their dataset have higher coupons (2.36% versus 1% in this dataset), higher yield at issuance (2.37% versus 1.53% in this dataset) and longer maturities (approximately 10 years versus 8.5 years in this dataset). Löffler et al. (2021) also studies global bond issues, using 186,685 conventional and 1,928 green bonds but do not report descriptive statistics. In general, these datasets are thus much larger because their scope is not restricted to EUR-denominated bonds. Compared to other studies, this dataset appears to consist of bonds with lower coupons and yields, larger issue amounts, but appears to be in between the datasets in terms of maturities. In general, the sample seems to be slightly different than other datasets but not significantly so. The next subsections provide more detail on issuer and bond characteristics of this dataset.

5.3.1 Issuer characteristics

With respect to characteristics of the issuers, figure 5 shows an overview of the type of issuers in the dataset and their corresponding ESG scores. With respect to the study of Gianfrate and Peri (2019), this dataset differs significantly in terms of the type of issuers. In this sample, more than 90% is issued by corporate entities, whereas in the dataset of Gianfrate and Peri (2019) corporate entities issue about 75% of the bonds. Kapraun and Scheins (2019) describes that most issuers in their dataset carry an ESG score between 40 and 60, which is also the case for this paper. However, they report a higher mean ESG score (66) than this dataset (48).

5.3.2 Bond characteristics

Bond characteristics include the composition of credit ratings, maturity, seniority, collateral types, bond structures and eligibility for the ECB buying program. Issuer characteristics include the type of issuers and the ESG scores of those issuers. To start, figure 6 provides an overview of the distribution of credit ratings for both conventional and green bonds. As we can see, the composition credit ratings of conventional and green bonds are roughly similar. We can observe a heavier weight for investment grade bonds in figure 7. Gianfrate and Peri (2019) and Kapraun and Scheins (2019) do not provide an overview of the composition of credit ratings, but the sample of Löffler et al. (2021) is also overweight in investment grade bonds, namely 64%. However, the sample of Löffler et al. (2021) also includes junk and non-rated bonds. Secondly, figure 8 shows the composition of the tenor of the bonds. The figure shows a similar distribution between conventional and green bonds, with the bulk of the bonds maturing between five and twenty years. Thirdly, figure 9 shows almost 80% green bonds are senior unsecured bonds, which is ten percentage points more than conventional bonds. Conventional bonds on the other hand are secured in 15% of the observations, which is approximately ten percentage points more than 4.8% of green bonds. The sample of Löffler et al. (2021) also contains relatively more unsecured bonds, namely 54% of the total sample. The sample of this research is thus overweight in senior and unsecured bonds. Figure 10 conveys the green bonds in this sample are often unsecured with respect to conventional bonds (approximately 70% of green bonds are unsecured, which is approximately 20 percentage points more than conventional bonds). Moving on, Gianfrate and Peri (2019), Kapraun and Scheins (2019) and Löffler et al. (2021) do not specify the proportion of bonds that contain options in their paper. Figure 11 shows that both conventional and green bonds carry options in approximately 40% of the observations. Lastly, Figure 12 displays that both conventional and green bonds are eligible for the ECB buying program for around 65% of observations.

In short, this research uses data from Bloomberg and Dealogic. The final sample consists of 4598 bonds of which 331 are green. Compared with other studies, this sample is relatively overweight in investment grade and senior unsecured bonds and corporate issuers. In terms of issuer characteristics, this dataset consists of more corporations and lower ESG scores. The dataset contains twice the number of green bonds than the closest study of Gianfrate and Peri (2019), so I conclude there are no significant concerns regarding the validity of the dataset. The next section will describe what methods will be used to analyse the data.

6 Methodology

This section describes the statistical methods this research employed to estimate the greenium and determine what potentially drives the greenium. This section is structured as follows. Firstly, section 6.1 will explain the methodological issue with estimating the greenium. Secondly, section 6.2 will briefly summarize the common matching methods. Thirdly, section 6.3 justifies the methodological approach of this research and provides the exact specifications. Furthermore, it details how this methodology improve the past approaches.

6.1 The main issue in understanding the greenium

The key question this research attempts to answer is what the effect of a green label is on the yield or price of a bond. As we learned in the literature review, past authors have either directly estimated the yield differences via regression models or used a matching procedure before. To increase the validity of the results, this research will not use fixed effects regression models and instead use matching methods before estimating yield differences or treatment effects, following the suggestion of Larcker and Watts (2020). By choosing to use a matching method, this research assumes an experimental setting, where the bonds are divided into treatment and control groups. The green bonds are in the treatment group (as these observations are assigned the 'treatment' of a green label) and the conventional bonds are in the control group. However, the data this research uses is not from a controlled experiment but rather observational data from an external database. To achieve valid results from this data sample, it is important to have comparable or 'balanced' treated and control groups. Low imbalance[24] means the treated and control groups are strongly similar, which reduces bias in the statistical estimators and increases the validity of the results (King et al., 2011). High imbalance means the two groups are only weakly similar, calling upon the researcher to use statistical techniques to still achieve a valid estimate. This call upon the researcher is defined as researcher discretion. A problem with researcher discretion is that every researcher tackles a problem differently, which may lead to varying results. As we learned in the literature review, estimates of the greenium vary widely which may be an indication of problematic researcher discretion in the field of studying greenium (Kapraun & Scheins, 2019).

[24] Imbalance is formally defined as the degree of non-similarity between treated and control groups. If the treated and control groups are perfectly balanced, a simple difference of the means would estimate a causal effect. (Iacus, King, & Porro, 2012)

To attain balance between the two groups, matching methods are available. Matching means pre-processing the data to ensure treated and control groups are more similar. The goal of matching methods is to reduce imbalance between the treated and control groups (Iacus et al., 2012). In short, it is necessary to find an adequate matching method to match the green and conventional bonds. The next section discusses common methods used in the literature.

6.2 Common matching methods

Authors in the field of green bond pricing primarily use direct methods or non-parametric methods such as the PSM method and CEM method.

6.2.1 The direct matching method

Zerbib (2019) used a so-called direct approach to match the conventional and green bonds. He did this by setting up rules the pairs of bonds should adhere to, e.g., that the coupon rate of the bonds should be similar and that the time to maturity could not differ more than two years between the pairs of bonds. In essence, the direct matching method is a simple method in the sense that the researcher sets up rules and matches observations based on those rules.

6.2.2 The propensity score matching (PSM) method

Gianfrate and Peri (2019) and Larcker and Watts (2020) used the PSM method. The PSM method matches similar observations with a two-step procedure. The first part of this method is to compute a continuous variable[25] called the propensity score. The propensity score is the probability that a bond receives a green label, based on the input covariates (Rosenbaum & Rubin, 1983). The second part is to match the conventional and green bonds based on their propensity scores. After establishing the propensity scores, there are multiple methods for matching the conventional and green bonds based on propensity scores, namely the i) nearest neighbour, ii) kernel density and iii) radius matching methods (Abadie & Imbens, 2016). The nearest neighbour matching method matches observations based on the numerical distance between propensity scores. A drawback of this method is that observations that are not very similar (hence, not close) are still matched since they are 'closest' in the dataset. Radius matching can mitigate this problem by restricting matches to be within a certain radius (range). Logically, the quality

[25] That is, a continuous variable that is between 0 and 1

of matches increases when the range decreases. Kernel density matching is similar to nearest neighbour matching in that it estimates matches based on their numerical distance between each other, but it improves the analysis by allocating more weight to matches that are closer together. The actual matching can be either with, or without replacement. Matching with replacement means that we allow the method to iterate the procedure until it finds the optimal distribution of matches. Without replacement (also called 'greedy matching') restricts the matches to the first match the method finds. Matching with replacement is preferable over greedy matching (King et al., 2011).

6.2.3 The coarsened exact matching (CEM) method

Löffler et al. (2021) was the first to use the relatively new CEM method to match green and conventional bonds. The CEM method works as follows. Firstly, the method pre-processes ('coarsens') the dataset temporarily into comparable 'strata' (i.e., groups). Moreover, the method gives higher weights to strata that contain more comparable observations. Secondly, the method exactly matches observations based on input covariates. Finally, the method deletes non-comparable observations. This is a large advantage compared to the PSM method, which keeps all observations. The final dataset then contains exactly matched pairs of conventional and green bonds (Blackwell, Iacus, King, and Porro (2009) and Iacus et al. (2012). The CEM method also has an option to delete observations until all strata are equally large (this is the K2K option) [26].

6.3 The methodological approaches of this research

The previous section described the common matching methods. This section lays out why this research uses the PSM and CEM method to match the conventional and green bonds and also provides the exact specifications of the models.

6.3.1 Justification

The direct and PSM methods are members of the equal percent bias reduction (EPBR) methods (Iacus, King, & Porro, 2011). These methods assume completely randomized experimental designs, where random observations receive treatment (in this case, a green label). These types of matching methods assume that if the balance in one variable is improved, this holds for all

[26] This is often only done when datasets have many observations.

other variables as well. This assumes that all covariates are equally sensitive to changes in the specification, ignoring potential nonlinear relationships. This is potentially problematic when attempting to reduce imbalance between treated and control groups. These methods require setting the matched sample size before using the method, but only show imbalance after matching is finished. In practice, this means researchers often need to repeat the process before they arrive at a satisfactory result (Iacus et al., 2012). Moreover, King et al. (2011) specifically argues the PSM method neglects important information and states matching with the PSM method can actually increase inefficiency, bias and researcher discretion, which is not desirable. This is because these types of methods violate the congruence principle, which means the matching methods eventually estimate results based on a metric that is based on the original data, but not the original data itself.

Iacus et al. (2011) introduced the CEM method, which is a method that belongs to the 'monotonic imbalance bounding' (MIB) matching methods and assumes a fully blocked experimental design. A fully blocked design is a design where two very similar observations are chosen, of which one receives treatment. The advantage of a fully blocked design is that it reduces potential bias, whereas imbalance may persist in a completely randomized design. The CEM method requires no assumptions about the data, because it focuses on the imbalance that is present in the dataset, instead of lowering the expected imbalance like the PSM method. The main benefit of CEM is that it reduces imbalance between treated (green bonds) and control (conventional bonds) groups and that it requires few assumptions. In sum, the CEM method theoretically dominates the direct and PSM matching methods because it i) more adequately controls for imbalance, ii) requires less assumptions and iii) does not require an auxiliary metric to estimate results with. Therefore, this research will mainly focus on using the CEM method to estimate the greenium. However, I will also use the more widely used PSM method, to reconcile with the similar study of Gianfrate and Peri (2019) and to investigate whether the results differ. The next sections provide the exact specification of the models.

6.3.2 OLS regression after matching with the CEM method

To ensure the bond pairs are as similar as possible, I exactly match the bonds on i) issuer ii) issue size, iii), year of issue, iv) coupon, v) time to maturity in years, vi) issuer sector, vii) optionality, viii) credit rating, ix) seniority type, x) collateral type and xi) eligibility for the ECB asset purchase program. Lastly, I include the bid-ask spread and 10-day volatility of the bond price (Sze et al. (2020) and Zerbib (2019)) to control for remaining omitted variables. To estimate the yield difference between green and conventional bonds, the regression model for the primary market is as follows:

$$Yield\ at\ issuance\ = \alpha + \beta_1 * green + \beta_2 * liquidity + \beta_3 * volatility + \epsilon$$

For the secondary market, the variable of interest is the yield to maturity (more specifically, this is the ask yield to maturity, following Löffler et al. (2021)). Similarly to the primary market, the regression model for the secondary market is as follows:

$$Yield\ to\ maturity = \alpha + \beta_1 * green + \beta_2 * liquidity + \beta_3 * volatility + \epsilon$$

In these two models, the variable green is a dummy variable that indicates whether the bond is labelled as green or not. The coefficient β_1 presents the difference in yield between green and conventional bonds in this model. A negative coefficient indicates a greenium, a positive coefficient indicates a green bond discount. The next section describes the other methodological approach, namely to estimate treatment effects after matching with the PSM method.

6.3.3 Treatment effects after matching with the PSM method

The second methodological approach to study the greenium is to estimate the treatment effect of the green label. As stated in section 6.2.2, the PSM method first calculates the propensity of a bond receiving a green label and then matches these propensity scores to calculate the treatment effect. The input variables to match the bonds on are similar to the CEM method. I used matching with replacement. After establishing the propensity scores, I followed Gianfrate and Peri (2019) and used their specifications of the nearest neighbour matching method, kernel and radius matching

To estimate the treatment effect of the green label for the primary market, I define the treatment effect as follows:

$$TE = Yield\ at\ issuance\ _i^{GB} - Issue\ price\ _i^{CB}$$

where TE is defined as the treatment effect, the difference in yield between green and conventional bonds. Similarly to the model above, the specification is as follows for the secondary market:

$$TE = Yield\ to\ maturity\ _i^{GB} - Yield\ to\ maturity\ _i^{CB}$$

Section 6.3.4 describes the methodological approach to study the potential determinants of the greenium.

6.3.4 Further analysis with OLS regression after matching with the CEM method

After analysing the existence of a greenium, this research aims to further analyse the difference between conventional and green bonds by including further control variables, employing an approach similar to Dorfleitner et al. (2021) and Kapraun and Scheins (2019). Subsequently, I included variables which tested the effect of i) number of issues per issuer and whether issuing a green bond for the first time had a significant effect on the yield at issuance or yield to maturity, ii) the ESG score of the issuer, iii) whether the green bond is externally verified and iv) the use of proceeds of the green bond. For brevity, the generic models look as follows:

$$Yield\ at\ issuance = \alpha + \beta_1 * green + \beta_2 * liquidity + \beta_3 * volatility + \beta_4 * extra\ control\ variables + \epsilon$$

$$Yield\ to\ maturity = \alpha + \beta_1 * green + \beta_2 * liquidity + \beta_3 * volatility + \beta_4 * extra\ control\ variables + \epsilon$$

For these models, coefficient $\beta 4$ subsequently provides the effect of i) issue experience, ii) ESG score of the issuer, iii) external review and iv) use of proceeds. The next section summarizes the methodological approach and explains how the methodological approach of this research could improve on earlier papers.

6.4 Improving past methodological approaches

The previous sections discussed the two methods that were employed in the analysis. This section explains how this paper attempts to improve the methodological approach of similar papers (recall figure 4). Firstly, a limitation of Löffler et al. (2021) is that they include bonds with no credit rating, which leads to distorted results as bonds with different credit ratings are still matched. Secondly, a limitation of Gianfrate and Peri (2019) is that they do not control for liquidity. Febi et al. (2018) showed it is imperative to control for liquidity, as liquidity significantly impacts bond prices. To advance the methodology of Gianfrate and Peri (2019), I will include the bid-ask spread to control for liquidity. Furthermore, following Sze et al. (2020) and Zerbib (2019), I control for volatility. Table 5 summarizes how these specifications could theoretically produce more robust results than Löffler et al. (2021) and Gianfrate and Peri (2019). It should be noted that at first glance, adding many control variables to ensure proper matching (and reducing the possibility of omitted variable bias) seems an adequate approach, but with matching methods there is a so-called 'curse of dimensionality'. This 'curse' implies there is a balance in adding control variables which reduces the number of matches that can be studied on the one hand and an increased risk of omitted variable bias on the other hand.

Table 5: Summary of methodological approach

This figure summarizes the limitations of closely related papers and shows how this research improves the methodological approach

Study	**Methodology**	**Matching method**	**Limitation**
Gianfrate and Peri (2019)	TE	PSM	Does not control for liquidity
Kapraun and Scheins (2019)	FE	Direct	Does not use a nonparametric matching method and does not control for volatility
Löffler et al. (2021)	OLS	CEM / PSM	Includes bonds that have no credit rating
Study	**Methodology**	**Matching method**	**Improvements**
This research	OLS / TE	CEM / PSM	1. Controls for liquidity using bid-ask spread 2. Excludes bonds that have no credit rating 3. Adds ECB eligibility as extra control 4. Controls for volatility following Sze et al. (2020) and Zerbib (2019)

This section discussed the methodological approach to estimate the greenium and to study the determinants of the greenium. The CEM matching method theoretically dominates the direct and PSM method. To reconcile with past authors, this research also estimates treatment effects after matching with the PSM method. After estimating the yield difference between green and conventional bonds, the analysis proceeded by adding extra control variables to test the effect of green bond specific variables. The next section presents the results.

7 Results

This section reports the results of the research and provides an answer to the hypotheses as stated in section 4. Firstly, section 7.1 will discuss the regression results of the CEM method and present the estimated treatment effects of the green bond label on the pricing of a green bond. Secondly, section 7.2 will analyse whether the results differ between sectors and time periods. Thirdly, section 7.3 will investigate the effects of green bond specific variables such as i) the ESG score of the issuer, ii) number of issues by the same issuer, iii) external review and iv) use of proceeds on the yield of green bonds. Lastly, two robustness tests provide a validity test of the results.

7.1 Estimating the greenium

7.1.1 OLS regression with the CEM method

Table 6 shows summary statistics on the matching process with the CEM method. The diagnostic summary shows the L1 statistic, which shows overall imbalance of the preprocessed dataset. Perfect imbalance would indicate an L1 statistic of 0 (King et al., 2011). The L1 statistic after matching is 0.671, which is inferior to the 0.244 statistic of Löffler et al. (2021). The lower imbalance of their research is probably due to i) the larger dataset of that research and ii) the lower number of control variables used. For this dataset, the specification of Löffler et al. (2021) results in 305 green bonds being matched to 1531 conventional bonds and a L1 statistic of 0.517. This shows Löffler et al. (2021) less strict criteria lead to more matches and evidently lower imbalance. Theoretically however, less strict criteria increase the possibility of omitting critical control variables.

The matching summary on the right displays that 42 green bonds are matched with 58 conventional bonds. The K2K option is inferior to the 'regular' CEM matching, since the L1 statistic of 0.690 is worse than the L1 statistic of 0.671. Therefore, the rest of the analysis will be performed using the pre-processed ('coarsened') dataset generated without the K2K option.

Table 6: CEM matching

This table shows the summary on the coarsened exact matching of the conventional and green bonds. The diagnostic summary shows the total imbalance (the multivariate L1 distance). The summary on the matching sample shows how many conventional and green bonds are matched or unmatched. The bonds are matched on i) issuer ii) issue size, iii), year of issue, iv) coupon, v) time to maturity in years, vi) issuer sector, vii) optionality, viii) credit rating, ix) seniority type, x) collateral type and xi) eligibility for the ECB asset purchase program

Panel A: Regular CEM

Diagnostic summary		Matching summary		
			Conventional	Green
Number of strata	4574	All	4598	331
Number of matched strata	40	Matched	58	42
Multivariate L1 distance	0.671	Unmatched	4540	289

Panel B: K2K option

Diagnostic summary		Matching summary		
			Conventional	Green
Number of strata	4574	All	4598	331
Number of matched strata	40	Matched	42	42
Multivariate L1 distance	0.690	Unmatched	4556	289

Before generating results, I tested for constant variance in the dependent variables. The null hypothesis of constant variance was rejected and therefore I proceeded by estimating results with robust standard errors. Table 7 presents the results for the regression estimates of the greenium in the primary and secondary market. Due to the stringent matching criteria, observations are limited. The models are able to explain more than 60% of the variance, as indicated by the R-squared. We can observe that the green bond dummy variable is negative, but insignificant. This indicates that after closely matching conventional and green bonds, the models do not estimate a greenium in the primary nor the secondary market. Furthermore, we can see it is important to control for liquidity as it has a significant effect on yield at issuance and yield to maturity. The coefficients for these variables are in line with past evidence. Sze et al. (2020) also reports a significantly positive coefficient for liquidity, Löffler et al. (2021) and Kapraun and Scheins (2019) found positive, but insignificant effects on the yields.

Table 7: Regression results after matching with the CEM method

This table reports the results with the CEM method. After exactly matching on variables discussed in table 6, the liquidity and 10-day volatility act as further controls. The yield at issuance variable indicates the greenium in the primary market and the yield to maturity variable indicates the greenium in the secondary market.

Dependent variable:	Yield at Issuance	Yield to Maturity
Model	(1)	(2)
Green bond	-0.254	-0.185
	(0.328)	(0.147)
Liquidity	6.328***	4.134***
	(0.902)	(0.634)
10D Volatility	-0.407*	-0.039
	(0.206)	(0.086)
Constant	0.119	-0.831***
	(0.169)	(0.106)
Observations	10	98
R-squared	0.873	0.627
Adjusted R-squared	0.809	0.615

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The next section will present the results of the other methodological approach, namely the PSM method.

7.1.2 Treatment effects with the PSM method

This section provides the results of the other methodological approach, namely estimating the greenium by calculating the treatment effect of a green label. To ensure the PSM method works properly, we need to satisfy three conditions, namely (i) the conditional independence assumption, (ii) the common support assumption and (iii) the balance assumption. The first condition (the conditional independence assumption) is that the observations are matched on observable control variables. Although this research uses more control variables than other papers, the possibility of an unobservable characteristic remains nonzero (Gianfrate & Peri, 2019) and can thus not be verified. The second condition requires that comparable observations exist. The balancing property did not hold when I included the issuer as control variable. Therefore, I excluded the issuers from the input variables. Column 7 in table 8 demonstrates that without controlling for the issuers the treated and control groups are not significantly different from each other and that the condition of 'common support' is verified. Although matching on issuer would be a theoretical improvement, Löffler et al. (2021) and Gianfrate and Peri (2019) did not control for it and therefore excluding it in this manner will not impede reconciling with their results. Thirdly, the PSM method requires similar propensity scores stem from similar characteristics. In other words, bonds with similar propensity scores should not be fundamentally different in terms of credit rating or time to maturity, for example. Table 8 shows the results of this test. The third condition is not fully satisfied, as Rubin's B is not below 25%. However, Rubin's R is between 0.5 and 2. In short, the balance between the groups is slightly inferior to the one of Gianfrate and Peri (2019). Again, this is most likely due to the higher number of control variables that is used in this research.

Table 8: Propensity balancing test

This table shows the results for the balancing test of the propensity scores. The balancing test calculates the compatibility of the unmatched and the matched samples. On the left, U stands for unmatched and M stands for matched. Columns 3 and 4 contain means of the variables, hence the word 'means' above those columns. Column 7 shows whether the unmatched and matched samples differ significantly from each other. A value above 0,05 indicates the samples do not differ significantly, which means they are comparable for analysis. Panel B shows additional statistics on the balancing properties. Ideally, Rubin's B should be less than 25 and Rubin's R be between 0.5 and 2 for the samples to be considered sufficiently balanced.

Panel A: Balancing test

		Mean				
Variable (1)	Sample (2)	Treated (3)	Control (4)	% Bias (5)	% Reduction (6)	T-test (7)
Amount issued	U	4.350	5.149	-29.900		0.070
	M	4.350	4.925	-21.500	28.000	0.357
Issue year	U	2017.700	2016.600	45.800		0.003
	M	2017.700	2018.000	-15.100	67.100	0.507
Coupon	U	4.875	5.988	-39.600		0.009
	M	4.875	4.775	3.600	91.000	0.878
Time to Maturity (in years)	U	8.800	9.604	-17.600		0.365
	M	8.800	9.225	-9.300	47.100	0.653
Sector	U	0.650	0.655	-0.900		0.954
	M	0.650	0.650	0.000	100.000	1.000
Optionality	U	0.475	0.374	20.400		0.196
	M	0.475	0.325	30.300	-48.300	0.175
Credit rating	U	0.175	0.209	-8.700		0.600
	M	0.175	0.200	-6.300	27.300	0.778
Seniority	U	3.750	3.388	33.300		0.083
	M	3.750	3.550	18.400	44.700	0.390
Collateral	U	3.650	3.411	12.500		0.458
	M	3.650	3.575	3.900	68.700	0.863
ECB	U	0.725	0.531	40.700		0.016
	M	0.725	0.850	-26.200	35.500	0.176

Panel B: Additional statistics

Sample	R-squared	p>chi2	Mean bias	Median bias	Rubin's B	Rubin's R
Unmatched	0.096	0	24.9	25.2	102.2*	0.54
Matched	0.0114	0.243	13.5	12.2	79.7*	1.11

Table 9 reports the estimated treatment effects after matching on the propensity scores. In panel A, models 1 and 2, we can observe significant treatment effects of 57.3 and 50 bps (significant at the 5% and 10% level, respectively). However, this does not hold for the other specifications, so we must be cautious to interpret this coefficient as (strong) evidence for a greenium, also because the nearest neighbour matching method is most likely to match less similar green and conventional bonds. This is because the nearest neighbour matching method simply selects the nearest propensity score, regardless of total difference[27].

Table 9: Treatment effect results

This table reports the average treatment effect on the treated observations (the green bonds) for the primary market (panel A) and secondary markets (panel B). NN stands for nearest neighbour and indicates the number of neighbours are used. R stands for radius and indicates the range of matches that is included. A radius of 0.01 indicates that propensity scores that are 0.01 units away from the propensity score that is used will be included.

Panel A: Primary market. Dependent variable: Yield at Issue						
Test	Nearest neighbour matching			Kernel matching	Radius matching	
Specification	NN = 3	NN = 5	NN = 8		R = 0.01	R = 0.005
Model	(1)	(2)	(3)	(4)	(5)	(6)
ATT	-0.573**	-0.500*	-0.310	-0.137	-0.171	-0.205
Std. Error	(0.282)	(0.262)	(0.238)	(0.235)	(0.215)	(0.218)
# Treated	40	40	40	39	40	40
# Untreated	106	162	249	449	794	764
Panel B: Secondary market. Dependent variable: Yield to maturity						
Test	Nearest neighbor matching			Kernel matching	Radius matching	
Specification	NN = 3	NN = 5	NN = 8		R = 0.01	R = 0.005
Model	(1)	(2)	(3)	(4)	(5)	(6)
ATT	0.026	0.002	0.020	0.022	0.008	0.007
Std. Error	(0.061)	(0.060)	(0.058)	(0.059)	(0.055)	(0.055)
# Treated	331	331	331	320	331	331
# Untreated	833	1232	1729	2852	4294	4273

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

To summarize the results on the yield differences, the results for the OLS regression model after matching with the CEM method show no evidence for a greenium. Similarly, the estimated treatment effects after matching with the PSM method show many insignificant results for a greenium. Therefore, I do not reject hypotheses $H1.1_0$ and $H1.2_0$. It appears there is no

[27] This is explained in section 6.2.2.

greenium for the whole sample of green bonds.

7.2 Analysis on subsamples of sectors and time periods

The next sections provide a deeper analysis of the greenium by separately investigating sectors and time periods. Firstly, it compares the greenium between sectors. Secondly, it shows whether a difference between time periods exists.

7.2.1 Greenium between sectors

To test hypotheses $H2.1_0$ and $H2.2_0$, I split the dataset into subsamples of issuers, namely into a subset of (i) financial, (ii) non-financial and (iii) SSA issuers. Table 14 shows the results. The analysis is impeded by lack of sufficient observations for SSA issuers and are therefore not reported. Figure 2 showed SSAs issue many green bonds globally, but evidently, they do so on other markets. This is not uncommon, as Gianfrate and Peri (2019) also did not report separate results for SSAs. Moreover, even in the large dataset of Löffler et al. (2021), SSAs only accounted for 5% of total issues. Furthermore, observations for the primary market are also scarce. Therefore, instead of yield at issuance, the issue price is the dependent variable in models 1 and 2. The intuition of the greenium is now opposite; a positive coefficient indicates a greenium. It appears green bonds that are issued by financial issuers carry a greenium of - 8.6 bps in the secondary market, which is a similar result to Hachenberg and Schiereck (2018) as we can see in table 2. The other coefficients are insignificant. Table 15 shows the estimations of the treatment effects for the particular sectors. In panel A, model 1, the treatment effect for green bond issues that occur in the financial sector is significant at - 34.5 bps. In panel A, model five shows the theoretically sounder radius matching method shows a significant negative treatment effect of - 40.7 bps. In panel B, model 5 we can also observe a significant negative effect of - 10.4 bps. The yield difference thus seems less pronounced in the secondary market. None of the other coefficients are significant. These results indicate green bonds of financial issuers are more expensive in both markets.

To summarize these results, there appears to be a significant difference in the yield of green bonds between sectors. The coefficients in tables 14 and 15 show there is enough evidence to reject hypotheses $H2.1_0$ and $H2.2_0$, as the coefficients for the yield at issuance and yield to maturity are significantly negative in multiple models. The green bonds of financial issuers differ significantly from non-financial issuers in both markets.

7.2.2 Greenium over time

Swinkels (2021) showed the green bond market evolved considerably over time. To test if the pricing differential between conventional and green bonds is stable over time, I split the sample into two time periods, namely from 2014-2017 (the years after the introduction of the Green Bond Principles) and from 2018-2021. Table 16 displays results of the CEM regression. Figure 1 showed relatively few green bonds were issued until 2016 and that impedes the analysis here as only nine green bond pairs are available for model 1. Moreover, none of the coefficients for the green bond dummy variable is significant, indicating the CEM method produces no statistically significant difference in issue prices or yields to maturity can be found.

Table 17 reports the results for the analysis of the two time periods using the PSM method. We can observe significantly negative treatment effects for the primary market in the 2014-2017 period, namely -44.8 (panel A, model 1) and -33.3 bps (panel A, model 5). Moreover, panel B, model 5 estimates a significant difference in yield to maturity between green and conventional bonds of 10.2 bps. Overall, this indicates green bonds were relatively more expensive in the 2014-2017 period. A plausible explanation could be that when the green bond was still a relatively new financial product, investors perceived the green bond as risky and demanded more compensation in the form of higher yield. However, this cannot be stated for certain. The next section tests the hypotheses on the effects of the greenium determinants.

7.3 Analyzing the effects of green bond specific variables on the yield of green bonds

This section analyzes the effects of the factors i) the number of issuances per issuer, ii) the ESG score of the issuer, iii) external verification and iv) use of proceeds on the yields of green bonds. Table 18 provides results for the impact of the determinants in the primary market, table 19 for the secondary market. I will discuss the results on the hypotheses subsequently, meaning I will provide a conclusion on each determinant on the primary and secondary market before moving to the next determinant. To avoid multiple collinearity, I removed the green bond dummy variable from the models. This is plausible, as the data of the added control variables are only available for green bonds.

For the analysis on the primary market, there were insufficient observations to estimate the model with yield at issuance as dependent variable. So, I estimated the models with the price at issue. In table 18, model one, we can see that the coefficient for the first issue is significantly positive. It seems the first green bond issue has a significantly higher price of 134 bps. This is an even stronger effect than what Fatica et al. (2020) found. The finding should be interpreted with caution, as the model has a limited number of bond pairs and a low R-squared. Model one further shows that green bonds returning issuers are priced significantly at issuance. For the secondary market, the coefficients for first and regular issues in table 19, model one, are insignificant. In short, the evidence shows issuing green for the first time leads to a higher issue price, even as issuing multiple green bonds. This effect does not persist in the secondary market. Therefore, I reject hypotheses $H3.1_0$, but I do not reject $H3.2_0$, as there is no evidence that the number of issuances is associated with a different yield to maturity.

To test hypotheses $H4.1_0$ and $H4.2_0$, model two in both tables estimates the effect of the ESG score of the issuer on the issue price and the yield to maturity. The coefficients for the ESG score in table 18 are insignificant, meaning the ESG score of an issuer does not seem to have an effect on the price at issue of the green bond. On the contrary, the ESG score does appear to have a significant effect on the yield to maturity in the secondary market. We can observe significantly positive coefficients for all groups. As theorized, a higher ESG score is associated with a lower yield to maturity, as the coefficient of the higher ESG score groups is lower than that of the lowest (20-40) ESG score group. This might indicate that investors perceive an issuer with a low ESG score as riskier and demand a higher yield as compensation. This result is in line with findings of Immel et al. (2021), who found that the yield spread between conventional and green bonds lowered with the ESG rating. Therefore, I do not reject hypothesis $H4.1_0$, but I do reject hypothesis $H4.2_0$.

Moving on, model three in tables 18 and 19 displays results on the effect of external reviews on the bond price. Many authors reported an external review affected the yield difference between green and conventional bonds. Unexpectedly, the coefficients for the external review variable are insignificant for both the primary and secondary markets. An explanation for this might be that investors currently possess tools to review green bonds themselves, making an external review by a third party less important. In short, the results of model three do not provide enough evidence to reject hypotheses $H5.1_0$ and $H5.2_0$. Contrary to the common result, an external review does not affect the issue price or yield to maturity of a green bond in this sample.

Lastly, model four investigates whether investors value green bonds differently based on their use of proceeds. In table 18 we see only three types of use of proceeds due to data constraints. The coefficients for renewable energy and mixed projects are strongly significant. In line with Russo et al. (2021), green bonds that support renewable energy projects are more expensive in terms of issue price. Perhaps investors accept lower yields when the issuer diversifies and engages in multiple green projects. More data is available for the secondary market. However, none of these coefficients are significant, meaning more evidence is required to establish a strong relation between the use of proceeds and the yield to maturity of a green bond. Moreover, since the coefficients are insignificant, this result indicates investors do not seem to value green bonds differently conditional on their use of proceeds in the secondary market. The coefficient for green bonds that serve multiple projects is significantly negative. Based on the evidence, I reject hypothesis $H6.1_0$ but I do not reject hypothesis $H6.2_0$. The findings on all hypotheses are summarized in table 10.
Before moving on to the next section, it must be noted that the results of the analysis must be interpreted with caution. Due to the stringent matching, relatively few matched conventional and green bonds are left over which could cause noise in the results. To test the validity of the results above, the next section provides a robustness test.

7.4 Robustness test

This section provides robustness tests to test the validity of the results. To do this, I used the same methodological approach but test the specifications of Löffler et al. (2021) and Gianfrate and Peri (2019).

Table 20 shows the results for the robustness test of the CEM method. The methodological approach is similar to table 7, except now I used the same matching criteria of Löffler et al. (2021). As their matching criteria are less stringent, their approach should yield more, but less

Table 10: Results on hypotheses

This table summarizes the results on the hypotheses as formulated in chapter 4.

	Hypotheses	Result
$H1.1_0$	There is no yield difference between green and conventional bonds in the primary market	Not rejected
$H1.2_0$	There is no yield difference between green and conventional bonds in the secondary market	Not rejected
$H2.1_0$	The greenium does not differ per issuer type on the primary market	Rejected
$H2.2_0$	The greenium does not differ per issuer type on the secondary market	Rejected
$H3.1_0$	The greenium is not related with the number of issuances by the same issuer in the primary market	Rejected
$H3.2_0$	The greenium is not related with the number of issuances by the same issuer in the secondary market	Not rejected
$H4.1_0$	The ESG score of an issuer has no effect on the greenium in the primary market	Not rejected
$H4.2_0$	The ESG score of an issuer has no effect on the greenium in the secondary market	Rejected
$H5.1_0$	An external review does not affect the greenium in the primary market	Not rejected
$H5.2_0$	An external review does not affect the greenium in the secondary market	Not rejected
$H6.1_0$	The yield at issuance of a green bond does not depend on the use of proceeds	Rejected
$H6.2_0$	The yield to maturity of a green bond does not depend on the use of proceeds	Not rejected

quality matches. As already mentioned in section 7.1.1, the specification of Löffler et al. (2021) led to lower imbalance for this dataset, implying more comparable groups. The table shows with these criteria, the model could use many more observations. Despite the higher number of observations, the R-squared of the models in table 7 are much higher at above 60%, indicating those models are better at explaining variance in the data than these models. Moreover, the coefficient for greenium in the secondary market is significant at the 10% level, showing weak evidence for a greenium of - 8.2 bps. When redoing the analysis between sectors, time periods and greenium determinants (not reported in this paper for brevity), the results show a similar trend; coefficients that were already significant show an even stronger significance. It seems more stringent matching leads to less significant results and perhaps a more realistic result.

To reconcile with Gianfrate and Peri (2019), I also redid the analysis by using their specification to estimate treatment effects, shown in table 21. Similarly to the message of the previous paragraph, table 13 conveys that for this dataset less stringent matching leads to lower imbalance. Gianfrate and Peri (2019) matched on i) the logarithm of issue size, ii) issue year, iii) time to maturity, iv) issuer type, v) credit rating and vi) collateral type. The results are roughly similar to table 9. Moving on to the analysis of the subsamples of sectors and time periods, the less stringent matching criteria also lead to more significant results for the coefficients that were already significant. As a final robustness test, I performed the analyses with the option adjusted spread, following the suggestion of Nanayakkara and Colombage (2019). The inferences remained similar, so this research finds no evidence there is a significant difference between using the yield to maturity or the option adjusted spread.

In sum, the robustness tests show what was empirically predicted. Inadequate or insufficient matching is associated with stronger evidence for a greenium for the whole sample, but also stronger evidence for a greenium in for example the period 2014-2017. Although the results may be stronger, they might also be less reliable as the quality of the matches are lower. The next section will conclude on the research question, discuss limitations of this research and also proposes avenues for future research.

8 Summary and conclusion

This section summarizes the research, suggests avenues for future research and lists limitations of this research. The research question this paper attempted to answer was: **Does a green bond premium for EUR-denominated bonds exist and if so, what are the determinants of that premium?** This research aimed to shed more light on the greenium by focusing on EUR-denominated bonds. A recurring theme throughout the existing literature is the heterogeneity in results on the green bond premium. In the spirit of Kapraun and Scheins (2019), this research investigated if and why a greenium existed in the European green bond market. To do so, this research employed two nonparametric matching methods, namely the CEM method (Löffler et al., 2021) and PSM method (Gianfrate and Peri (2019) & Larcker and Watts (2020)) with stricter criteria to match green and conventional bonds.

To answer the research question, the main result of this research is that this analysis did not find a significant greenium for the whole sample. The research also studied the greenium in specific sectors, time periods and also tested the impact of four green bond specific variables on the pricing of green bonds. The results showed green bonds of financial issuers were significantly more expensive at issuance, but also on the secondary market. Secondly, the results displayed evidence that the greenium was more pronounced in the period of 2014-2017, probably due to higher perceived risk for the then relatively new financial product. Thirdly, this research tested the effects of a first green bond issue and if there were reputational benefits of returning to the green bond market. In line with Fatica et al. (2020), a first green bond issue and repeated issue appear to lead to financial benefits for issuers. Fourthly, the results indicated investors require higher yields when the ESG score of the issuer is lower, probably because they perceive investing in green bonds of an issuer with a low ESG score as riskier in terms of the true environmental benefit. An implication for practitioners is that improving the ESG score of the company is an investment that will pay itself back, as a higher ESG score means investors accept lower yields. Fifthly, an external review did not appear to have an impact on green bond yields which is in contrast with past evidence. For this sample, it seems issuers are no longer rewarded by investors for externally verifying their green bonds. Perhaps the market is currently able to distinguish between the true greenness of bonds themselves, reducing the importance of an external review. Finally, the results provide weak evidence investors tend to reward projects that focus on renewable energy and diversify projects, as those green bonds had lower yields compared to other green bonds.

To put this research in context of other papers, the results of this research are in line with Dorfleitner et al. (2021), Hachenberg and Schiereck (2018) and Larcker and Watts (2020), who used different methodological approaches but also did not report a greenium and argued investors do not need trade profit with a sustainable investment. There are two reasons for this result. Firstly, the sample of this research was smaller than similar papers of Löffler et al. (2021) and Kapraun and Scheins (2019) because this research focused on EUR-denominated bonds, resulting in less potential matches of conventional and green bonds and thus less data to analyse. Secondly, this research implemented stricter criteria to match the bonds than Löffler et al. (2021) and Gianfrate and Peri (2019), which also led to less potential matches. In short, this research therefore suffers from the so-called 'curse of dimensionality'; the stricter the criteria, the better the quality, but also the lower the number of possible matches. Therefore, it is plausible this analysis did not find a greenium due to the methodological choices to focus on one region and apply stricter matching criteria. However, as we learned from the literature review, not matching conventional and green bonds adequately leads to biased results. The robustness tests with specifications of Löffler et al. (2021) and Gianfrate and Peri (2019) showed more significant results, strengthening the argument of this paper that the stronger estimates of the greenium in their articles might be due to inadequate or insufficient matching.

The contributions of this research to the existing literature are as follows. Firstly, this research attempted to improve the methodological approaches of Löffler et al. (2021) and Gianfrate and Peri (2019) by removing bonds without a credit rating from the dataset and controlling for liquidity by including the bid-ask spread. Furthermore, this research added the eligibility of the ECB asset purchase program to the matching criteria, which arguably leads to more adequate matching of the green and conventional bonds. As the results showed, these alterations led to other results compared with similar studies. Secondly, this research deepened the analysis on variables that are unique to the green bond market, such as (i) the number of green bond issues per issuer, ii) the ESG score of the issuer, iii) the impact of an external review and iv) the effect of the use of proceeds of the green bond.

This paper proposes two avenues for future research. Firstly, this paper proposes a wider use of the CEM method and to study the greenium in other markets. A second interesting research field would be the effect of the increased standardization in definitions and reporting of the new EU taxonomy on green bond prices. Finally, future research could investigate order books of green and conventional bonds. Should the oversubscription of green bonds (relative to conventional bonds) be a significant factor, future research could substantiate the often-mentioned argument that excess demand increases the greenium.

The limitations of this research can be categorized as i) lack of sufficient observations for SSA issuers, yield at issuance, ii) limitations of matching methods and iii) limitations that persist despite matching methods. Firstly, the final sample lacked sufficient observations for sovereign, supranational and agency issuers and yield at issuance, which impeded the analysis. The lack of observations meant this research could not properly analyse the yield differences for bonds issued by SSAs. Moreover, the lack of observations for yield at issuance meant this research had to use the price at issue for some models. Although the intuition remains similar, the effect cannot be compared one-on-one with yield at issuance. Secondly, although the matching methods used in this research are theoretically sound (CEM) and widely used (PSM) method, both methods have fundamental limitations. Both methods require many observations and both methods suffer the 'curse of dimensionality', as indicated by the low number of bond pairs for the CEM method. Thirdly, matching methods cannot capture non-observable characteristics such as the non-financial motives of image building[28], which inevitably leads to a slightly biased result (Gianfrate & Peri, 2019). Lastly, as Ehlers and Packer (2017) noted, green bonds are still labelled either as green or conventional, although nuances between the effectiveness for the environment may differ greatly.

[28] Issuers may for example decide to issue a green bond to boost their reputation or to comply with social norms

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Appendix

A. Tables with descriptive information

Table 11: Definitions of variables

This table defines the variables used for this research. The sources of the data are Bloomberg (a) and Dealogic (b).

Variable	Definition
Bond characteristics variables	
Amount Issued (a)	Total amount issued in millions
Collateral type (a)	The type of collateral describes the collateral that is available for bondholders if the issuer defaults or is sold.
Coupon (a)	The periodic interest payment of the bond
Credit rating (a)	This variable lists the Bloomberg composite credit rating of the three large credit rating agencies Fitch, Moody's and S&P
ECB eligibility (a)	Variable that indicates whether a bond is eligible for the buying program of the European Central Bank
External review (b)	Variable that indicates if a bond is externally reviewed
Issue date (a)	Date when the bond is issued
Green instrument (a)	Dummy variable that indicates whether a bond is labelled by the issuer as green
Maturity date (a)	Data when the bond matures
Payment Rank (a)	The payment rank refers to the order of payment of the bondholder when the issuer defaults or gets sold.
Use of proceeds (b)	Variable that describes the main use of proceeds of the bond.
Bond pricing data	
Ask price (a)	Clean ask price of the bond
Bid price (a)	Clean bid price of the bond
Liquidity (a)	This variable is computed as the difference between the bid and ask prices
Yield at Issue (a)	Yield to maturity when the bond is issued
Yield to Maturity (a)	Yield to maturity in the secondary market
Volatility (a)	Volatility is defined as the 10-day volatility of the bond price, following Sze et al. (2020)
Issuer information	
ESG score (a)	Score that indicates environmental performance of the issuer, on a scale from 0-100.
Sector type (a)	Code that describes the sector type of the issuer

B. Graphs and figures

Figure 5: Sector composition and issuer ESG scores
This figure has two parts, both explaining the characteristics of issuers in the dataset. The figure on the left shows the distribution of issuer types. The figure on the right portrays the categories of ESG scores.

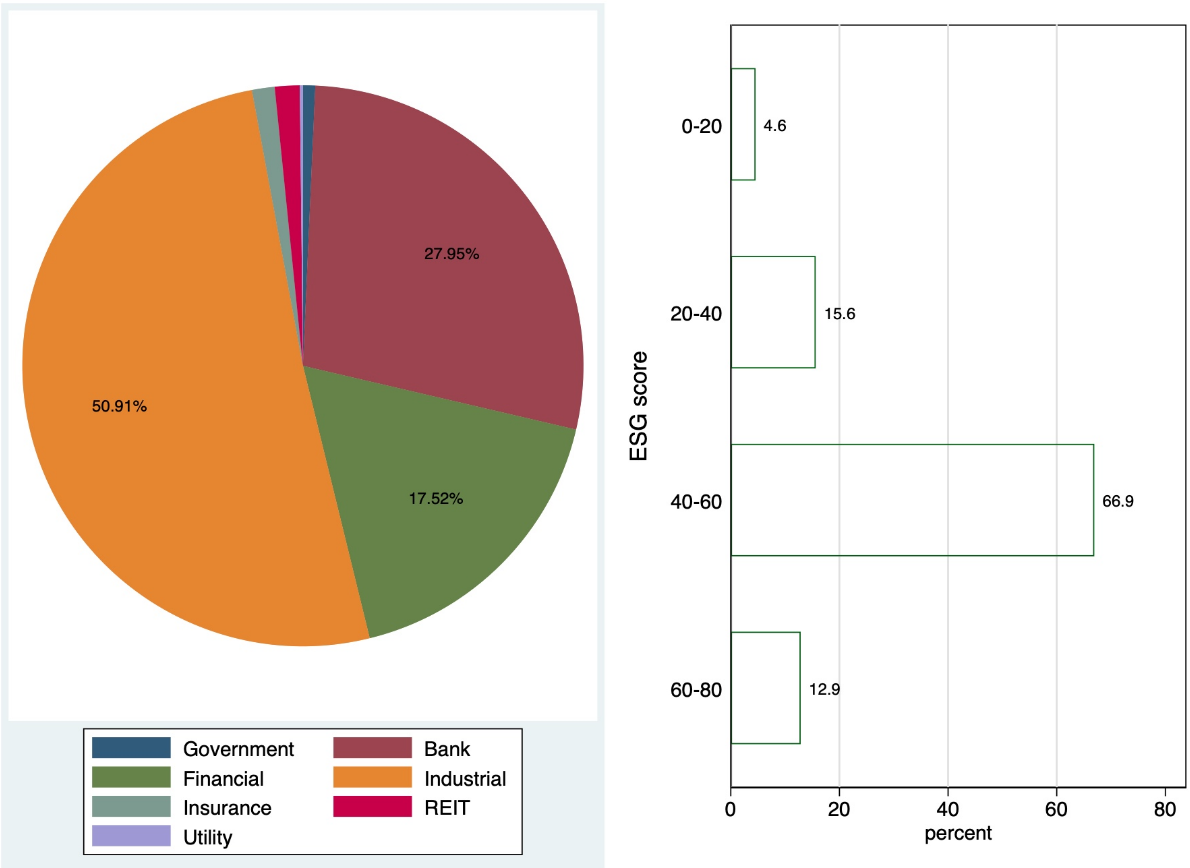


Figure 6: Credit rating composition
This figure shows the composition of credit ratings

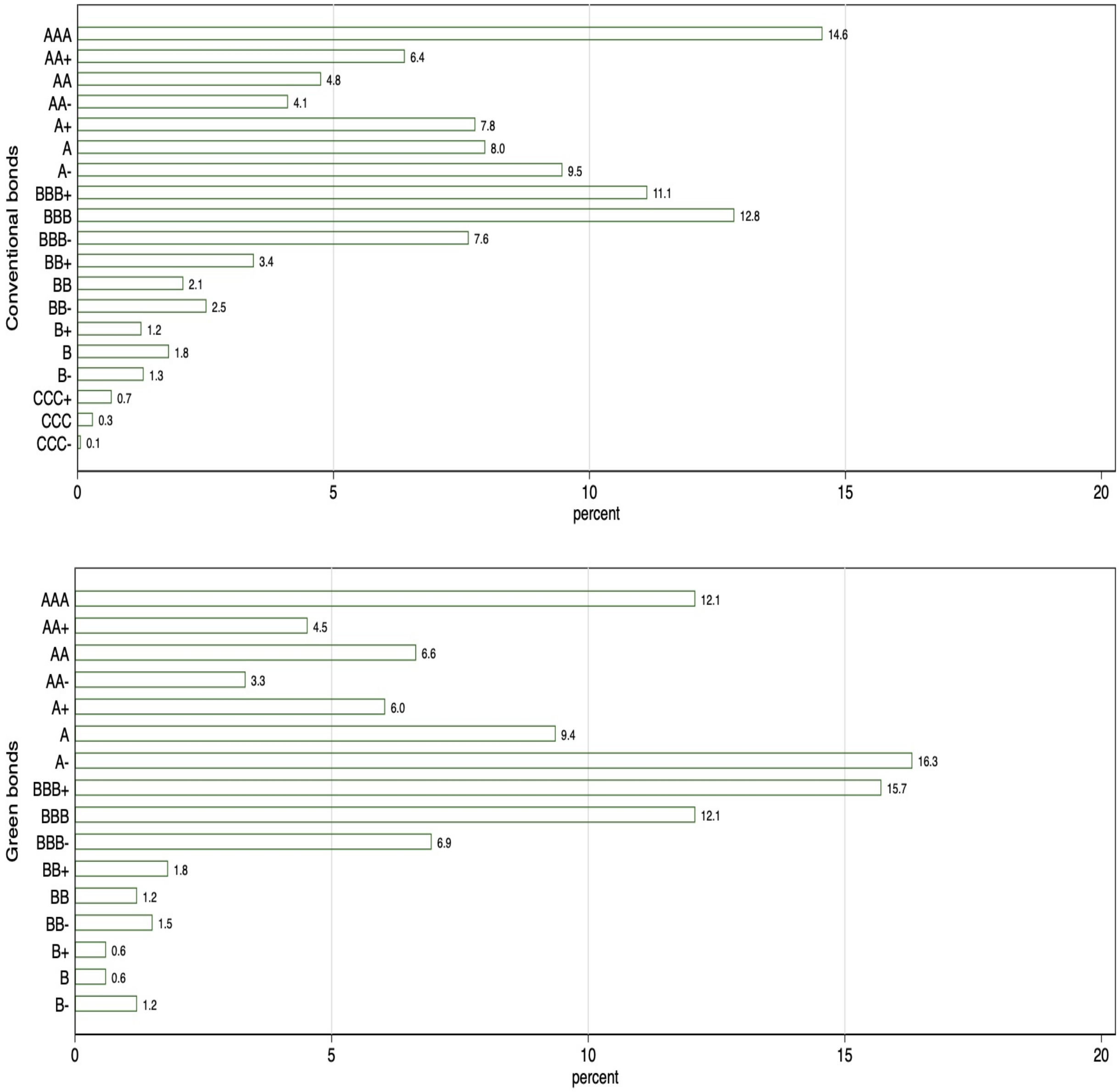


Figure 7: Proportion of investment grade and high yield bonds
This figure shows the proportion of investment grade and high yield bonds

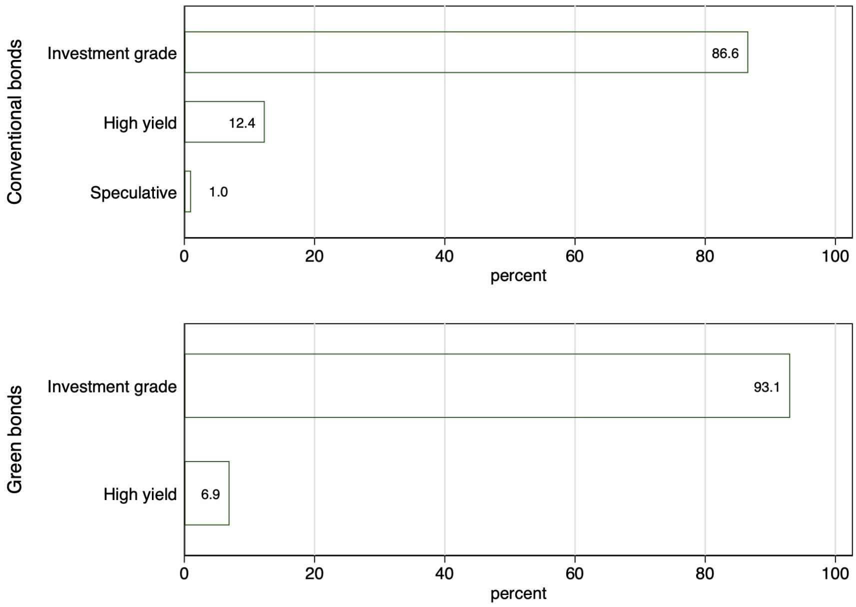


Figure 8: Time to maturity composition
This figure shows groups for time to maturity, measured in years.

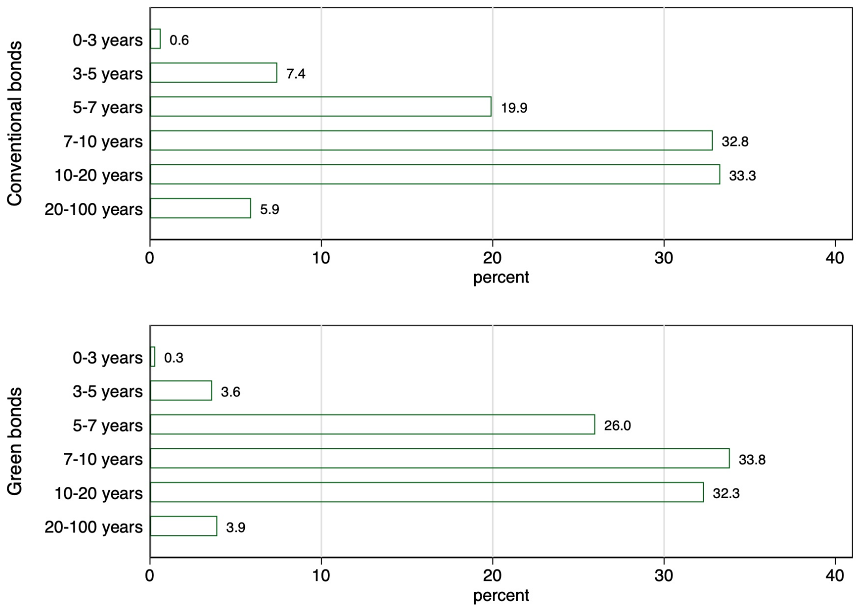


Figure 9: Seniority composition
This figure shows the degree of seniority for conventional and green bonds.

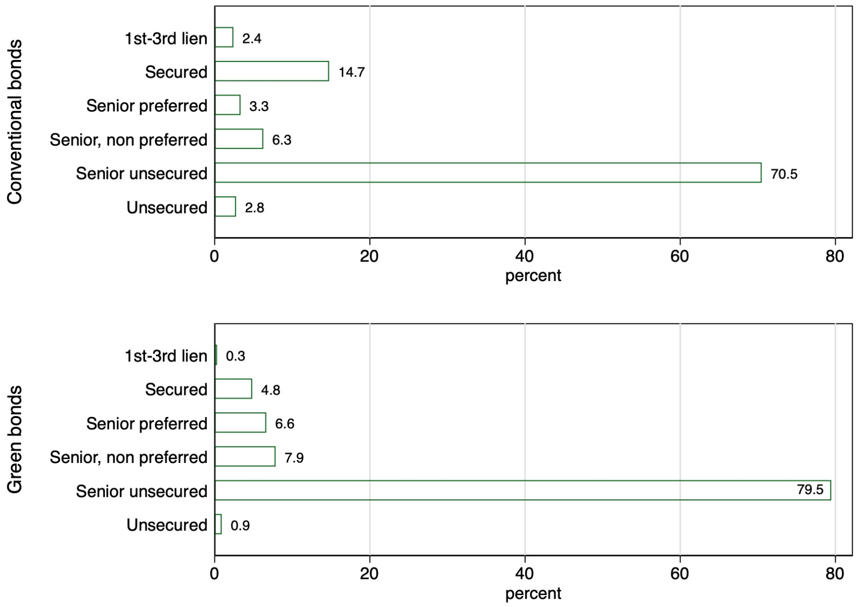


Figure 10: Collateral composition
This figure shows an overview of the collateral types

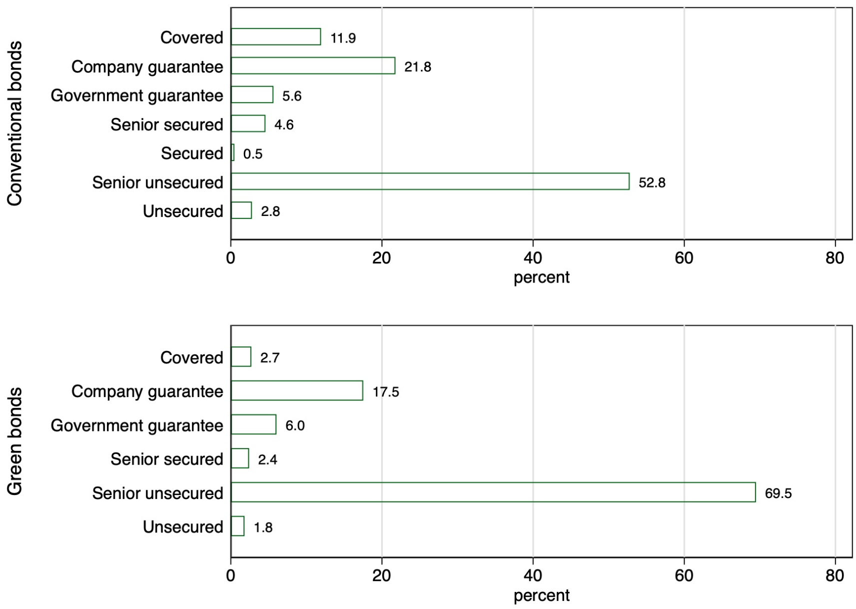


Figure 11: Bond structures
This figure illustrates how many bonds in the sample carry an option

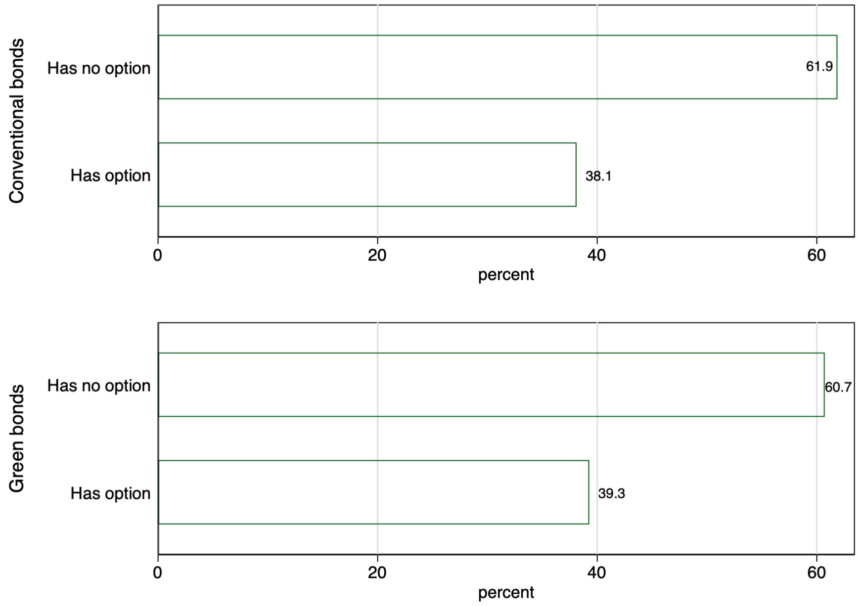


Figure 12: Eligibility for the ECB asset purchase program
This figure expresses how many conventional and green bonds are eligible for the asset purchase program of the ECB

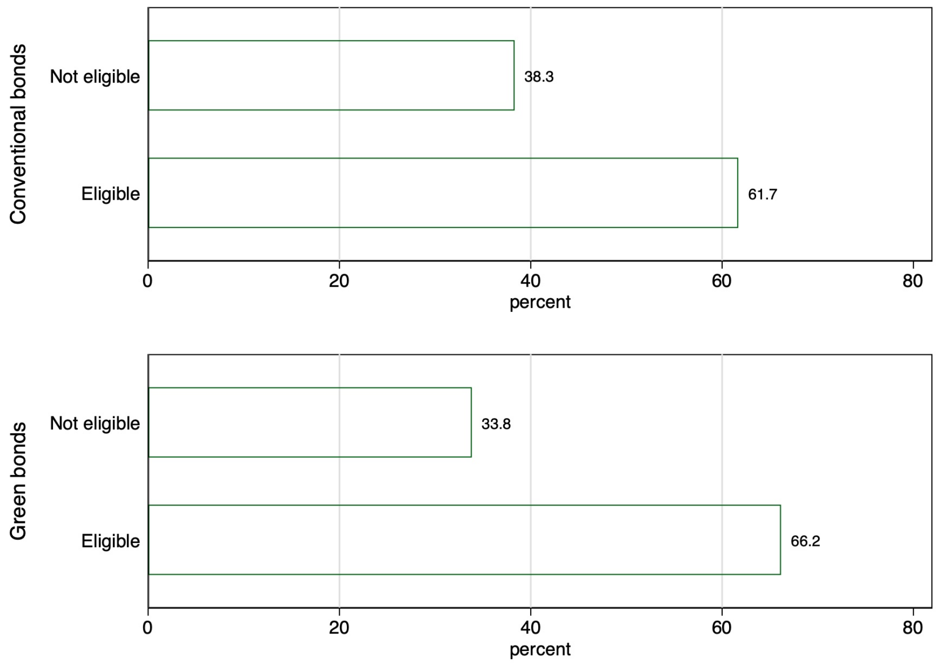


Figure 13: Issue experience
This figure provides details about the number of issuers per issue for the sample. A regular issuer is an issuer who has issued more than two green bonds.

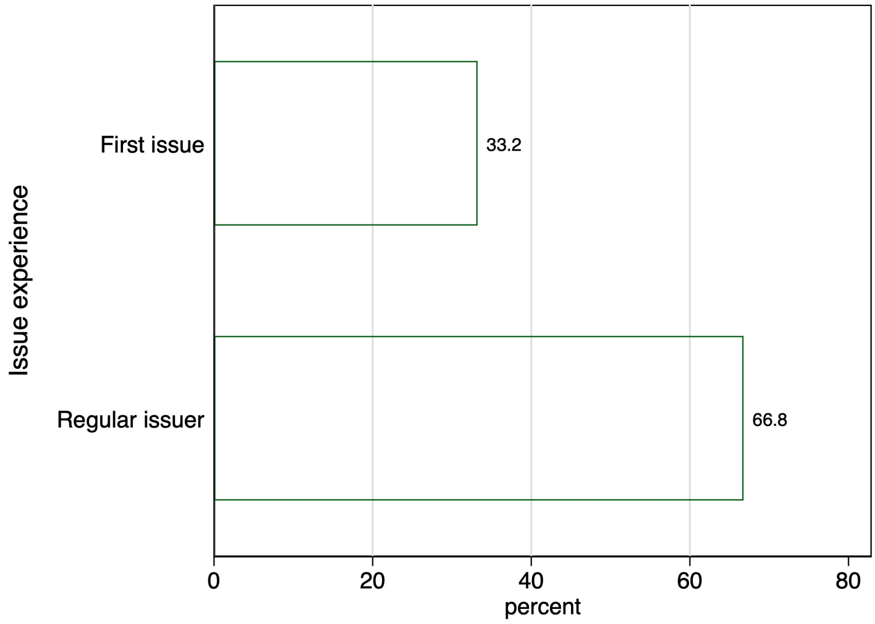


Figure 14: External review
This figure displays the proportion of green bonds that are externally reviewed.

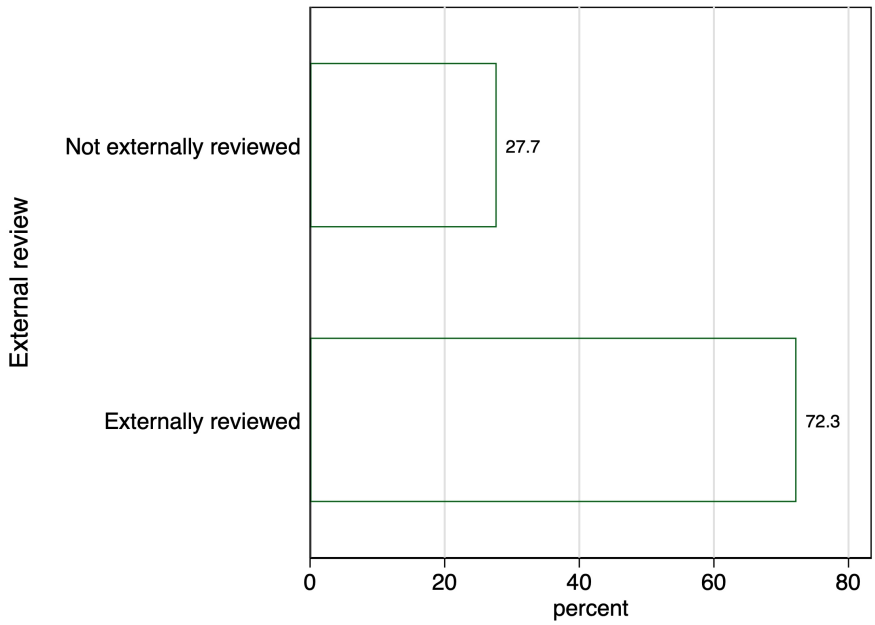
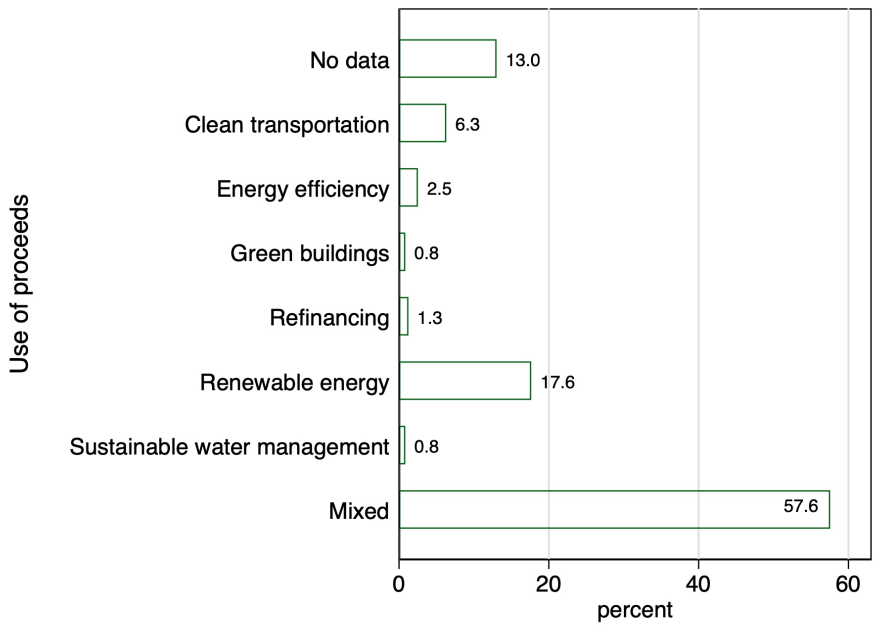


Figure 15: Use of proceeds

This figure shows what the proceeds of the green bonds are used for. "Mixed" use of proceeds means the proceeds are used for multiple eligible projects.



C. Additional tables for the results section

Table 12: CEM matching with procedure of Loffler et al. (2021)

This table shows the summary on the coarsened exact matching of the conventional and green bonds with the specification of. The diagnostic summary shows the total imbalance (the multivariate L1 distance). The summary on the matching sample shows how many conventional and green bonds are matched or unmatched. The bonds are matched on i) issue size, ii), year of issue, iii) time to maturity in years, iv) issuer sector, v) optionality, vi) credit rating, vii) seniority type

Panel A: Regular CEM				
Diagnostic summary		Matching summary		
			Conventional	Green
Number of strata	1288	All	4598	331
Number of matched strata	176	Matched	1531	305
Multivariate L1 distance	0.517	Unmatched	3067	26
Panel B: K2K option				
Diagnostic summary		Matching summary		
			Conventional	Green
Number of strata	1288	All	4598	331
Number of matched strata	176	Matched	303	303
Multivariate L1 distance	0.479	Unmatched	4295	28

Table 13: Propensity balancing test with the specification of Gianfrate & Peri (2019).

This table shows the results for the balancing test of the propensity scores. The balancing test calculates the compatibility of the unmatched and the matched samples. On the left, U stands for unmatched and M stands for matched. Columns 3 and 4 contain means of the variables, hence the word 'means' above those columns. Column 7 shows whether the unmatched and matched samples differ significantly from each other. A value above 0,05 indicates the samples do not differ significantly, which means they are comparable for analysis. Panel B shows additional statistics on the balancing properties. Ideally, Rubin's B should be less than 25 and Rubin's R be between 0.5 and 2 for the samples to be considered sufficiently balanced.

Panel A: Balancing test

		Means				
Variable (1)	Sample (2)	Treated (3)	Control (4)	% Bias (5)	% Reduction (6)	T-test (7)
Amount issued (ln)	U	2018.4	2017.4	49.9	0	0
	M	2018.4	2018.5	-2.3	95.4	0.819
Issue year	U	20.312	20.495	-31.8	0	0
	M	20.317	20.306	1.9	93.9	0.83
Time to Maturity (in years)	U	9.0882	9.189	-2.1	0	0.804
	M	9.0237	8.6095	8.6	-311	0.365
Sector	U	0.10588	0.16002	-16	0	0.06
	M	0.10651	0.10651	0	100	1
Credit rating	U	0.52941	0.54744	-3.4	0	0.658
	M	0.53254	0.53846	-1.1	67.2	0.917
Collateral	U	3.8	3.2195	30.2	0	0
	M	3.7929	3.7041	4.6	84.7	0.66

Panel B: Additional statistics

Sample	R-squared	p>chi2	Mean bias	Median bias	Rubin's B	Rubin's R
Unmatched	0.058	0	22.2	23.1	73.1*	0.68
Matched	0.003	0.976	3.1	2.1	12	1.39

Table 14: Greenium between sectors

This table shows results for the greenium estimates between sectors. There were not enough observations to generate results for SSAs. The price at issuance variable indicates the greenium in the primary market and the yield to maturity variable indicates the greenium in the secondary market. For clarity, bond prices and yields are inversely related. Hence, a higher bond price or lower yield are both considered a green bond premium.

Dependent variable:	Issue Price	Issue Price	Yield to maturity	Yield to maturity
Sector	Financials	Corporations	Financials	Corporations
Model	(1)	(2)	(3)	(4)
Green bond	0.343	-0.270	-0.086**	-0.209
	(0.361)	(0.267)	(0.036)	(0.347)
Liquidity	-2.093	0.081	1.480***	4.566***
	(1.611)	(0.499)	(0.167)	(0.815)
10D Volatility	0.280	-0.253	0.106***	-0.023
	(0.244)	(0.173)	(0.019)	(0.186)
Constant	99.940***	100.105***	-0.589***	-0.893*
	(0.237)	(0.448)	(0.035)	(0.497)
Observations	28	21	63	34
R-squared	0.086	0.104	0.798	0.507
Adjusted R-squared	-0.0284	-0.0536	0.788	0.470

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15: Treatment effects between sectors

This table reports the average treatment effect on the treated observations (the green bonds) for the primary market (panel A) and the secondary market (panel B) between the two sectors. NN stands for nearest neighbour and indicates the number of neighbours are used. R stands for radius and indicates the range of matches that is included. A radius of 0.01 indicates that propensity scores that are 0.01 units away from the propensity score that is used will be included.

Panel A: Primary market. Dependent variable: Yield at Issue

Test	Nearest neighbour matching (NN=3)		Kernel matching		Radius matching (R = 0.005)	
Sector	Financials	Corporations	Financials	Corporations	Financials	Corporations
Model	(1)	(2)	(3)	(4)	(5)	(6)
ATT	-0.345**	-0.258	-0.111	-0.317	-0.407***	-0.018
Std. Error	(0.161)	(0.342)	(0.128)	(0.321)	(0.150)	(0.288)
# Treated	15	24	15	24	15	24
# Untreated	38	69	122	162	170	411

Panel B: Secondary market. Dependent variable: Yield to maturity

Test	Nearest neighbour matching (NN=3)		Kernel matching		Radius matching (R = 0.005)	
Sector	Financials	Corporations	Financials	Corporations	Financials	Corporations
Model	(1)	(2)	(3)	(4)	(5)	(6)
ATT	-0.054	0.135	-0.014	0.075	-0.104***	0.140
Std. Error	(0.044)	(0.108)	(0.035)	(0.103)	(0.038)	(0.097)
# Treated	162	165	162	165	162	165
# Untreated	379	444	1407	1306	1824	2264

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 16: Greenium over time, CEM method

This table reports the results with the CEM method between the two time periods for both the primary and secondary markets. The price at issuance variable indicates the greenium in the primary market and the yield to maturity variable indicates the greenium in the secondary market. For clarity, bond prices and yields are inversely related. Hence, a higher bond price or lower yield are both considered a green bond premium.

Dependent variable:	Issue Price	Issue Price	Yield to Maturity	Yield to Maturity
Period	2014-2017	2018-2021	2014-2017	2018-2021
Model	(1)	(2)	(3)	(4)
Green bond	-0.477	0.292	-0.002	-0.225
	(0.484)	(0.288)	(0.052)	(0.150)
Liquidity	10.553*	-0.820	1.663**	4.238***
	(5.271)	(0.708)	(0.606)	(0.384)
10D Volatility	-2.167**	0.057	0.039	-0.021
	(0.788)	(0.107)	(0.114)	(0.072)
Constant	99.896***	99.992***	-0.667***	-0.861***
	(0.272)	(0.294)	(0.045)	(0.168)
Observations	11	38	14	83
R-squared	0.380	0.062	0.904	0.611
Adjusted R-squared	0.114	-0.0210	0.878	0.600

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 17: Treatment effects over time

This table reports the average treatment effect on the treated observations (the green bonds) for the primary market (panel A) and the secondary market (panel B) between the two time periods. NN stands for nearest neighbour and indicates the number of neighbours are used. R stands for radius and indicates the range of matches that is included. A radius of 0.01 indicates that propensity scores that are 0.01 units away from the propensity score that is used will be included.

Panel A: Primary market. Dependent variable: Yield at Issue

Test	Nearest neighbour matching (NN=3)		Kernel matching		Radius matching (R = 0.005)	
Period	2014 - 2017	2018-2021	2014 - 2017	2018-2021	2014 - 2017	2018-2021
Model	(1)	(2)	(3)	(4)	(5)	(6)
ATT	-0.448*	-0.245	-0.104	-0.222	-0.333*	-0.155
Std. Error	(0.229)	(0.407)	(0.182)	(0.396)	(0.185)	(0.364)
# Treated	18	22	18	22	18	22
# Untreated	51	62	429	126	464	247

Panel B: Secondary market. Dependent variable: Yield to maturity

Test	Nearest neighbour matching (NN=3)		Kernel matching		Radius matching (R = 0.005)	
Period	2014 - 2017	2018-2021	2014 - 2017	2018-2021	2014 - 2017	2018-2021
Model	(1)	(2)	(3)	(4)	(5)	(6)
ATT	-0.074	-0.015	-0.023	0.026	-0.125***	0.035
Std. Error	(0.053)	(0.077)	(0.049)	(0.073)	(0.046)	(0.069)
# Treated	80	251	80	251	80	251
# Untreated	208	631	649	2052	1566	2588

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 18: Effect of greenium determinants in the primary market

This table shows results for the effects of i) number of issues, ii) ESG score, iii) external review and iv) use of proceeds on the issue price of a green bond (primary market). The dependent variable is thus the issue price. Please consult chapter 4 for the hypotheses on the effects of the variables. For clarity, bond prices and yields are inversely related. Hence, a higher bond price or lower yield are both considered a green bond premium.

Variable of interest	# issues	ESG score	External review	Use of proceeds
Model	(1)	(2)	(3)	(4)
Liquidity	-1.419	-1.547	-1.232	-2.448*
	(1.197)	(1.948)	(1.124)	(1.151)
10D Volatility	0.197	0.368	0.307	0.267
	(0.171)	(0.452)	(0.305)	(0.243)
First issue	1.338**			
	(0.558)			
Regular issuer	0.901*			
	(0.470)			
ESG score: 20-40		0.439		
		(0.262)		
ESG score: 40-60		0.054		
		(0.431)		
ESG score: 60-80		-0.317		
		(0.735)		
External review			0.302	
			(0.855)	
Use of proceeds (Clean transportation)				-0.598
				(0.433)
Use of proceeds (Renewable energy)				-2.217***
				(0.589)
Use of proceeds (Mixed)				-1.400**
				(0.543)
Constant	99.278***	99.538***	99.838***	101.801***
	(0.475)	(0.467)	(0.819)	(0.676)
Observations	29	20	20	20
R-squared	0.227	0.114	0.096	0.235
Adjusted R-squared	0.0984	-0.202	-0.0733	-0.0376

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 19: Effect of greenium determinants in the secondary market

This table shows results for the effects of i) number of issues, ii) ESG score, iii) external review and iv) use of proceeds on the yield to maturity of a green bond (secondary market). The dependent variable is thus the yield to maturity. Please consult chapter 4 for the hypotheses on the effects of the variables. For clarity, bond prices and yields are inversely related. Hence, a higher bond price or lower yield are both considered a green bond premium.

Variable of interest	# issues	ESG score	External review	Use of proceeds
Model	(1)	(2)	(3)	(4)
Liquidity	3.560***	3.340***	4.129***	3.648***
	(0.473)	(1.061)	(0.615)	(0.753)
10D Volatility	-0.081	-0.091	-0.332*	-0.216
	(0.089)	(0.112)	(0.189)	(0.171)
First issue	0.320			
	(0.275)			
Regular issuer	0.077			
	(0.126)			
ESG score: 20-40		0.689*		
		(0.340)		
ESG score: 40-60		0.459**		
		(0.224)		
ESG score: 60-80		0.572***		
		(0.166)		
External review			-0.865	
			(0.577)	
Use of proceeds (Clean transportation)				-0.985
				(0.721)
Use of proceeds (Energy efficiency)				-0.737
				(0.627)
Use of proceeds (Green buildings)				-0.279
				(0.455)
Use of proceeds (Renewable energy)				-0.933
				(0.644)
Use of proceeds (Mixed)				-0.728
				(0.590)
Constant	-0.905***	-1.232***	0.152	0.098
	(0.186)	(0.355)	(0.652)	(0.710)
Observations	40	35	29	29
R-squared	0.628	0.606	0.730	0.712
Adjusted R-squared	0.586	0.538	0.698	0.617

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 20: Robustness test for the CEM method

This table reports the results for the robustness test. The methodology is similar to the other tables, except the specification of Löffler et al. (2021) is used here. The conventional and green bonds are exactly matched on i) issue year, ii) issue size, iii) time to maturity, iii) issuer type, iv) optionality, v) rating and vi) seniority. The yield at issuance variable indicates the greenium in the primary market and the yield to maturity variable indicates the greenium in the secondary market.

Dependent variable:	Yield at Issuance	Yield to Maturity
Model	(1)	(2)
Green bond	-0.106	-0.082*
	(0.144)	(0.046)
Liquidity	3.773***	3.007***
	(0.542)	(0.245)
10D Volatility	-0.408***	-0.078**
	(0.080)	(0.032)
Constant	0.731***	-0.570***
	(0.134)	(0.056)
Observations	257	1,809
R-squared	0.327	0.389
Adjusted R-squared	0.319	0.388

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 21: Robustness test for the PSM method

This table reports robustness test for the PSM method. The average treatment effect on the treated observations (the green bonds) for the primary market (panel A) and secondary markets (panel B). NN stands for nearest neighbor and indicates the amount of neighbors are used. R stands for radius and indicates the range of matches that is included. A radius of 0.01 indicates that propensity scores that are 0.01 units away from the propensity score that is used will be included.

Panel A: Primary market. Dependent variable: Yield at Issue

Test	Nearest neighbor matching			Kernel matching	Radius matching	
Specification	NN = 3	NN = 5	NN = 8		R = 0.01	R = 0.005
Model	(1)	(2)	(3)	(4)	(5)	(6)
ATT	-0.586**	-0.429*	-0.314	-0.253	-0.329	-0.348
Std. Error	(0.255)	(0.238)	(0.225)	(0.227)	(0.214)	(0.218)
# Treated	40	40	40	39	40	40
# Untreated	115	168	242	509	830	801

Panel B: Secondary market. Dependent variable: Yield to maturity

Test	Nearest neighbor matching			Kernel matching	Radius matching	
Specification	NN = 3	NN = 5	NN = 8		R = 0.01	R = 0.005
Model	(1)	(2)	(3)	(4)	(5)	(6)
ATT	-0.011	-0.016	0.000	-0.037	-0.035	-0.030
Std. Error	(0.062)	(0.059)	(0.058)	(0.058)	(0.055)	(0.055)
# Treated	331	331	331	331	331	331
# Untreated	1019	1357	1824	3438	4229	4221

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1