The Green Advantage:

Exploring the Convenience of Issuing Green Bonds

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Abstract

Despite the growing relevance green bonds, the actual value of the "green" label on the pricing at issuance of these instruments is unexplored. This paper investigates whether green bonds are priced at premium in comparison to bonds with similar characteristics except for the "greeness". By adopting a propensity score matching approach, we study 121 senior bullet Euro-denominated green bonds issued between 2013 and 2017. We find that green bonds are issued with a statistically significant average negative premium of around 18 basis points. The premium is larger for corporate issuers (21 basis points). Also, we show that the premium persists in the secondary market. Overall, we show that the market factor a premium in the pricing of green bonds and therefore they are relatively more convenient for issuers.

Keywords: green bond; sustainability; responsible investment; propensity score; securities issuance.

1. Introduction

During the 21st Conference of Parties (COP21) in 2015, the 196 participating countries agreed to "make finance flows consistent with a pathway towards low greenhouse gas emissions and climate-resilient development" in order to "hold the increase in the global average temperature to well below 2 °C above pre-industrial levels". The issue of how to finance the transition to a global low-carbon economy in order to achieve this ambitious goal appears more and more crucial, especially when considering the massive amount of financing necessary to shift from rhetoric to action. OECD estimated that approximately USD 103 trillion of additional investments will be required between 2016 and 2030 to meet global development needs in a way that is climate compatible (OECD 2017). With banks having restricted lending capabilities and public budgets often under strain, private sector sources of capital need to be engaged. In this perspective, green bonds are considered to be a fundamental financial tool to facilitate the transition towards a low-carbon economy (World Bank, 2015).

Green bonds are a relatively new type of bonds defined by the International Capital Markets Association (ICMA) as "any type of bond instrument where the proceeds will be exclusively applied to finance or re-finance, in part or in full, new or/and existing eligible green projects". In other words, green bonds are conventional bonds with just one distinguishing feature: proceeds are used for environment-friendly projects, primarily related to climate change mitigation and adaptation. The Green bond market aims therefore to enable and develop the key role debt capital markets can play in funding projects that contribute to environmental sustainability. The evolution of this market over the last years confirms the tremendous potential of this financial instrument. Indeed, since the European Investment Bank (EIB) issued the first Green bond in 2007, the market has kept growing and becoming more sophisticated.

This paper investigates how the market prices green bonds, and whether issuers are able to achieve a lower yield by issuing a bond labelled as "green" rather than an equivalent non-green bond ("conventional bond" in the remaining of the paper). Empirically, we adopt a propensity score matching approach to study the pricing of green bonds in the Euro primary and secondary markets.

Our paper is, to the best of our knowledge, the first measuring the primary yield of green bonds and thus estimating the relative convenience to issue bonds labelled as green versus conventional ones. Our results show that there is a significantly Green bond premium (meaning a spread discount) incorporated in the Euro-denominated Green bonds' primary yields. Furthermore, the premium is consistent across issuers' types. The same analysis performed on the same sample of Euro-denominated bonds but considering the bonds' bid I-spreads (Interpolated spreads) at different dates instead of the spreads at issuance advocates for the existence of a lower (in absolute terms) but still significant Green bond premium also in the secondary market. Our findings suggest that, even taking into account the extra-costs needed to obtain a green certification for the issuance, green bonds are relatively more convenient for the issuers. Hence, green bonds are potentially beneficial not only to society, but also to the issuers because they can reduce the cost of debt capital.

The remainder of the paper is organised as follows. Section 2 introduces the relevant literature on the Green bonds market performance in primary and secondary markets. Section 3 describes the database and the samples that will be used to carry out the analysis. Section 4 presents the main methodological approach. Section 5 describes the findings obtained using this empirical model. Section 6 discusses the sources of the Green bond premium. Section 7 contains a discussion about our findings and concludes.

2. Literature Review

Green bonds are a recent phenomenon and the actual boom of this class of bonds started in 2013. Consequently, an initial exhaustive Green bonds database has become to emerge only recently. This explains why to date the scholarly literature covering Green bonds is limited.

Barclays (2015) first attempted an estimation of the performance of Green bonds finding a -20 basis points difference between the spread of Green bonds and comparable conventional issues (therefore investors pay a premium for Green bonds).

On the other hand, Ge and Liu (2015) examining how a firm’s corporate social responsibility (CSR) performance is associated with the cost of its new bond issues in the US market, found that firms with better CSR performance are able to issue bonds at lower cost. Similar conclusions have been reached by Oikonomou, Brooks and Pavelin (2014). Bauer and Hann (2010), analyzing a large cross-industrial sample of US public corporations, found that environmental concerns are associated with a higher cost of debt financing and lower credit ratings, and proactive environmental practices are associated with a lower cost of debt. Stellner, Klein and Zwergel (2015) found only weak evidence that superior corporate social performance (CSP) results in systematically reduced credit risk; besides, they found a decrease of corporate bonds’ z-spreads of around 9.6 basis points if the CSP of a company mirrors the environmental, social, and governance (ESG) performance of the country it is located in. On the contrary, Menz (2010), focusing on the European corporate bond market, observed that the risk premium for socially responsible firms was, *ceteris paribus*, higher than for non-socially responsible companies, although this finding is only slightly significant.

In 2016 I4CE stated that “there is no clear evidence that Green bonds reduce the cost of capital for low-carbon projects organizations”, while HSBC (2017) argued that Green bonds price the same as conventional bonds but trade higher. The Climate Bonds Initiative (2016) looked for the existence of a “Greenium” at issuance (i.e. a persistent negative new issue premium associated with Green bonds) focusing on 14 bonds; they conclude that it seems to exists only for some bonds. However, they found that Green bonds' spreads tighten considerably in the immediate secondary market.

Bloomberg (2017) found, in line with Barclays, the existence of a strongly negative Green premium of about -25 basis points in the secondary market. On the other hand, Karpf and Mendel (2017) investigated the yield term structure of Green and conventional bonds in the U.S. municipal bonds market and found that Green bonds seem to be penalized by the market, as they are traded at higher yields, which implies a positive premium. Zerbib (2017) has analyses the Green bond premium focusing on 135 investment grade senior bullet fixed-rate Green bonds issued worldwide. The paper shows that bondholders pay an average Green premium (statistically significant) of 8 basis points in the secondary market. Natixis (2017), focusing on the bonds issued by the governmental agencies finds that, although there is a "shy Green advantage" in the supranational, sub-sovereign, and agency (SSA) primary market, the Green premium on the secondary market is not so evident and is quite volatile. Morgan Stanley (2017) finds that investors can buy Green bonds at similar spread levels to conventional bonds after adjusting for sector, curve and currency.

All in all, the evidences about the existence of a Green-related premium/discount in the secondary and primary bond markets are mixed. Further research on this topic is therefore needed, especially with more data available and apparent growing interests from both issuers and investors. Our study extends the literature on Green bonds by providing evidence of the existence of a significant negative Green premium in the Euro-denominated primary market adopting a propensity score matching methodology and suggesting that this premium persists also in the secondary market.

3. Data description

We set up our samples in order to evaluate, through propensity score matching techniques, the difference between yields at issuance of Green bonds and their conventional peers. Our data come from "Bond Radar" of Bloomberg. Specifically, our initial sample comprises all the bonds issued from January 2007 to December 2017. For every bond, Bond Radar provides detailed information about the bond issues' and issuers charcteristics. In addition, Bond Radar provides the emission yield/spread: this is generally the yield of a government bond with a corresponding maturity or the mid-swap rate, which depends on the currency of denomination and tenor of the security. In particular, USD-denominated bonds usually have the price expressed as a spread over the related benchmark government bond, while the large majority of EUR-denominated bonds are priced over the Euro mid-swap rate ("€MS"). As a consequence, when we analyse the Euro market, the outcome variable is not the primary yield, but the spread over the Euro mid-swap rate. The advantage for our analysis of using the spread as outcome variable is that, while the primary yield widely depends on the macroeconomic conditions of the market (captured by the €MS), the spread is just a function of the country, industry, firm and bond specific characteristics. Moreover, during the execution of a new issue the €MS is given and investors demand only affects the spread. In other words, if there exists a Green bond premium, it is totally incorporated in the spread. Hence, considering the spread alone instead of the yield greatly improves our ability to isolate the effect that the Green label may have on the price of a new bond. In addition, this helps to reduce the "issue-date bias", i.e. the bias that arises when the only relevant difference between two matched issues (apart from the pricing) is the date of issuance: at least the difference in price/yield due to the different levels of the Euro mid-swap rate at different dates is eliminated.

As of December 2017, Bond Radar reports 7589 public EUR-denominated bonds issued since January 2007, of which 154 are classified as Green. We eliminates from the sample all the floating rate notes (FRN) (to avoid the uncertainty that floating rates could have on the pricing at issuance), all those bonds for which the yield/spread is not available or with a size lower than EUR 200 million, all the high yield and unrated bonds (6 bonds in total) and also all those bonds not priced on the Euro mid-swap rate.

Following these changes, there are 121 Green bonds left in the database and these include instruments of various kinds: corporate, sovereign, agency, municipal, supranational, financial, as well as covered and callable bonds. Since the first Green bond in our sample dates back to 2013, for the reason just described and in order to decrease the "issue-date bias", we exclude all the bonds issued before January 2013.

Therefore, our comprehensive sample ("*All*") comprises 3055 bond issues, of which 121 are labelled as "Green". Following an analogous procedure, we define two subsamples: "*Corporate Issuers"* and "*Non-corporate Issuers"*, which contain respectively all the bonds issued by corporations and all the bonds issued by the other market players. *Corporate Issuers* is constituted by 781 observations of which 43 are labelled as Green; *Non-corporate Issuers* is constituted by 2155 observations of which 78 are labelled as Green. Table 1 shows the descriptive statistics of the comprehensive sample.

TABLE 1

Descriptive Statistics

Variable	*Mean*	*Std. Dev.*	*Min*	*Max*
Volume (EUR mln)	620.3306	332.6452	250	2000
Tenor	8.153538	3.949145	3.019178	30.40274
Spread	27.71901	40.7732	-32	140

4. Methodology

To address the question of whether there is a Green bond premium/discount in the Euro primary market, we should compare the spreads of the Green bonds with those of their conventional peers. To perform such comparison we use propensity score matching techniques which are suited to empirical settings where there is a "treatment", a group of treated observations and a group of untreated observations. This is exactly our case: we refer to "getting the Green label" as the treatment, to Green bonds as the treatment group, and to conventional bonds as the untreated group. The change in the outcome variable (i.e. the primary market spread) due to the treatment is our treatment effect.

The problem of computing the treatment effect is that a real counterfactual framework would require observing each bond being priced in both states (with and without treatment), and this is clearly not possible: we can observe only one outcome for each bond. Consequently, given an observed outcome (e.g. the spread given that the bond is labelled as Green), the counterfactual outcome has to be estimated. PSM techniques allow to estimate the counterfactuals.

Specifically, in this paper we will estimate the "average treatment effect on the treated" ("atet" or "ATT") and not the "average treatment effect on the population" ("ATE"). The reason for this choice is that Green bonds represent less than 5% of the population; this means that, while it is feasible to accurately estimate the counterfactual for Green bonds (and hence the ATT), the vice versa does not hold. In fact, the additional challenge when estimating ATE is that both counterfactual outcomes have to be constructed.

To obtain the best possible estimation of the counterfactuals and ATT, we would need to build a control group (a group of conventional bonds) that is ideally identical to the treated group in everything but for the treatment status. However, treated and untreated bonds usually differ in other characteristics apart from treatment status, and assignment to treatment and control group will not be random. For instance, firms that operate in the utility and power sector may have a higher probability of issuing Green bonds because they are clearly more involved in climate change and environment-related issues. Hence, comparing the mean values of the spreads between treated and untreated bonds would lead to biased results and it is not advisable.

A way for overcoming this problem is to find a control group that is as similar as possible to the treated group in all relevant (observable) pre-treatment characteristics “X”. That being done, differences in outcomes of this well selected and thus adequate control group and of treated group can be attributed to the treatment, i.e. to the Green label. The problem is that, as the number of characteristics determining selection increases, it is more and more difficult to find comparable individuals (“curse of dimensionality”). Rosenbaum and Rubin (1983 and 1984) describe how we can bundle such characteristics in a single-index variable, the propensity score, which makes it possible to achieve consistent estimates of the treatment effect in the same way as matching on all covariates.

To be more specific, estimating an ATT using propensity score matching involves a two-step procedure (Wamser, 2014). In the first step, we estimate a propensity score to predict the probability of bonds of being Green, using a Logit or Probit function. In the second step, we match green (treated units) and conventional bonds (control units) and estimate the treatment effect by computing the difference in the spread (outcome variable) between matched units. The matching procedure is based on the propensity score, which is a continuous variable, that we obtained in the first part of the process. Despite all matching estimators compare the outcome of a treated unit with outcomes of control group members, we need to make sure to use the appropriate PSM estimators among those available. Moreover, three main conditions need to be satisfied in order to effectively use PSM techniques. The first one is the “conditional independence assumption” (CIA), which requires that the outcome variable (the spread) must be independent of treatment conditional on the propensity score. In other words, it requires that the common characteristics that affect treatment assignment and outcomes be observable. This is a strong assumption and it is impossible to verify so that bias resulting from unobservable characteristics can never be ruled out. This is clearly the main limit of this kind of techniques. The second condition is the "common support", i.e. the presence in both groups of units with similar propensity scores. Implementing the common support is necessary to avoid the comparison of "incomparable members" of the groups. The third and last condition is that the propensity score balances the covariates: similar propensity scores have to be based on similar observed characteristics.

In our analysis, we apply the nearest neighbours matching (NN) with 3, 5, and 8 matches, the kernel matching and the radius matching with different levels of the radius ("r").

With the nearest neighbours matching the indicated numbers of units from the comparison group (3, 5 or 8 in our case) are chosen as matching partners for a single treated unit that is closest in terms of propensity score. In particular, we implement this matching method "with replacement", i.e. we allow members of the control group to be used more than once as matching partners for treated units. Matching with replacement enhances the average quality of matching and decreases the bias (assuming some re-use occurs) but, at the same time, increases the variance of the estimator (Smith and Todd, 2005). A possible drawback of this methods is that the indicated number of matches are assigned to every treated bond, no matter how close propensity scores actually are, which may result in a rather unsatisfying matching quality.

Radius matching may help to solve this problem: treatment units are matched to control units only if the propensity scores of the latter are within a certain, pre-definite, range. The smaller we define the radius (r), which defines the tolerable distance within which units are matched, the better is the quality of the matches. However, if the propensity scores are "well balanced" between the treatment and control groups, occurrence of bad matches increases with radius matching compared to nearest neighbours matching.

Finally, the Kernel matching estimator calculates the weighted averages of all units in the control group to construct the counterfactual outcome; the closer the propensity score of a given untreated unit is to the one of the treated unit, the higher its weight will be.

To evaluate different matching methods, we need to take into account the trade-off between the number of matches (quantity) and their quality. Testing the balancing properties (third condition) of the various methods that we implement, we find that the most balanced matching is obtained by applying the nearest neighbours matching with 8 control units for every Green bond. The results of these tests will be shown in section 5.

5. Results

The section is structured as follows: in paragraph 5.1 we analyse the comprehensive sample and show the procedure to compute the propensity score step by step as well as the results of the nearest neighbours matching with 8 matches for each Green bond; then, we present and compare the results of the different matching techniques. In paragraph 5.2, we perform the same analysis on the subsamples of corporate and non-corporate issuers. Finally, in paragraph 5.3 we look for the existence of a Green premium/discount in the secondary market.

5.1 Primary Market

The first stage of the process to estimate the ATT involves obtaining the propensity score. In order to do so, we use a binary outcome model. The results are reported in table 2.

TABLE 2

Probability of treatment

	Logit	*Probit*
Y_2013	-2.200325***	-110444***
Y_2014	-.8086119***	-.4507358***
Y_2015	-.8670505***	-.4532353***
Y_2016	-.6470752**	-.3472059***
ln(Volume)	-.7196377***	-.3723906***
Tenor	-.0544328**	-.0305401***
AAA - AA	1.163726	.5238154
AA(-) - A	2.035177***	.9863102***
A(-) - BBB	1.3763**	.6405561**
Covered	-1.868883***	-.707749***
Western Europe	.6114553	.3257968
Asia, Australia, New Zealand	.5164872	.2891308
CEEMEA	-.9872744	-.4485569
HG Global	.5841408	.2790287
Agency - Sovereign	.7874929	.4082205
Banking	-.2370798	-.1550609
Basic Materials	-.7380122	-.3243915
Manufacturing	-2660922**	-1.173896***
Municipality - Local Government	-1.776484**	-.7500504**
Supra	1.049454	.5621605*
Transport and Logistics	-.8308692	-.398562
Utilities and Power	1.210989**	.6388076**
cons	.7147529	.3400976

Notes: Dependent variable: Green. (***) (**) (*) indicate significance at the (1%) (5%) (10%) level. Y_2017, BBB(-) - BB(+), North America and Real estate omitted because of collinearity. Logit pseudo R2: 0.2000; Probit pseudo R2: 0.2073.

As expected, a bond is more likely to be labelled as Green if the issuer belongs to the utility and power sector or if it is not covered (the corresponding coefficients are statistically significant at the 5% and 1% level respectively). On the contrary, bonds issued by manufacturing companies, municipalities and local governments are less likely to be Green. We also find that, overall, the larger the size and the longer the tenor, the less likely a bond is to be treated. Finally, bonds issued recently are associated with a higher probability of treatment, and this is coherent with the market history.

We then assess if the propensity score (estimated through the Logit function) is properly specified by applying the “blocking” procedure (Rosenbaum and Rubin, 1983): first, data are sorted by propensity score and divided into blocks of observations with similar propensity scores; within each block, it is tested whether the propensity score is balanced between treated and control observations. If not, blocks are too large and need to be split. If, conditional on the propensity score being balanced, the covariates are unbalanced, the specification of the propensity score is not adequate and has to be re-specified.

In our case, the optimal number of blocks, which ensures that the mean propensity score is not different for treated and controls in each block, is 10 and the balancing property of the propensity score is completely satisfied (i.e. also the covariates are balanced within each block). We then conclude that the propensity score is well specified. “Appendix b” shows the inferior bound, the number of treated and the number of controls for each block.

Table 3 presents propensity score matching results for five different matching procedures (in columns).

TABLE 3

Primary market spreads treatment effects

Matching:	Neighbours matching (NN=8)	Neighbours matching (NN=5)	Neighbours matching (NN=3)	Radius matching (r=0.001)	Radius matching (r=0.0005)	Kernel matching
ATT	-18.4707***	-18.5610***	-14.8995***	-19.3955***	-15.1717**	-16.739***
Std. Err.	4.3737	4.7578	4.9963	5.8811	6.7426	4.3126
# treated	121	121	121	116	100	121
# untreated	535	385	254	1484	893	2934

Notes: The ATT and Std. Err. figures are expressed in basis points. Columns refer to the different matching methods: Nearest neighbour matching (NN 3,5,8); Radius (r =0.001) matching with 0.1% radius; Radius (r=0.0005) matching with 0.05% radius; Kernel matching. ATT is the Average Treatment effect on the Treated. # treated (# untreated) is the number of treated (control) units. The propensity score is based on the logit model reported in Table 2. (***) (**) (*) indicate significance at the (1%) (5%) (10%) level. In all estimations, a common probability support of the treated and control units is enforced in order to ensure better comparability of matched units.

As already highlighted, the propensity score matching approach relies on three basic conditions: the CIA assumption, the common support, and the propensity score balancing the covariates. CIA assumption is not testable. On the contrary, common support is implemented and the results in table 3 demonstrate that there is an optimal overlap between the treated and untreated groups. In particular, the 121 Green bonds are all "on support" when nearest neighbours matching is applied.

The third condition requires that, given random assignment to treatment, bonds with the same propensity score should have the same distribution of observable variables used to predict the propensity score. As this balancing property is testable, we provide such tests in Table 4.

TABLE 4

Pstest - Balancing Property

Variable	*Unmatched* *Matched*	*Mean* *Treted*	*Mean* *Control*	*%Bias*	*%Reduction* *|Bias|*	*t-test* *t*	*t-test* *|p|>t*
Y_2013	U	.04959	.1878	-43.7		-3.87	0.000
	M	.04959	.03616	4.2	90.3	0.51	0.608
Y_2014	U	.15702	.17928	-5.9		-0.63	0.531
	M	.15702	.17975	-6.1	-2.1	-0.47	0.638
Y_2015	U	.18182	.21063	-7.2		-0.76	0.445
	M	.18182	.17562	1.6	78.5	0.13	0.900
Y_2016	U	.21488	.21575	-0.2		-0.02	0.982
	M	.21488	.22521	-2.5	-1086.9	-0.19	0.847
Y_2017	U	.39669	.20654	42.2		5.02	0.000
	M	.39669	.38326	3.0	92.9	0.21	0.831
ln(Volume)	U	63.227	6.557	-41.7		-3.87	0.000
	M	63.227	63.155	1.3	96.9	0.11	0.916
Tenor	U	81.535	83.259	-3.9		-0.38	0.701
	M	81.535	79.422	4.8	-22.6	0.41	0.683
AAA - AA	U	.36364	.46319	-20.3		-2.15	0.031
	M	.36364	.36674	-0.6	96.9	-0.05	0.960
AA(-) - A	U	.29752	.22154	17.4		1.96	0.050
	M	.29752	.28512	2.8	83.7	0.21	0.833
A(-) - BBB	U	.31405	.23381	18.0		2.03	0.042
	M	.31405	.31095	0.7	96.1	0.05	0.959
BBB(-) - BB(+)	U	.02479	.08146	-25.4		-2.26	0.024
	M	.02479	.03719	-5.6	78.1	-0.55	0.580
Covered	U	.03306	.25222	-65.9		-5.53	0.000

	M	.03306	.02893	1.2	98.1	0.18	0.854
Western Europe	U	.86777	.83776	8.5		0.88	0.379
	M	.86777	.86054	2.0	75.9	0.16	0.870
Asia, Australia, New Zealand	U	.09091	.05181	15.2		1.88	0.061
	M	.09091	.09917	-3.2	78.9	-0.22	0.827
CEEMEA	U	.01653	.04431	-16.2		-1.47	0.141
	M	.01653	.01963	-1.8	88.8	-0.18	0.857
HG Global	U	.00826	.00307	6.9		0.98	0.327
	M	.00826	.00826	0.0	100.0	-0.00	1.000
North America	U	.01653	.06305	-23.9		-2.09	0.036
	M	.01653	.0124	2.1	91.1	0.27	0.789
Agency - Sovereign	U	.22314	.14349	20.6		2.43	0.015
	M	.22314	.22004	0.8	96.1	0.06	0.954
Banking	U	.21488	.41616	-44.3		-4.43	0.000
	M	.21488	.25723	-9.3	79.0	-0.77	0.440
Basic Materials	U	.02479	.04908	-12.9		-1.22	0.221
	M	.02479	.01756	3.8	70.2	0.39	0.697
Manufacturing	U	.00826	.08691	-37.6		-3.06	0.002
	M	.00826	.00103	3.5	90.8	0.82	0.410
Municipality - Local Govt.	U	.02479	.10157	-31.9		-2.78	0.005
	M	.02479	.01756	3.0	90.6	0.39	0.697
Supra	U	.18182	.08248	29.6		3.82	0.000
	M	.18182	.18595	-1.2	95.8	-0.08	0.934
Transport and Logistics	U	.00826	.02011	-10.0		-0.92	0.358
	M	.00826	.0062	1.7	82.6	0.19	0.850
Utilities and Power	U	.27273	.07089	55.4		8.16	0.000
	M	.27273	.24277	8.2	85.2	0.53	0.596
Real Estate	U	.04132	.02931	6.5		0.76	0.446
	M	.04132	.05165	-5.6	14.0	-0.38	0.704

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.207	211.12	0.000	23.5	19.2	157.7*	0.37*	100
Matched	0.011	3.64	1.000	3.1	2.7	24.1	1.45	50

* if B>25%, R outside [0.5; 2]

Notes: Tests correspond to the nearest neighbours matching results (NN 8) provided in Table 3.

For all the variables included in the model, we cannot reject the null hypothesis about the equality of the means between the treated and control groups (see p-values last column). Notably, following the matching all the "%bias" are below 10%, with the difference between the means reduced by more than 80% for the majority of the variables. Moreover, the Rubin's B and R are respectively lower than 25% and inside the range 0.5 - 2. These tests therefore demonstrate that also the balancing property is satisfied.

The estimates of the average treatment effect on the treated shown in Table 3 indicate that the Green label does have a significant impact on bonds pricing in the primary market. Besides, this finding looks rather robust, irrespective of the matching method used. The estimates are in the range between -14.8 basis points (NN 3) and -19.4 basis points (radius matching, r=0.0001); for instance, when using nearest neighbours matching (NN=8 or NN=5), we estimate a coefficient of about -18.5 basis points, which is significant at the 1% level. Kernel matching makes the ATT estimate increase by 2 basis points. The biggest average treatment effect on the treated is estimated when applying radius matching with r=0.1% (-19.4 basis points), while the greatest standard error is associated with the radius matching with r=0,05%.

To recap, findings in Table 3 confirm the existence of a Green bond premium in the primary market: Green issues, on average, achieve a tighter pricing than their conventional peers.

5.2 Primary Market by Issuer type

In this section we try to understand whether or not the results obtained on *All* are valid independently on the kind of issuer. In particular, we divide bonds issued by corporations from those issued by other market players, i.e. banks, governments, local governments, municipalities, and supranational institutions. Table 5 summarizes the results of the analyses.

TABLE 5

Primary market spreads treatment effects

Sample2 - Corporations						
Matching:	Neighbours matching (NN=8)	Neighbours matching (NN=5)	Neighbours matching (NN=3)	Radius matching (r=0.001)	Radius matching (r=0.01)	Kernel matching
ATT	-20.7972***	-22.5101***	-19.7093***	-19.7984**	-21.4414***	-21.4521***
Std. Err.	5.3495	5.3078	6.0445	10.6917	7.4041	6.9267
# treated	43	43	43	28	38	43
# untreated	164	120	83	128	680	738
Sample3 – Non-corporate Issuers						
Matching:	Neighbours matching (NN=8)	Neighbours matching (NN=5)	Neighbours matching (NN=3)	Radius matching (r=0.001)	Radius matching (r=0.01)	Kernel matching
ATT	-13.5107***	-15.4172***	-16.1458***	-17.3836***	-14.8235***	-14.2617***
Std. Err.	4.9638	5.1295	6.3890	6.5454	4.9675	4.5535
# treated	78	78	78	66	78	78
# untreated	364	256	166	924	2065	2077

Notes: The ATT and Std. Err. figures are expressed in basis points. Columns refer to the different matching methods: Nearest neighbour matching (NN 3,5,8); Radius (r =0.001) matching with 0.1% radius; Radius (r=0.01) matching with 1.0% radius; Kernel matching. ATT is the Average Treatment effect on the Treated. # treated (# untreated) is the number of treated (control) units. The propensity scores are based on the Logit models reported in “Appendix c” and “Appendix d”. (***) (**) (*) indicate significance at the (1%) (5%) (10%) level. In all estimations, a common probability support of the treated and control units is enforced in order to ensure better comparability of matched units.

Interestingly, although the existence of a negative premium is confirmed for both samples, it is more marked for bonds issued by corporations. Indeed, the ATT for these bonds (the majority of them operates in the utility and power sector) ranges from -22.5 basis points (NN=5) to -19.7 basis points (NN=3) with an average Green premium of -20,95 basis points; on the other hand, the Green bond premium for non-corporate issuers ranges from -17.4 basis points (radius matching with r=0,1%) to -13.5 basis points (NN=8) with an average premium of -15.26 basis points. These results are consistent with those obtained on the comprehensive sample: the weighted average of the average premiums of the two subsamples (-17,28 basis points) is basically the same of the average premium found in the full sample (-17,21 basis points).

Furthermore, all the ATTs but the one estimated through radius matching (r=0.001) for corporate issuers are statistically significant at the 1% level. In both samples the greatest standard error is associated with the radius matching (r=0.001) while the lowest is associated with the nearest neighbours matching with 8 matches.

We conclude this part of the section by running an OLS regression of the spreads on the variables used to estimate the propensity scores plus an indicator (dummy) variable for Green bonds; we run such regression on each sample. The results are presented in Table 6.

TABLE 6

Primary market OLS regressions Results

Variable:	Coeff.	Std. Err.	t	p > | t |	Regression's R2
Sample1					
Green dummy	-16.6274***	3.5097	-4.74	0.000	0.7326
Sample2					
Green dummy	-23.4239***	6.8984	-3.40	0.001	0.5346
Sample3					
Green dummy	-10.2563**	4.0630	-2.52	0.012	0.7526

Notes: (***) (**) (*) indicate significance at the (1%) (5%) (10%) level.

The coefficients, i.e. the estimates of the Green premium, are all negative, statistically significant and in line with the results obtained by using propensity score matching techniques.

However, while for *corporate issuers* the estimate is lower of about 2-4 basis points than the estimates found through PSM, for *non-corporate issuers* the value is 3 to 7 basis points higher, depending on which PSM method we consider.

5.3 Secondary market

In this subsection we compare Green and conventional bonds' spreads in the secondary market. Before presenting the results, we need to outline some limits of the analysis. The main limit is that we do not correct the spreads for liquidity, i.e. we do not address the problem of a possible difference in liquidity between bonds (liquidity bias). As noticed in section 3, to carry out the analysis we download the bid I-spread of the bonds from Bloomberg BVAL at different dates. Since these data are market based, they may be strongly affected by the liquidity of the bonds. Indeed, the actual problem when dealing with bonds, especially when they are labelled as Green, is that they are usually bought in the primary market by institutional investors and held until maturity. Hence, even if they could be potentially liquid, in practice they are not traded in the secondary market so that their market prices are often not reliable. The second issue is that we just download the data at three different dates, six months apart from each other: 14 December 2017, 7 July 2017 and 10 January 2017. This implies that we cannot observe the potential volatility of the premium and its evolution over time. We do not take into consideration earlier data because there would be too few Green bonds available to effectively implement propensity score matching techniques.

We will consider only the spreads as of 14 December 2017 when we will focus on *corporate issues* and *non-corporate issues* because of the lack of Green bonds that had already been issued in July and January 2017.

Table 7 shows the results of the propensity score matching techniques applied on *corporate issues*. As can be noticed, as of 14 December 2017 there seems to exist a negative Green premium of about -5 basis points. In particular, the ATT ranges from -3.8 (Kernel matching) to -7.6 basis points (radius matching with r equal to 0,05%).

TABLE 7

Secondary market spreads treatment effects

Sample1 - 14 December 2017						
Matching:	Neighbours matching (NN=8)	Neighbours matching (NN=5)	Neighbours matching (NN=3)	Radius matching (r=0.001)	Radius matching (r=0.0005)	Kernel matching
ATT	-5.3835*	-5.7496*	-6.0403*	-5.3254	-7.6081**	-3.7479
Std. Err.	2.9694	3.1301	3.4593	3.4189	3.6575	3.1441
# treated	118	118	118	117	114	118
# untreated	544	393	257	1511	988	2799
Sample1 - 7 July 2017						
Matching:	Neighbours matching (NN=8)	Neighbours matching (NN=5)	Neighbours matching (NN=3)	Radius matching (r=0.001)	Radius matching (r=0.0005)	Kernel matching
ATT	-12.6903***	-13.7331***	-13.4411***	-10.5077**	-13.8539***	-9.1069***
Std. Err.	2.4451	2.9662	2.9687	4.4314	5.1945	3.6512
# treated	93	93	93	91	84	93
# untreated	433	301	206	1449	969	2307
Sample1 - 10 January 2017						
Matching:	Neighbours matching (NN=8)	Neighbours matching (NN=5)	Neighbours matching (NN=3)	Radius matching (r=0.001)	Radius matching (r=0.01)	Kernel matching
ATT	-11.2795**	-10.9044**	-11.5484**	-10.7148*	-9.0500*	-8.8365*
Std. Err.	4.5088	4.5872	5.4508	6.0463	5.1661	5.0084
# treated	70	70	70	68	70	70
# untreated	353	240	153	832	1726	1740

Notes: The ATT and Std. Err. figures are expressed in basis points. Columns refer to the different matching methods: Nearest neighbour matching (NN 3,5,8); Radius (r =0.001) matching with 0.1% radius; Radius (r=0.0005) matching with 0.05% radius; Kernel matching. ATT is the Average Treatment effect on the Treated. # treated (# untreated) is the number of treated (control) units. (***) (**) (*) indicate significance at the (1%) (5%)

(10%) level. In all estimations, a common probability support of the treated and control units is enforced in order to ensure better comparability of matched units.

The estimates of the average treatment effects are statistically significant at the 10% level using the nearest neighbours matching and the radius matching with r equal to 0,05%, while “flat pricing” cannot be rejected when the Kernel matching and the radius matching with r equal to 0,1% are applied. However, the balancing property of the propensity score for *Sample1* are not completely satisfied. Conversely, Balancing properties are satisfied when *the two sub-samples* are considered; the results are presented in Table 8.

TABLE 8

Secondary market spreads treatment effects

Sample2 - 14 December 2017						
Matching:	Neighbours matching (NN=8)	Neighbours matching (NN=5)	Neighbours matching (NN=3)	Radius matching (r=0.01)	Radius matching (r=0.005)	Kernel matching
ATT	-6.3983***	-6.5285**	-6.8388**	-7.7848	-8.0361	-7.9898
Std. Err.	2.2150	2.5653	2.6041	6.6697	7.9352	5.8925
# treated	43	43	43	39	39	43
# untreated	201	145	92	710	608	720
Sample3 - 14 December 2017						
Matching:	Neighbours matching (NN=8)	Neighbours matching (NN=5)	Neighbours matching (NN=3)	Radius matching (r=0.01)	Radius matching (r=0.001)	Kernel matching
ATT	-8.1224***	-9.2630***	-9.7928***	-7.9354**	-8.9207**	-7.6106**
Std. Err.	2.8486	2.8785	3.1063	3.2113	4.1932	3.0290
# treated	75	75	75	74	71	74
# untreated	319	236	155	1942	1134	1963
Sample3 - 7 July 2017						
Matching:						Kernel matching

	Neighbours matching (NN=8)	Neighbours matching (NN=5)	Neighbours matching (NN=3)	Radius matching (r=0.005)	Radius matching (r=0.01)	
ATT	-13.1598***	-14.4105***	-13.8049***	-11.6023***	-10.3959***	-10.3287***
Std. Err.	3.5333	3.6376	4.2413	3.8061	3.5815	3.2994
# treated	63	63	63	63	63	63
# untreated	358	204	130	1731	1807	1811

Notes: The ATT and Std. Err. figures are expressed in basis points. Columns refer to the different matching methods: Nearest neighbour matching (NN 3,5,8); Radius (r =0.01) matching with 1.0% radius; Radius (r=0.001) matching with 0.1% radius; Kernel matching. ATT is the Average Treatment effect on the Treated. # treated (# untreated) is the number of treated (control) units. (***) (**) (*) indicate significance at the (1%) (5%) (10%) level. In all estimations, a common probability support of the treated and control units is enforced in order to ensure better comparability of matched units.

As of 14 December 2017, the ATT for corporations is estimated to be between -7.6 basis points (kernel matching) and -9.8 basis points (NN 3), while the ATT for the other issuers is estimated to be between -10.3 basis points (kernel matching) and 14.4 basis points (NN5). in both cases, the ATTs estimated through the nearest neighbours matching are statistically significant at least at the 5% level. On the contrary, radius and kernel matching gives very high standard errors when the *corporate issuers* subsample is analysed so that we cannot say that the corresponding ATTs are statistically different from zero.

As of 7 July 2017 and 10 January 2017, the ATTs are respectively between -9.1 basis points and -13.9 basis points, and between -8.8 basis points and -11.5 basis points. Notably, all the matching methods but the radius matching (r=0.1%) give estimates of the ATT significant at the 1% level when implemented on the data of July. On the other hand, in January the estimates are significant at the 5% level when using nearest neighbours matching and statistically different from zero with a confidence level of 10% when using radius and Kernel matching. These findings seem to confirm that the Green label does have an impact on the bonds yields also in the secondary market, even if lower than in the primary market. The presence of a Green premium in the secondary market is in line with the majority of the literature (Barclays 2015, CBI 2016, Bloomberg 2017, Zerbib 2017, Morgan Stanley 2017). Moreover, looking at the difference between the ATT of December and the ones of July and January the question whether the Green premium changes over time as the market grows and evolves arises. A possible explanation of that difference is that, as the supply of Green bonds is surging, the demand is not growing at the same pace, so that the yields of Green bonds tend to converge towards those of their conventional peers. In theory, this should also be reflected in the primary market spreads, but with a PSM approach such a change cannot be spotted, especially considering the scarcity of data available.

Another possible explanation is that the difference is due to the volatility of the bonds' Green premiums. As already noted in section 2, Natixis (2017) has studied the trend of the Green premiums between October 2016 and March 2017 of the EIB Green bonds and has shown that these are quite volatile; for example, the Green premium of the Nov-26 Green bond issued under the "Climate Awareness Program" was around -7 basis points in January 2017, -3/4 basis points in March 2017 and -2 basis points in April 2017. In any case, our analysis suggests that Euro-denominated Green bonds trade at significantly lower yields than conventional bonds in the secondary market.

7. Conclusion

In this paper we investigate the existence of a Green bond premium in the Euro-denominated primary market through a propensity score matching approach. The Green bond premium is defined as the difference between the actual spread achieved by Green bonds at issuance and the spread that these would have achieved if they had been conventional bonds. In other words, the main goal of this research is to understand if Green bonds can represent an effective instrument for achieving a lower cost of capital for organizations that need to finance or re-finance Green projects. To accomplish our objective and to ensure high-quality data, we analyse a sample of 121 fixed-rate, Euro-denominated bonds issued by some of the most active issuers worldwide and priced (at issuance) on the Euro mid-swap rate.

We show that there exist a Green premium on the primary market and that it is negative and statistically significant. in particular, the Green bond premium is estimated to be around -17/18 basis points when the whole sample is considered, around -20/21 basis points when the focus only on bonds issued by corporations, and around -15 basis points when all issuers but corporations are taken into consideration.

Such a premium is significant relative to the potential costs of getting the Green label or rating; the Climate Bonds Initiative, for instance, asks a flat fee equal to 0.1 basis points of the issue value in order to certificate the Green label (although it also requires the engagement of third-party that verifies all the reports and procedures). Moreover, even if the Green assessment were as expensive as normal credit ratings, it would cost up to 3-5 basis points (White 2002), which is still far lower than the Green premium that we estimate. Overall we show that the market factor a premium in the pricing of green bonds and therefore they are relatively more convenient for issuers.

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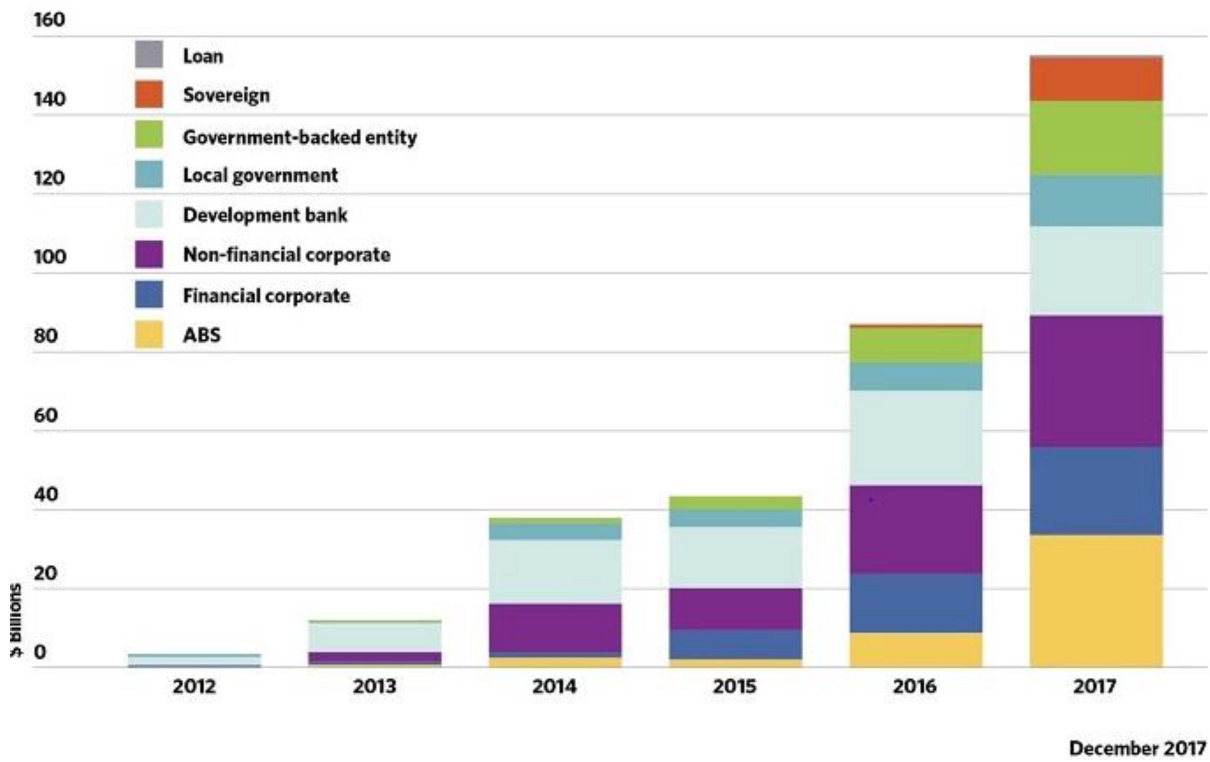
Appendix

Appendix a



Source: Climate Bonds Initiative, Green Bond Highlights 2017.

Appendix b

Inferior bound, number of treated and number of controls for each block

Inferior of block of pscore	Green 0	Green 1	Total
0	985	1	986
.00625	499	5	504
.0125	426	6	432
.025	221	3	224
.0375	183	9	192
.05	173	10	183
.075	122	27	149
.1	234	45	279
.2	88	15	103
.4	3	0	3
Total	2,934	121	3,055

Appendix c

Sample3 - Probability of treatment

	Logit
Y_2014	1.171917**
Y_2015	1.471078***
Y_2016	1.271122**
Y_2017	1.908739***

ln(Volume)	-1.054376***
Tenor	-.0655497**
AAA - AA	1.206851
AA(-) - A	2.228912**
A(-) - BBB	.7500341
Covered	-2.024707***
Western Europe	1.816065
Asia, Australia, New Zealand	1.614353
HG Global	1.895226
Agency - Sovereign	-.0476043
Banking	-1.04451**
Municipality - Local Government	-2.891775***
cons	.581952

Notes: Dependent variable: Green. (***) (**) (*) indicate significance at the (1%) (5%) (10%) level. Y_2013, BBB(-) - BB(+), CEEMEA and Supra omitted because of collinearity. Logit pseudo R2: 0.2111.

Appendix d

Sample2 - Probability of treatment

	Logit
Y_2013	-2.305471**
Y_2015	-1.302253*
Y_2016	.1.209189
Y_2017	.7327609
ln(Volume)	1.338574***
Tenor	.0140515
A(-) - BBB	.099343
BBB(-) - BB(+)	-1.260071
Western Europe	-.8405245
CEEMEA	-.775396
North America	-.447516
Basic Materials	.1769816
Manufacturing	-1.741288
Utilities and Power	2.293241**
Real Estate	1.265523
cons	-1.187702***

Notes: Dependent variable: Green. (***) (**) (*) indicate significance at the (1%) (5%) (10%) level. Y_2014, AA(-) - A, Asia Australia and New Zealand, and Transport and logistics omitted because of collinearity. Logit pseudo R2: 0.2677.