Journal of Cleaner Production 219 (2019) 127–135

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

The green advantage: Exploring the convenience of issuing green bonds

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ARTICLE INFO

Article history:
Received 7 September 2018
Received in revised form
26 January 2019
Accepted 3 February 2019
Available online 10 February 2019

Keywords:
Green bonds
Sustainability
Responsible investment
Propensity score
Fixed income
Climate change

ABSTRACT

The issue of how to finance the transition to a low-carbon economy in order to achieve the Paris Agreement's goal is crucial, especially considering the enormous amount of financing necessary to shift from rhetoric into action. Green bonds have recently emerged as one of the best candidates to help mobilizing financial resources towards clean and sustainable investments. Despite the growing relevance of green bonds, there is limited evidences on whether such bonds are actually convenient in comparison to other bonds with similar characteristics except for the “greeness”. By adopting a propensity score matching approach, we study 121 European green bonds issued between 2013 and 2017. We find that green bonds are more financially convenient than non-green ones. The advantage is larger for corporate issuers, and it persists in the secondary market. Our findings support the view that these bonds can potentially play a major role in greening the economy without penalizing financially the issuers.

1. Introduction

While all countries committed under the Paris Agreement to limit global temperature rise to 1.5C-2C, the major question remains how can the world achieve this temperature goal. IPCC (2018) finds that “rapid, far-reaching and unprecedented changes in all aspects of society” must happen to ensure targeted temperature. Those changes will require profound transitions in land, energy, industry, buildings, transport, and cities.

The financial system will be crucial to support and to accelerate investments in the clean energy and technologies needed to decarbonise the economy. This is why the 196 participating countries in the Paris Agreement committed 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.

IPCC (2018) estimates that those “finance flows” amount to about $2.4 trillion (roughly, 2.5% of the global Gross Domestic Product annually) between 2016 and 2035. Such enormous figure is also consistent with the analysis by the OECD (2017), according to which approximately $103 trillion of additional investments will be required between 2016 and 2030 to meet global development needs in a way that is climate compatible. Similarly, McKinsey (Woetzel et al., 2016) anticipates cumulative needs for about USD 49 trillion, excluding primary energy and energy efficiency, between 2016 and 2030. Batthacharya et al. (2016) estimates these infrastructural needs to be between USD 75 and 86 trillion, including primary energy and energy efficiency. All the estimates imply that a large portion of the global financial system needs to be activated to prevent the ultimate climatic collapse.

The IPCC report is an alarming warning and it implicitly confirms the unprecedented investment opportunity that can be unlocked when sustainable finance becomes mainstream. With banks having restricted lending capabilities and public budgets under strain in many countries, *private* sector sources of capital need to be engaged and green bonds are considered among the key instruments to mobilize private financial resources towards the progressive decarbonisation of the global economy (OECD, 2017).

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 – public debt issued by corporates, municipalities and other

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https://doi.org/10.1016/j.jclepro.2019.02.022
0959-6526/

governmental entities – with a distinguishing feature: proceeds are used for environment-friendly projects, primarily related to climate change mitigation and adaptation. 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. Green bond issuance is estimated in $250 billion for 2018 by Moody's and the Climate Bond Initiative and expected to reach $1 trillion by 2021.

While the relevance of green bonds is widely recognized by financial professionals, little is known about the *convenience* of green bonds for corporate and non-corporate issuers. This paper investigates how the financial market prices green bonds, and whether issuers can lower their financial costs by issuing a bond labelled as "green" rather than an equivalent non-green bond ("conventional bond" in the remaining of the paper). Indeed, for companies and non-corporate organizations the most important driver in investment decisions is the funding cost. Since the majority of the electricity generation costs are in the financial costs of capital (OECD, 2015), even small differences in the cost of bonds can have a substantial impact on the long-run sustainability of energy and large industrial facilities. Therefore, assessing the relative convenience of green bonds, in terms of returns to be paid to investors, is of paramount importance. Our paper is, to the best of our knowledge, the first measuring the financial cost for issuers 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 statistically significant advantage, for the issuers, when a bond is labelled as green. Such advantage is quantifiable, on average, in lower interests paid annually to investors of 18 basis points (meaning 0.18% of the bond value). Furthermore, such advantage is achieved by both companies and non-corporate entities like municipalities and governmental agencies. These 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 financing.

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 data 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 implications of the findings and the limitations of the paper, and Section 7 concludes.

2. Literature review

Green bonds are a recent phenomenon with a widespread growth across countries started not earlier that 2013. Consequently, the scholarly literature on green bonds is limited. 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 et al. (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. 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. Zerbib (2019) has analysed the green bond advantage focusing on 135 investment grade green bonds issued worldwide. The paper shows that bondholders pay of 8 basis points (statistically significant) to buy green bonds after issuance. Evidences have been collected for non-corporate issuers as well. Karpf and Mandel (2017) investigated green and conventional bonds in the U.S. municipal bonds market and found that green bonds seem to be penalized by the market.

All in all, the evidences about the existence of a green advantage in the primary market (when bonds are initially issued) and in the secondary market (when bonds are traded following the issuance) 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 advantage for the primary market of European green bonds adopting a propensity score matching (PSM) methodology and suggesting that this premium persists also after the issuance (the secondary market).

3. Data description

We set up our samples in order to evaluate, through propensity score matching techniques, the difference between returns 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 characteristics including the returns offered to investors.

As of December 2017, Bond Radar reports 7589 public EUR-denominated bonds issued since January 2007, of which 154 are classified as green. We eliminate from the sample all the bonds with variable interest payments (to avoid the uncertainty that varying payments could have on the pricing at issuance), all those bonds for which the return is not available or with a size lower than EUR 200 million (in order to have only liquid bonds), all bonds at high risk of default and those that are not priced using European rates.

Following these changes, there are 121 green bonds left in the dataset and they are issued by entities of different nature: corporates, sovereign states, national and multinational agencies, municipalities, financial institutions. 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 entities. *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 for the comprehensive sample.

4. Methodology

To address the question of whether issuing green bonds is convenient, we should compare the returns of the green bonds with those of their conventional peers. To make the comparison we use propensity score matching techniques which are suited to empirical

Table 1
Descriptive statistics.

Variable	Mean	Std. Dev.	Min	Max
Volume (EUR mln)	620	333	250	2000
Maturity (Years)	8.15	3.95	3.02	30.40
Spread (Basis point)	28	41	−32	140

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 return at issuance) 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” (ATT).

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 returns between treated and untreated bonds would lead to biased results.

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, 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 and a 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 returns (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 returns) 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 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 persistence of the relatively favourable trading of green bonds in the secondary market.

5.1. Primary market

The first stage of the process to estimate the ATT involves obtaining the propensity score. 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

Table 2
Primary market spreads treatment effects (in basis points).

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	−18.47***	−18.56***	−14.90***	−19.40***	−15.17**	−16.74***
Std. Err.	4.37	4.76	5.00	5.88	6.74	4.31
# 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. (***) (**) (*) 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.

well specified. “Appendix b” shows the inferior bound, the number of treated and the number of controls for each block.

Table 2 presents propensity score matching results for five different matching procedures (in columns).

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 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 2 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 2 confirm the existence of a relative convenience of issuing green versus conventional bonds in the primary market. Green bonds, on average, cost less to issuers 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 4 summarizes the results of the analyses.

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 −23 basis points (NN = 5) to −20 basis points (NN = 3) with an average advantage of −21 basis points; on the other hand, the Green bond advantage for non-corporate issuers ranges from −17 basis points (radius matching with r = 0,1%) to −14 basis points (NN = 8) with an average of −15 basis points. These results are consistent with those obtained on the comprehensive sample: the weighted average of the average convenience of the two subsamples is the same of the average convenience found in the full sample (−17 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 5.

The coefficients, i.e. the estimates of the Green convenience (lower returns paid to investors), are 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 3–7 basis points higher, depending on which PSM method we consider.

5.3. Secondary market

In this subsection we compare green and conventional bonds pricing 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 returns 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 returns 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 returns 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

Table 3
Pstest - balancing property.

Variable	Unmatched	Mean			%Reduction	t-test	
	Matched	Treted	Control	%Bias	|Bias|	t	|p|>t
Y_2013	U	.050	.188	−43.7		−3.87	0.000
	M	.050	.036	4.2	90.3	0.51	0.608
Y_2014	U	.157	.179	−5.9		−0.63	0.531
	M	.157	.178	−6.1	−2.1	−0.47	0.638
Y_2015	U	.182	.211	−7.2		−0.76	0.445
	M	.182	.176	1.6	78.5	0.13	0.900
Y_2016	U	.215	.216	−0.2		−0.02	0.982
	M	.215	.225	−2.5	−1086.9	−0.19	0.847
Y_2017	U	.397	.207	42.2		5.02	0.000
	M	.397	.383	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	.364	.463	−20.3		−2.15	0.031
	M	.364	.367	−0.6	96.9	−0.05	0.960
AA(−) - A	U	.298	.222	17.4		1.96	0.050
	M	.298	.285	2.8	83.7	0.21	0.833
A(−) - BBB	U	.314	.234	18.0		2.03	0.042
	M	.314	.311	0.7	96.1	0.05	0.959
BBB(−) - BB(+)	U	.025	.081	−25.4		−2.26	0.024
	M	.025	.037	−5.6	78.1	−0.55	0.580
Covered	U	.033	.252	−65.9		−5.53	0.000
	M	.033	.029	1.2	98.1	0.18	0.854
Western Europe	U	.868	.838	8.5		0.88	0.379
	M	.868	.861	2.0	75.9	0.16	0.870
Asia, Australia, New Zealand	U	.091	.052	15.2		1.88	0.061
	M	.091	.099	−3.2	78.9	−0.22	0.827
CEEMEA	U	.0165	.044	−16.2		−1.47	0.141
	M	.0165	.020	−1.8	88.8	−0.18	0.857
HG Global	U	.008	.003	6.9		0.98	0.327
	M	.008	.008	0.0	100.0	−0.00	1.000
North America	U	.0165	.063	−23.9		−2.09	0.036
	M	.0165	.012	2.1	91.1	0.27	0.789
Agency - Sovereign	U	.223	.143	20.6		2.43	0.015
	M	.223	.220	0.8	96.1	0.06	0.954
Banking	U	.215	.416	−44.3		−4.43	0.000
	M	.215	.257	−9.3	79.0	−0.77	0.440
Basic Materials	U	.025	.0491	−12.9		−1.22	0.221
	M	.025	.018	3.8	70.2	0.39	0.697
Manufacturing	U	.008	.087	−37.6		−3.06	0.002
	M	.008	.001	3.5	90.8	0.82	0.410
Municipality - Local Govt.	U	.025	.102	−31.9		−2.78	0.005
	M	.025	.018	3.0	90.6	0.39	0.697
Supra	U	.182	.082	29.6		3.82	0.000
	M	.182	.186	−1.2	95.8	−0.08	0.934
Transport and Logistics	U	.008	.020	−10.0		−0.92	0.358
	M	.008	.006	1.7	82.6	0.19	0.850
Utilities and Power	U	.273	.071	55.4		8.16	0.000
	M	.273	.243	8.2	85.2	0.53	0.596
Real Estate	U	.041	.029	6.5		0.76	0.446
	M	.041	.052	−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 2. Y_2013, Y_2014, Y_2015, Y_2016 and Y_2017 are dummy variables indicating whether or not a given bond has been issued in that year; ln(Volume) is the natural logarithm of the size (amount issued in € million) of a given bond; Tenor is the time to maturity (in years) of a given bond at launch; AAA – AA, AA(−) – A, A(−) – BBB and BBB(−) - BB(+) are dummy variables indicating whether or not the credit rating of a given bond falls in that category; Covered is a dummy variable indicating whether or not a given bond is classified as a "covered bond" (i.e. backed by a separate group of assets of the issuer); Western Europe, "Asia, Australia, New Zealand", CEEMEA, HG Global and North America are dummy variables indicating whether or not the issuer of a given bond has the majority of its operations (and risks) in that region; Agency – Sovereign, Banking, Basic Materials, Manufacturing, Municipality - Local Govt., Supranational, Transport and Logistics, Utilities and Power and Real Estate are dummy variables indicating whether or not the issuer of a given bond operates in that sector.

only the returns 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 6 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 relative convenience for Green bonds 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%).

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"

Table 4
Primary market spreads treatment effects (in basis points).

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	−20.80***	−22.51***	−19.71***	−19.80**	−21.44***	−21.45***
Std. Err.	5.35	5.31	6.04	10.69	7.40	6.93
# 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	−13.51***	−15.42***	−16.15***	−17.38***	−14.82***	−14.26***
Std. Err.	4.96	5.13	6.39	6.54	4.97	4.55
# 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. (***) (**) (*) 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.

Table 5
Primary market OLS regressions Results.

Variable:	Coeff.	Std. Err.	t	p > |t|	Regression's R2
Sample1					
Green dummy	−16.63***	3.51	−4.74	0.000	0.733
Sample2					
Green dummy	−23.42***	6.90	−3.40	0.001	0.535
Sample3					
Green dummy	−10.26**	4.06	−2.52	0.012	0.753

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

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 *the* comprehensive sample are not completely satisfied. Conversely, balancing properties are satisfied when *the two sub-samples* are considered; the results are presented in Table 7.

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' returns also in the secondary market, even if lower than in the primary market. The presence of a Green convenience in the secondary market is in line with the results of Zerbib (2019). Moreover, looking at the difference between the ATT of December and the ones of July and January the question whether the convenience 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 relatively limited number of green bonds to date.

6. Discussion

In this paper we evaluate the convenience of issuing green bonds for companies and non-corporate entities that want to invest in green projects such as renewable energy plants, energy and water efficiency, electrification of transport, fuel switching, bioenergy. We show that green bonds are actually more convenient than conventional bonds, because on average, *coeteris paribus*, they have to offer to the investors lower returns. Importantly, such result is stronger for corporate issuers with the implication that private sector - whose support will be necessary to achieve the Paris Agreement's temperature goal – are better off financially when they issue bonds that are labelled as green. Green bonds have some additional transaction cost because issuers must certify, monitor and report on the *green use* of proceeds. The magnitude of the savings for issuers (in terms of interests paid) exceeds the costs to get 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 savings we estimate (15–21 basis points).

The relative financial savings obtained by the issuers appear to be the consequence of a strong demand for these financial products, which reflects the interest of investors willing to fund green projects. With regard to the possible drivers of this growing demand, it is clear that green bonds allow investment firms to fulfil the requests of clients sensitive to environment-related issues. More and more institutional investors are decarbonising their portfolios and redirecting funds towards environment-friendly investments because they regard climate change as growing threat to the long-term economic growth. Additionally, in some case the demand has been sustained also by national regulations; for instance, the French energy transition law forces institutional investors to report on how they are contributing to reduce CO_2

Table 6
Secondary market spreads treatment effects (in basis points).

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	−5.38*	−5.75*	−6.04*	−5.33	−7.61**	−3.75
Std. Err.	2.97	3.13	3.46	3.42	3.66	3.14
# 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	−12.69***	−13.73***	−13.44***	−10.51**	−13.85***	−9.11***
Std. Err.	2.45	2.97	2.97	4.43	5.20	3.65
# 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	−11.28**	−10.90**	−11.55**	−10.71*	−9.05*	−8.84*
Std. Err.	4.51	4.59	5.45	6.05	5.17	5.01
# 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.

Table 7
Secondary market spreads treatment effects (in basis points).

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	−6.40***	−6.53**	−6.84**	−7.78	−8.04	−7.99
Std. Err.	2.22	2.57	2.60	6.67	7.94	5.89
# 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	−8.12***	−9.26***	−9.79***	−7.94**	−8.92**	−7.61**
Std. Err.	2.85	2.88	3.11	3.21	4.19	3.03
# treated	75	75	75	74	71	74
# untreated	319	236	155	1942	1134	1963
Sample3 - 7 July 2017						
Matching:	Neighbours matching (NN = 8)	Neighbours matching (NN = 5)	Neighbours matching (NN = 3)	Radius matching (r = 0.005)	Radius matching (r = 0.01)	Kernel matching
ATT	−13.16***	−14.41***	−13.80***	−11.60***	−10.40***	−10.33***
Std. Err.	3.53	3.64	4.24	3.81	3.58	3.30
# 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.

emissions and, more broadly, on how they are managing climate-related risks (article 173, French Treasury, 2015). Bank of England and the Securities and Exchange Board of India (UNEP, 2016) have issued requirements to promote and develop the green bond markets. It is likely and desirable that in the coming years an increasing number of countries will take actions to sustain and promote the development of this market. For example, governments could offer tax advantages for green investors in order to help drive the market.

Focusing on Europe, a boost to new green bonds' issuances is expected following the release of the *European Commission's Action Plan: Financing Sustainable Growth* (European Commission, 2018), especially because of the adoption of a common European Union green asset taxonomy. Banks are expected to start implementing the reporting recommendations set out by the *Taskforce for Climate-related Financial Disclosure* (TFCD, 2017) and monetary policies that favour the investment in green-labelled assets become more and more likely. Hence, green bonds not only can help issuers to achieve better financial results and the global economy to become more sustainable (therefore benefitting the society), but they can also help investors to comply with the current and future regulation.

The main limitation of our results is the relatively small sample of bonds studied. Considering the tremendous potential of this kind of financial instruments in facilitating the transition towards a sustainable economy, we believe that the existence and magnitude of a relative convenience to issue green bonds should be studied on larger samples and in other geographical regions. In particular, as the quantity and quality of data will improve, further investigation could shed light on several aspects relevant for issuers, investors, and policymakers. This research agenda should encompass whether green bonds' convenience has materially changed over time and how much it has varied across industries and regions. Second, it would be important to better analyse and understand the composition of the demand for these bonds and its drivers in order to design policies able to sustain and foster the growth of the market. Finally, the definition of the green label should be studied more in depth. Being new financial instruments, these bonds suffer of a certain ambiguity in terms of what can be labelled as green and what cannot. The creation of reliable and consistent criteria for the labelling requires both scientific analysis and political and standard-setting decisions. This is why, for example, the European Commission is working towards a formal taxonomy of what is really green in finance thus avoiding the misuse of the label.

7. Conclusion

Limiting warming to 1.5 °C is possible but doing so will require unprecedented changes in the economic and social systems. Financial markets will play a major role in those disruptive changes and practitioners, policymakers, and scholars are converging in stressing how crucial the support of finance is in delivering an actual and timely transition to a low carbon economy. Green bonds are widely assumed to be one of the key instruments to mobilize financial resources towards to achieve the temperature goal of the Paris Agreement.

Since the European Investment Bank issued the first green bond in 2007, the growth of these bonds has been exponential. In this paper we investigate whether green bonds are as convenient as similar conventional bonds for the issuers. We specifically study European green bonds using a propensity score matching approach.

We show that green bonds can represent an effective way for achieving a lower cost of capital for organizations that need to finance or re-finance green projects. Since there is limited evidence on corporate decisions in issuing green bonds, our findings also fill in the literature gap and provide insights the convenience of these financial instruments for companies. This will also help policymakers identify which policies can deter or encourage the market and issuers to access innovative green financing instruments.

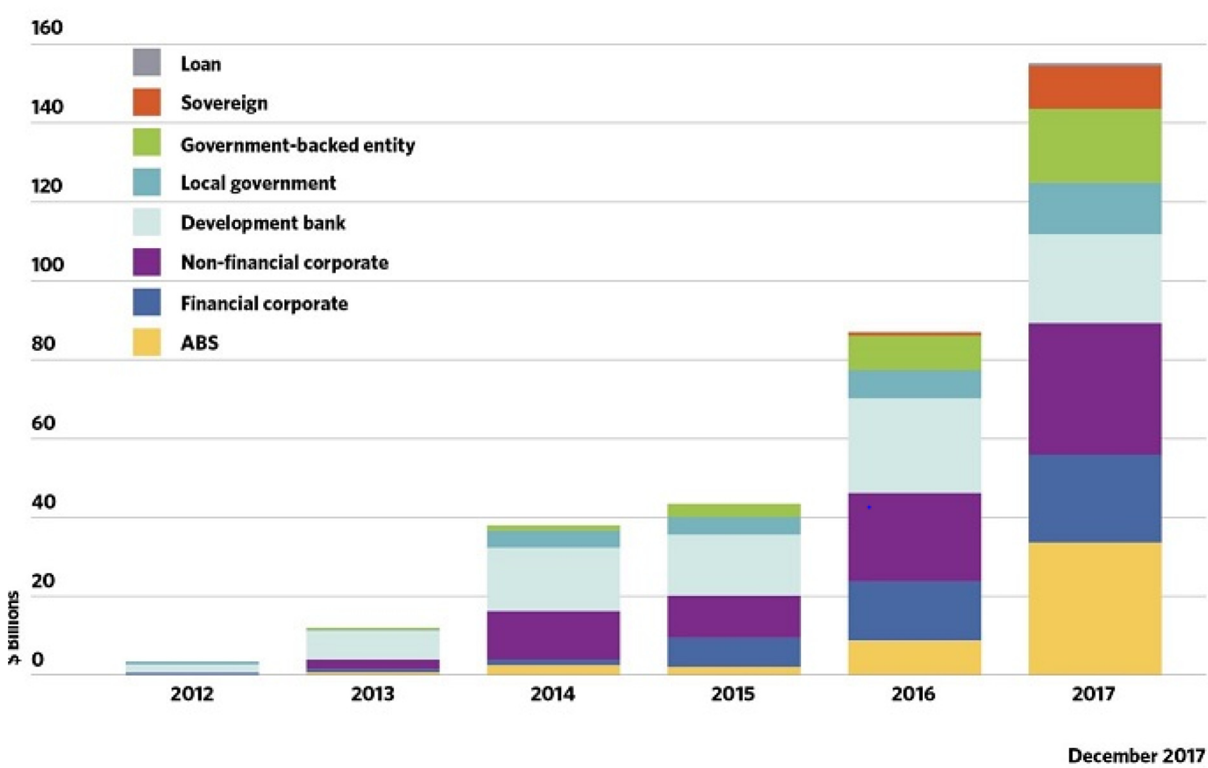
Acknowledgments

We are grateful for comments from three anonymous referees, Oğuzhan Karakaş (discussant), Dirk Schoenmaker, and participants at Erasmus University's Dynamics of Inclusive Prosperity Conference and at CEP's Scaling up Green Finance Conference.

Appendixes

Appendixes

Appendix a



Appendix b. Inferior bound, number of treated and number of controls for each block

Inferior of block of pscore	Green 0	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	2934	121	3055

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