Is there a greenium on corporate bonds?

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***Abstract*—The green bond market has increased rapidly in recent years and whether green bonds provide cheaper funding to issuers by trading at a premium is still an open debate. The aim of this paper is to assess whether there exists a greenium. The analysis is based on a dataset containing information about the companies that issued both green and brown bonds, the yield to maturity, issue date, amount issued and the country of issue. Four methodologies have been employed, all resulting in a non-statistically significant coefficient for the dummy variable green bonds, suggesting that there exists no greenium. Therefore we conclude that the spread between green and brown bonds is non-negative, meaning that green bonds are not traded at a premium.**

I. Introduction

Climate change and environmental issues due to human activity represent the most acute instance to be tackled by the policy-makers of this historical period. In contrast to conventional risks whose impact is usually bounded and limited, the risks of climate change are systemic [1]. The direct impact of climate change is, indeed, local, but given the interconnection of socioeconomic and financial systems it's easy to assume that the risk can propagate itself across sectors [2]. Although science and technology, together with shifts in everyday behavior, are of central importance, also finance can be an important driver in the environmental transition. Green Bonds, i.e. bonds whose proceeds are committed to finance environmental and climate-friendly projects, such as renewable energy, green buildings, or resource conservation, represent an important trend in the financial sector [3]. Indeed, they offer issuers and investors both a low-risk financial instrument and an opportunity to reach their sustainability goals, constituting an effective instrument to stimulate capital flows to green investments [4].

In this short essay, we investigate if there exists a **spread between green and conventional bonds issued by corporate entities** (i.e. green bonds trade at a *greenium*). At first glance, conventional and green bonds are alike in fundamental characteristics and therefore there is no rationale for a difference in pricing [5]. However, we draw on an empirical investigation held by the German government to state that, if such an alleged spread between *"brown"* and *green* bonds exists, it is likely to be negative. The *Staatsmacht* issued one conventional and one green bond with identical characteristics [6] and the green bond had a lower yield to maturity of 2 basis points (bps) in the secondary market. This indicates that investors are willing to trade potential revenues for the allocation of financial resources towards the green transition and, looking at the other side of the market, firms can borrow money more cheaply, with the constraint of a partial allocation of resources for the environmental cause.

This paper will investigate whether the existence of a *greenium* is proven by further significant empirical evidence. Although short, our paper is deemed to be ambitious. Despite our results are in line with those reported by previous works, the use of additional and/or different data allows us to provide an insightful contribute to the existing literature.

Firstly, our analysis concerns corporate bonds and not only municipal ones [7]. Secondly, the market we focus on overlooks the limited European market [8], as our work is based on a geographically longitudinal sample that includes several areas. In fact, we have data on Anglo-Saxon, European and Asian countries. On the top of that, the dataset is transversal as also developing economies in Asia such as China or Indonesia are represented. On the whole, our analysis is comparable with previous ones [9] that try to assess the existence of the greenium while also aiming at improving the methodology approach by comparing the relatively new coarsened exact matching (CEM) and the more widely used propensity score matching (PSM) methods. As ours, the results of such analysis confirm the non-existence of the greenium for most bonds.
The conclusions of this study can be helpful for both sides of the market: for the investors that can understand how to better manage portfolios of green bonds, and for issuers of green bonds to optimize the emission, for example choosing the better geographical market-advantage is larger for corporate issuers.

The paper is organized as follows: in Session II the data and methodology are presented; Session II explains the methodology implemented; in Session III the results are stated and Session IV presents the conclusions.

II. Data and methodology

A. Data

The data of our analysis include all corporate bonds (green and non-green) issued by numerous companies in selected countries from $1/1/2019$ to today with the following characteristics: $1)$ issued by non-financial firms; $2)$ bonds or notes (i.e., no commercial paper or certificates of deposit); $3)$ fixed-coupon; $4)$ no optionality features (callable, putable, convertible, etc.). The data source employed is Refinitiv Eikon. The data-set is comprised of $31,370$ observations. To facilitate comparisons, the dataset is cleaned and then examined. After cleaning the data by dropping the missing values and the outliers, the resulting number of observations is $18,346$.
The process of cleaning the data starts by destringing the variables, i.e. converting them from strings into numeric variables. Moreover we created a new variable, which represents the difference between maturity and the issue date. To deal with heavy-tailed data that is positively skewed because of large outliers among the YTM values, a *trimming* procedure

is adopted.

Our analysis is focused on understanding whether there exists a greenium and, therefore, we created a dummy variable to identify whether the bond issued was green or brown by assigning the value 1 if the bond is green and 0 otherwise. We find that a number of 1664 firms issue only one bond, thus being irrelevant by the purpose of our analysis. Our dataset reports $8,764$ firms belonging to 39 different industries (**Figure II-A**) which, at some date (in total, at 1,136 time dates), have issued either a Green or a Brown bond. More precisely, our dataset displays the *Issuer, Coupon, Maturity, Issue Date, ISIN code, Principal Currency, Country of Issue, Amount issued, Sector, Seniority and Yield to Maturity* of 31370 Green and Brown bonds. All amounts issued are expressed in US dollars.

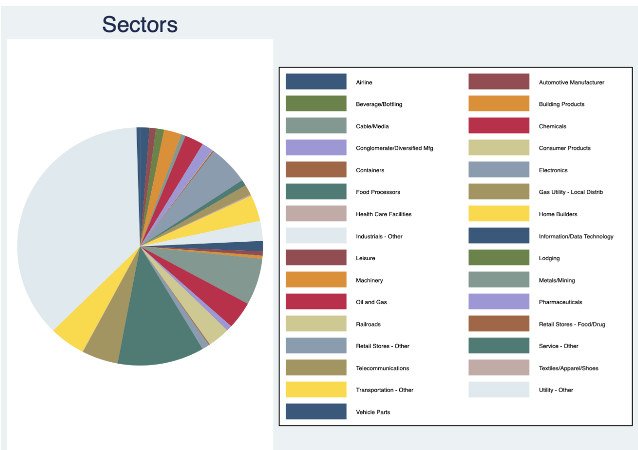

Fig. 1. Sectors in which the bonds have been issued.

The amount of brown corporate bonds and green bonds issued are respectively $2,930$ and 664. The amount of brown bonds issued is much larger than green bonds, as it can be seen in the pie chart below (**Figure II-A**), in which a summary statistics is provided. The average issuance amount is 2.56 million, the

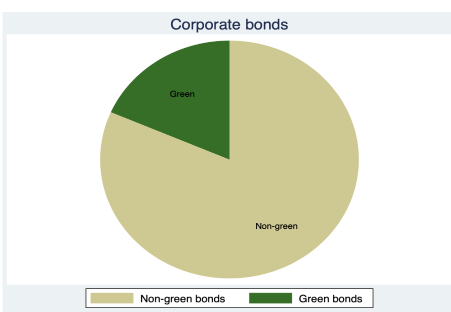

Fig. 2. Share of green bonds and non-green bonds.

average maturity is 8.4 years and all the bonds being fixed rate, the average coupon is 2.83%. The 664 green bonds of public firms correspond to 26 unique firm observations (since some companies issue multiple green bonds in a given year). The information used are collected from 39 countries and include bonds from 39 different industries. As shown in the pie charts below, most of the bonds have been issued in countries such as China, United States, Japan and South Korea and belong to the industrial sector.

B. Methodology

The key question this research attempts to answer is what is the effect of a green label on the yield or price of a bond. As we learned in the literature review, estimation of the yield difference between green and non-green bonds, also called *greenium*, have already been estimated by other authors via regression models or through matching procedures. To increase the validity of the results, this research will use plurimum methods: a fixed effects regression model and matching methods before estimating yield differences or treatment effects, following the suggestion of Larcker and Watts (2020) [7]. By choosing to use matching methods, this research assumes an experimental setting, where the bonds are divided into treatment and control groups. The green bonds are in the treatment group (as these observations are assigned the 'treatment' of a green label) and the conventional bonds are in the control group.

To achieve valid results from this data sample, we acknowledge the importance of having a comparable or '*balanced*' treated and control groups. Indeed, low imbalance reveals strong similarity between the treated and control groups, which reduces bias in the statistical estimators and increases the validity of the results [1]. On the other hand, high imbalance means the two groups are only weakly similar, calling upon the researcher to use statistical techniques to still achieve a valid estimate.

Despite our data limitation, we attempted at decreasing the imbalance between the two groups through *matching methods* that pre-process the data to increase similarity between the treated and control groups. In particular we performed regressions based on:

- *Fixed effects*;
- *Grouping*;
- *Propensity score matching* method;
- *The Coarsened Exact Matching (CEM)* method.

Regarding the **Fixed effect method**, it has been employed in order to tackle the issue of endogeneity bias. Indeed, it is possible that firm characteristics for which we cannot control for are correlated with our variable of interest, the yield to maturity of bonds, leading to biased estimates. By swiping away "firm constant" explanatory variables, i.e. variables that are invariant for all cross sectional firms, the FE transformation addresses this issue. The intuition is that if we want to allow for arbitrary correlation between the unobserved exogeneity and the regressors there is no way to distinguish the effect of a time constant observable variable from the effect of the time constant unobservable variable.

We have also performed some **grouping** among variables, in order to control for additional effects other than the specific firm one which is already accounted for in the panel setting. Specifically, data have been divided by means of yield to maturity (lower than 3%, between 3 and 5%, and greater than 5%) and years (2019, 2020, 2021, 2022, 2023).

As for the *Propensity score matching* and the *CEM* approaches, we apply a similar methodology to that employed by De Groot [9]. The **PSM** method is aimed at coupling similar observations in order to control for constant effects that do not concern our analysis. Our goal is to to estimate the causal effect of a treatment (in our case, being a green bond) by creating a matched sample of individuals who are similar on observed covariates, but differ in their treatment status. It is a two-step procedure: 1) we compute the a continuous variable (between 0 and 1) called *propensity score*, which in our case is the probability that a bond receives a green label, based on the input covariates (coupon, currency, country of issue, amount issued, seniority, sector and maturity); 2) we match brown and green bonds based on the "nearest neighbour" method, which matches observations based on the numerical distance between propensity scores [9]. In our analysis, we chose to use a logistic regression model to estimate the propensity scores.

As for the **CEM**, this method pre-processes ('coarsens') the dataset temporarily into comparable 'strata' (i.e., groups); it gives higher weights to strata that contain more comparable observations; then, it exactly matches observations based on input covariates. Finally, the method deletes non-comparable observations. This is a large advantage compared to the PSM method, which keeps all observations. The final dataset contains exactly matched pairs of conventional and green bonds [10] [11]. The CEM method also has an option to delete observations until all strata are equally large (this is the K2K option).

Justification: It is relevant to explain that our methodological choice derives from the limitations of the PSM matching methods and the fixed effects method, whose implementation we considered in relation to our operational context. Indeed, the fixed effects and the propensity score matching (PSM) assume completely randomized experimental designs where all covariates are equally sensitive to changes in the specification, ignoring potential nonlinear relationships.

This is potentially problematic when attempting to reduce imbalance between treated and control groups, as this means researchers need to repeat the process before a satisfactory result is reached [11].

Moreover, King et al. (2011) [1] specifically argue the PSM method neglects important information and state matching with the PSM method can actually increase inefficiency, bias and researcher discretion, which is not desirable.

On the other hand, the CEM method, introduced by Iacus et al. (2011) [11], assumes a fully blocked experimental design, where two very similar observations are chosen, among which one receives treatment. The advantage of this design is that it reduces potential bias and requires no assumptions about the data, as it focuses on the imbalance that is present in the dataset, instead of lowering the expected imbalance like the PSM method.

Overall, we figured that the CEM method dominates the direct and PSM matching methods because it i) more adequately controls for imbalance, ii) requires less assumptions and iii) does not require an auxiliary metric to estimate results with.

Therefore, this research will mainly focus on using the CEM method to estimate *greenium*.

III. RESULTS

The results of the different approaches are stored in the tables of chapter *V. Appendix*.

A. Fixed effects and grouping

The fixed effects methodology leads to non statistically significant results in most of the settings it was applied to, as it can be read from **Table I** and **Table II**. Our main model consists in a regression of yield to maturity over a dummy representing green bonds, the logarithm of the amount of bonds issued, the coupon generated by bonds, the maturity of the bonds and two categorical variables entailing the seniority and the year of issuance of the bonds. In such setting, the p-value we mostly care about, i.e. that of the dummy *Green_type*, shows a magnitude of 0.681, which signals the clear invalidity of the related coefficient, i.e. 0.014. Also the majority of the other variables' coefficients are to be considered irrelevant because of the high value of their t-statistic, but this is not of particularly importance for our analysis, since they were only included as controls for our variable of interest *Green_type*.

Even when grouping yields to maturity in order to catch dissimilarities with the "standard" model, we do not get to observe any relevant result. The coefficients of our variable of interest keep showing high p-values, i.e. 0.351 for y.t.m lower than 2.5%, 0.740 for y.t.m. between 2.5% and 5%, and 0.291 for y.t.m. higher than 5%.

The only relevant result we managed to observe is the one we obtained when we grouped by year. In fact, by only keeping data regarding bonds emissions of 2023, we measure a positive greenium with a statistically significant p-value of 0.010. Despite such estimate is in contrast with our expectations, which regarded a negative greenium, we are not concerned, as this estimation covers a reduced sample of 112 observations, and because of the methodology gaps of fixed effects regression in this context. Moreover, recalling the concept of p-value, it's possible to state that one in ten times (10%), we will not get a result significantly different from 0. The conclusion in the above-mentioned case will be obtained by pure chance. It's self-evident that the statistical uncertainty of the result added with the small sample size makes the 2023 group regression not worthy of academic trust.

B. PSM method

As for the *Propensity score matching* method, the output of the `psmatch2` command (**Figure IV**) includes information on the covariate balance between the treatment and comparison groups, as well as the results of the matching process. The logistic regression results show the estimated coefficients and standard errors for each covariate in the propensity score model. The "Variable Sample" table shows the average yield for the green and conventional bonds before and after matching. Finally, the "psmatch2" table shows the number of treated and control observations in each stratum of the common support region, which is the region where there is overlap in the propensity score distributions for the two groups.

After matching to the nearest neighbour, we conduct a t-test to compare the mean value of the yield between the treated (green bonds), referred to as "Group 1" and the matched control group (brown bonds), referred to as "Group 0". This way, we can determine whether the treatment had a significant effect on the outcome variable, given the observed covariates. If the t-test results in a significant difference between the treated and control groups, it suggests that the treatment had a significant effect on the outcome variable. Otherwise, it suggests that the treatment did not have a significant effect on the yield to maturity. In our case, Group 0 (brown) has 2.642 observations, with a mean of 12.06 and a standard error of 0.18, while Group 1 (green) had 597 observations, with a mean of 12.28 and a standard error of 0.42. The "diff" column shows the difference between the mean values of the two groups, which is -0.22. The output also shows the null hypothesis (H0) for the test, which is that the difference between the mean values of the two groups is equal to zero. The p-value for the test is 0.3033, which is greater than the conventional level of statistical significance of 0.05. This suggests that there is not a statistically significant difference between the mean value of the yield in Group 0 and Group 1.

C. CEM method

Table III shows the summary statistics on the matching process with the Standard CEM method. The CEM diagnostic summary shows the L1 statistic, displaying overall imbalance of the preprocessed dataset. Perfect imbalance would indicate an L1 statistic of 0 [1]. The L1 statistic after matching is of a magnitude nearest to the value of 0 (more precisely $1.148e^{-15}$, which is inferior to the 0.244 statistic of [6]. A lower imbalance may be related to a i) larger dataset or ii) a lower number of control variables used. Theoretically, however, less strict criteria increase the possibility of omitting critical control variables.

Our dataset counts 31370 Green and Brown bonds, 26 unique firm observations which motivates our choice of three variables $i.seniority\_n$ $i.issuer\_n$ $i.countryofissue\_n$ to perform the matching. As being shown in the **Figure V**, our specification results in a relevant 132 matched strata out of 3006 in the *Standard CEM Regression*, among which 154 conventional bonds are matched to 219 conventional bonds. **Figure VI** reveals the output of the K2K option is inferior to the 'regular' CEM matching, as expected. Indeed, the L1 statistic of $1.148e^{-15}$ is worse to that of k2k of 0, which reveals an exact matching. Although precise, the k2k specification of the CEM method is only able to match 14 observations. Hence, we convene on relying on the Standard CEM output for the purpose of interpretation.

It is on the evidence of **Table III** that we conclude that no greenium is estimated by the Matching model. We can observe that the Green Bond dummy variable is negative, but insignificant. This indicates that after closely matching conventional and green bonds, no evidence for a significant difference in yields is found.

Besides, the coefficients for this variable is in line with past evidence: [6] and [12] also found positive, but insignificant effects on the yields.

IV. Conclusion

This paper sheds light on the differences in yields paid by green and brown bonds. We have employed various methods to test whether green bonds trade at a negative spread to conventional bonds (*greenium*) and we have found that there is no noticeable difference between yields. This conclusion is inconsistent with the hypothesis that firms issue green bonds because they provide a cheaper source of financing (*cost of capital theory*) [3]. According to this theory, investors may be willing to accept lower yields in order to contribute towards the effort of combating climate change. As a result, green bonds may serve as a more cost-effective means of financing. This could potentially lead to a positive response in the stock market, as shareholders stand to benefit from the availability of more affordable debt financing. However, the results of this study do not support the argument that the cost of capital is a significant factor, as there is no evidence to suggest that corporate green bonds are priced at a premium compared to non-green bonds.

Our results are also in line with the the findings of Larcker and Watts (2020) [7] and of Flammer (2021) [3]. They have also conducted interviews with traders, portfolio managers and other industry practitioners, whose general sentiment was that they would not invest in green bonds if the returns were not high enough.

Our research warrants a discussion about the possible reasons of why there is no *greenium*. First of all, the most simple explanation is that the projects the green bonds are to issued to finance are profitable enough to generate competitive returns. Second of all, the current absence of a *greenium* could be due to the fact that the market for green bonds is still fairly young, with corporate green bonds representing only a small portion of the overall corporate bond market (e.g. in 2018 the issuance of corporate bonds was $95.7B while the size of the overall market was estimated at $102.8T) [3]. Given that the market is still at an early stage, it could be the case that corporate green bonds can be issued to finance projects that are profitable enough to sustain competitive returns, but this does not mean that it will be the same in the future. As the green bond market continues to grow, investors may become more environment-conscious and may decide to settle for a lower yield. Finally, we cannot ignore the fact that we are working on a relatively small sample, which may not be representative of the whole green bond market and that our methods of analysis do not entirely mitigate the problem of the endogeneity of green bonds [13]. With a larger number of observations or with the employment of quasi-experiments, researches may be able to provide valuable insights into the relationship between yields to maturity and green bonds.

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V. APPENDIX

TABLE I
REGRESSION WITH FIXED EFFECTS GROUPING BY YIELD TO MATURITY

	Standard Fixed Effects	FE with ytm $<$ 2.5%	FE with ytm $\geq$ 2.5% & $<$ 5%	FE with ytm $\geq$ 5%
Green Bond	0.0147	-0.0146	-0.00819	-0.0648
	(0.41)	(-0.94)	(-0.33)	(-1.06)
Amount Issued	0.0200	-0.0257	-0.00690	0.0262
	(1.47)	(-1.15)	(-0.45)	(1.09)
rcoupon	0.0766*	0.180**	-0.0235	0.0611*
	(2.24)	(3.77)	(-1.22)	(1.78)
Secured	0		0	0
	(.)		(.)	(.)
Senior Secured	-0.827*	0	0.0610	-1.097**
	(-2.56)	(.)	(0.84)	(-3.98)
Senior Secured - First Lien	-0.565		0.475**	-0.834*
	(-1.57)		(4.25)	(-2.30)
Senior Secured - First Mortgage	-0.671*		-0.155	-0.865**
	(-1.97)		(-1.16)	(-4.03)
Senior Secured - General	Refunding Mortgage	0		0
0				
	(.)		(.)	(.)
Senior Unsecured	-0.231	0.192**	0.281*	-0.421**
	(-0.73)	(4.88)	(2.14)	(-2.99)
Subordinated Unsecured	-0.152		0.199	
	(-0.48)		(1.62)	
Unsecured	-0.219	0.110**	0.442**	-0.762**
	(-0.65)	(2.70)	(2.75)	(-5.33)
Maturity Years	0.0297**	0.0678**	0.0373**	0.00321
	(6.47)	(11.67)	(4.56)	(1.26)
year=2019	0	0	0	0
	(.)	(.)	(.)	(.)
year=2020	-0.0714*	0.0704**	-0.0490	-0.142*
	(-1.94)	(3.09)	(-1.34)	(-1.92)
year=2021	0.0654	0.158**	0.101**	-0.00310
	(1.59)	(8.43)	(2.73)	(-0.03)
year=2022	0.145*	0.0206	0.284**	-0.0160
	(2.39)	(0.48)	(4.52)	(-0.19)
year=2023	0.0974	-0.000114	0.279**	-0.0517
	(1.28)	(-0.00)	(4.14)	(-0.54)
Constant	3.268**	0.748*	3.471**	5.484**
	(7.35)	(1.67)	(9.74)	(9.88)
Observations	3593	656	1991	946

t statistics in parentheses
* $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

TABLE II
REGRESSION WITH FIXED EFFECTS GROUPING BY YEAR

	Standard Fixed Effects	FE 2019	FE 2020	FE 2021
Green Bond	0.0147	-0.0146	-0.00819	-0.0648
	(0.41)	(-0.94)	(-0.33)	(-1.06)
Amount Issued	0.0200	-0.0257	-0.00690	0.0262
	(1.47)	(-1.15)	(-0.45)	(1.09)
rcoupon	0.0766*	0.180**	-0.0235	0.0611*
	(2.24)	(3.77)	(-1.22)	(1.78)
Secured	0		0	0
	(.)		(.)	(.)
Senior Secured	-0.827*	0	0.0610	-1.097**
	(-2.56)	(.)	(0.84)	(-3.98)
Senior Secured - First Lien	-0.565		0.475**	-0.834*
	(-1.57)		(4.25)	(-2.30)
Senior Secured - First Mortgage	-0.671*		-0.155	-0.865**
	(-1.97)		(-1.16)	(-4.03)
Senior Secured - General	Refunding Mortgage	0		0
0				
	(.)		(.)	(.)
Senior Unsecured	-0.231	0.192**	0.281*	-0.421**
	(-0.73)	(4.88)	(2.14)	(-2.99)
Subordinated Unsecured	-0.152		0.199	
	(-0.48)		(1.62)	
Unsecured	-0.219	0.110**	0.442**	-0.762**
	(-0.65)	(2.70)	(2.75)	(-5.33)
Maturity Years	0.0297**	0.0678**	0.0373**	0.00321
	(6.47)	(11.67)	(4.56)	(1.26)
year=2019	0	0	0	0
	(.)	(.)	(.)	(.)
year=2020	-0.0714*	0.0704**	-0.0490	-0.142*
	(-1.94)	(3.09)	(-1.34)	(-1.92)
year=2021	0.0654	0.158**	0.101**	-0.00310
	(1.59)	(8.43)	(2.73)	(-0.03)
year=2022	0.145*	0.0206	0.284**	-0.0160
	(2.39)	(0.48)	(4.52)	(-0.19)
year=2023	0.0974	-0.000114	0.279**	-0.0517
	(1.28)	(-0.00)	(4.14)	(-0.54)
Constant	3.268**	0.748*	3.471**	5.484**
	(7.35)	(1.67)	(9.74)	(9.88)
Observations	3593	656	1991	946

t statistics in parentheses
* $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

```
Logistic regression                                     Number of obs =  3,127
                                                        LR chi2(8)    =  11.39
                                                        Prob > chi2   = 0.1805
Log likelihood = -31.492783                             Pseudo R2     = 0.1531
```

rcoupon	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
currency_n	.027658	.2200961	0.13	0.900	-.4037223	.4590384
countryofissue_n	-.0131511	.153033	-0.09	0.932	-.3130903	.2867881
ramount	1.25e-10	1.12e-09	0.11	0.911	-2.07e-09	2.32e-09
seniority_n	-.220163	.3989854	-0.55	0.581	-1.00216	.561834
sector_n	.0208788	.039713	0.53	0.599	-.0569574	.0987149
year	3.011027	1.791247	1.68	0.093	-.4997534	6.521807
Maturity	-.0043675	.0047458	-0.92	0.357	-.0136691	.0049342
matyears	1.562494	1.735056	0.90	0.368	-1.838154	4.963142
_cons	-5976.906	3520.352	-1.70	0.090	-12876.67	922.8567

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
ytm	Unmatched	4.23840585	1.57709947	.430350105	.01566633	27.47
	ATT	4.23840585	1.49814729	2.74025857	.117585618	23.30

Note: S.E. does not take into account that the propensity score is estimated.

psmatch2: Treatment assignment	psmatch2: Common support On suppor	Total
Untreated	161	161
Treated	500	500
2	740	740
3	932	932
4	505	505
5	174	174
6	79	79
7	33	33
8	2	2
9	1	1
Total	3,127	3,127

Fig. 3. Propensity score matching results.

Two-sample t test with equal variances

Group	Obs	Mean	Std. err.	Std. dev.	[95% conf.	interval]
0	2,524	12.49398	.1848279	9.285647	12.13155	12.85641
1	575	12.60574	.423892	10.16457	11.77318	13.43831
Combined	3,099	12.51472	.1698135	9.453292	12.18176	12.84768
diff		-.1117625	.4368987		-.968403	.7448781

```
    diff = mean(0) - mean(1)                                      t =  -0.2558
H0: diff = 0                                     Degrees of freedom =     3097

    Ha: diff < 0               Ha: diff != 0               Ha: diff > 0
 Pr(T < t) = 0.3991        Pr(|T| > |t|) = 0.7981        Pr(T > t) = 0.6009
```

Fig. 4. Two-sample t-test results.

TABLE III
STANDARD CEM REGRESSION

	Regression with CEM	Regression without CEM	Regression with CEM k2k
Green Bond	-0.0981	-0.0147	0.445
	(-1.12)	(-0.64)	(0.79)
Senior Secured	0	-0.905**	
	(.)	(-3.13)	
Senior Secured - First Mortgage	2.798**	-0.519	
	(3.44)	(-1.39)	
Senior Unsecured	1.888**	-0.312	
	(4.80)	(-1.09)	
Unsecured	1.870**	-0.102	
	(3.65)	(-0.35)	
Constant	2.245**	6.368**	3.174**
	(3.33)	(16.63)	(7.98)
Observations	373	3594	28

t statistics in parentheses
* $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

```
Matching Summary:
-----------------
Number of strata: 3006
Number of matched strata: 132

              0     1
      All  2930   664
  Matched   219   154
Unmatched  2711   510


Multivariate L1 distance: 1.148e-15

Univariate imbalance:

              L1     mean      min      25%      50%      75%      max
 rcoupon  9.7e-16  6.7e-15        0        0     -.05        0        0
matyears  1.0e-15  1.2e-14        0        0        0        0        0
```

Fig. 5: Summary Statistics of standard CEM regression

```
Matching Summary:
-----------------
Number of strata: 3529
Number of matched strata: 14

              0     1
      All  2930   664
  Matched    14    14
Unmatched  2916   650


Multivariate L1 distance: 0
```

Fig. 6: Summary Statistics of CEM k2k regression