M2 EGR 2024-2025 Empirical Project: Final Report

Assessing Green Bond Yield Differentials: A Multi-Method Exploration

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March 25, 2025

Contents

1 Introduction

Green bonds, dedicated to financing projects with positive environmental outcomes, have witnessed considerable expansion in recent years. As this market segment grows, both regulators and investors increasingly question whether these instruments systematically differ in yield from conventional bonds, a phenomenon commonly referred to as the "greenium." Potential sources of such a greenium include heightened demand from sustainability-focused investors, a reputational advantage for issuing firms, and regulatory requirements compelling institutions to hold green assets. Notwithstanding these potential benefits, liquidity factors complicate the pricing of green bonds, as their relatively smaller issuance volumes or specialised investor bases may affect trading frequency, bid–ask spreads, and overall market depth.

In light of these complexities, this study evaluates whether—and to what extent—green bonds display distinct yield characteristics compared to otherwise similar conventional bonds. Green bonds remain a comparatively novel financial instrument, and questions persist about their risk-return profile, their capacity to command a pricing premium, and the role of liquidity constraints in explaining any such premium or discount.

We adopt two complementary empirical approaches to investigate these issues. First, we perform a matching analysis akin to Pietsch and Salakhova (2022), pairing each green bond with conventional counterparts that closely align in terms of maturity, coupon, and issuance year. By doing so, we seek to isolate the effect of the "green" label on yields. Secondly, we run a panel regression to attempt to isolate the effect of a bond being green, whilst also accounting for bond characteristics and macroeconomics variables. Thirdly, we estimate Nelson–Siegel yield curves for green and conventional bonds, examining whether the shape and level of the yield curve differ systematically between the two bond types. This strategy allows us to identify term-structure dynamics not readily visible when relying solely on pairwise matching.

Our findings highlight three key insights. First, matching methods are critical: one-to-many matching can dilute the greenium signal, whereas strict one-to-one matching consistently reveals a negative and robust negative yield gap. Second, when we incorporate issuer fixed effects and macroeconomic controls in a panel regression framework, the statistical evidence for a greenium largely vanishes, suggesting that subtle sample selection and measurement choices influence greenium estimates. Finally, differences in bond characteristics such as coupon rate and days to maturity do appear to explain part of the yield differentials even when using matching method, but not fully, indicating that bond seniority and liquidity factors not collected for this analysis may each play a role.

From a methodological standpoint, we refine the matching process to ensure that bond comparisons occur within narrow time windows, thereby mitigating the risk of spurious yield differences arising from intra-day price fluctuations. We also adjust the weighting of variables, such as coupon rates, to reflect their contribution to observed yield differentials. Substantively, our analysis contributes to ongoing discussions concerning the extent to which green financial instruments are priced distinctly from conventional bonds, and whether their liquidity profile supports or undermines any apparent yield premium.

The remainder of this paper is organised as follows. Section 2 reviews the extant literature on green bond pricing and its linkage to liquidity and other market frictions. Section 3 describes our empirical methodology, detailing both the matching approach and the Nelson–Siegel estimation. Section 4 discusses the data collection process, highlighting key filters and cleaning procedures, before Section 5 presents our empirical results and an array of robustness checks (Section 6). Finally, Section 8 concludes, offering reflections on methodological and policy implications, as well as avenues for future research.

2 Literature Review

Academic interest in green bonds has grown alongside their increasing market capitalisation, particularly in the context of green finance and its potential to influence capital allocation. A considerable strand of the literature centres on the "greenium," wherein green bonds may trade at lower yields (or higher prices) than otherwise comparable securities. MacAskill et al. (2021) offer a comprehensive review of this issue, establishing that many empirical studies indeed report a modest negative yield spread for green issues—though the extent of this spread varies by market segment and estimation method.

An influential approach to identify yield differentials is the matching framework pioneered by Zerbib (2019), who used a two-step matching and regression method to control for maturity, credit quality, and coupon structure. Their findings suggest a small but negative greenium, typically on the order of a few basis points. Pietsch and Salakhova (2022) refine this approach by introducing optimal matching algorithms that incorporate additional bond-level characteristics and external reviews. They show that credible green certification and issuer reputation can amplify the greenium, reflecting investors' willingness to pay a premium for bonds with demonstrable environmental attributes. In contrast, Hachenberg and Schiereck (2018) and Febi et al. (2018) emphasise the role of liquidity, finding that green bonds may occasionally trade on tighter spreads when liquidity is sufficiently robust.

Beyond matching, a second line of research estimates yield curves directly. Paola Fandella (2024) employ both Nelson–Siegel–Svensson models and synthetic bond approaches, uncovering contradictory results: some specifications detect a negative greenium, whereas others indicate insignificant or even positive yield differentials. This methodological variability underscores the sensitivity of greenium estimates to the choice of model. Similarly, Renjie and Xia (2023) derive synthetic bonds to show a more pronounced greenium, arguing that conventional matching methods underestimate investors' "green halo" preferences. These findings collectively indicate that yield-curve modelling can capture term-structure nuances missed by simpler pairwise comparisons.

Additional research also analyses the underlying drivers of the greenium. Flammer (2021) and Fatica and Panzica (2021) link green bond issuance to improvements in environmental performance, suggesting that issuers can leverage green financing to enhance their sustainability credentials—perhaps prompting investors to accept lower yields. Meanwhile, factors such as credit risk, issue size, sector affiliation, and the degree of external verification significantly moderate the observed yield difference (MacAskill et al. 2021; Zerbib 2019). Furthermore, macro-level influences—most notably interest-rate environments, as noted by Nagel (2016), and economic volatility—can affect the perceived benefits of holding green securities. Another bias may also be at play, companies that emit green bonds may have superior governance standard than non-green emitting competitors, where non quantifiable so-called soft factors can have an impact on the cost of debt firms face. Not isolating these factors can would cause a misestimation of the true effect of a bond being green and violate our treatment assumption. The estimation of the greenium in this case would be too optimistic as the unobservable factors would act as an unmeasured confounder that introduce bias.[1] Estimating the ATT would not only estimate the direct effect but also the indirect effect.

Liquidity pervades much of the literature on green bond pricing. Amihud and Mendelson (1986) demonstrate how illiquidity can widen yield spreads, a finding corroborated in green bond contexts by Hachenberg and Schiereck (2018). Indeed, one rationale for any greenium may be that certain long-term investors face fewer constraints trading these bonds, especially if held to maturity for sustainability-driven mandates. When green bonds trade infrequently or in smaller issuance sizes, illiquidity might offset their potential yield advantage. As Paola Fandella

[1] we present a stylised example in the Appendix, Figure 11 .

(2024) illustrate, controlling for liquidity in yield-curve estimation can invert prior inferences about green premiums with the authors finding a negative greenium when using a fixed-effect regression after previously finding a positive greenium when using a matching method.
In light of this literature, our investigation extends two principal strands of research. First, we adopt a matching method akin to Pietsch and Salakhova (2022) but expand upon the authors work by testing different matching methods. Second, we supplement this matching analysis with a Nelson–Siegel curve estimation to test whether green and conventional yield curves diverge in systematic ways. By synthesising these approaches, our study attempts to offer a rigorous perspective on the elusive greenium, clarifies its sensitivity to methodological choices, and addresses the broader debate over whether environmental preferences materially alter bond pricing.

3 Empirical strategy: Method and models

The strategy adopted to carry out this study was threefold: get the data for green and conventional bonds and proceed to a matching method to get pairs of similar bonds with just their green component as an important difference. Secondly, a panel data regression model was implemented using the greenium as dependent variable. Finally, a Nelson-Siegel-Svensson curve was estimated to represent the yield to maturity of green and conventional bonds. These three methods allow us to compare the our estimations of the greenium across different identification strategies.

3.1 Matching Method

When choosing a matching method to create a dataset of comparable green and conventional bonds, several methods are possible: Zerbib (2019) employ a synthetic matching approach that blends manual selection with interpolation. Pietsch and Salakhova (2022) use a k-prototypes matching algorithm, a clustering algorithm that extends K-means to mixed-type data (numerical and categorical). This method allows to handle mixed-types data effectively, reducing the "curse of dimensionality" by grouping observations into clusters. Nevertheless, it is highly sensitive to the choice of K, and struggles with unbalanced categorical distribution. In their approach, Pietsch and Salakhova (2022) also highlight that a bond's price is shaped by several bond-level characteristics such as maturity, duration, seniority, or coupon type. To account for this, they minimise differences in these attributes through the application of a matching algorithm. The matching methodology implemented in our analysis follows a systematic approach to pairing green and conventional corporate bonds issued by the same company. The objective is to ensure comparability between the two bond types by matching them based on key financial characteristics while preserving the temporal structure of the dataset. This is achieved through a one-to-one optimal assignment algorithm, specifically the Hungarian algorithm, applied to a distance matrix computed from standardised bond attributes.
The matching process begins with data preparation, where essential bond attributes, including yield to maturity (YTM), coupon rate, days to maturity, modified duration, and last price, are converted into numerical formats to facilitate subsequent computations. Additionally, the emission year of each bond is extracted from indicator variables, ensuring that this information is incorporated into the matching criteria. A temporal component is introduced by transforming the issuance date into a numerical variable representing the number of days since the Unix epoch, thereby allowing for a time-sensitive matching process.
The dataset is then structured to ensure that matching occurs strictly within the same issuing entity. Bonds are classified into two distinct groups: green bonds and conventional bonds. The matching procedure is only performed for companies that have issued both types of bonds,

thereby maintaining issuer-level comparability. Green bonds are matched to conventional counterparts based on a weighted Euclidean distance calculated across several standardised financial characteristics: coupon rate, days to maturity, year of issuance, and a transformed time variable. To ensure comparability across variables with differing scales, all features are standardised, and some are differentially weighted — for example, the coupon rate is down-weighted to account for structural differences, while the time variable is given an adjustable weight to emphasise temporal proximity. The resulting distance matrix is then used in the Hungarian algorithm, a combinatorial optimisation technique that identifies the globally optimal one-to-one pairing by minimising the total matching cost. This approach produces a matched dataset of green and conventional bonds that are as similar as possible, thereby strengthening the validity of subsequent comparisons of YTM.

3.2 Nelson-Siegel-Svensson

We additionally estimate a Nelson-Siegel-Svensson model for green and conventional bonds to provide an overview of their yield as well as an idea of the dynamics of the greenium. Already used widely by central banks, this model has been also used for green bonds (Paola Fandella 2024). The method estimates the yield curve for both green bonds and conventional bonds using the following formula:

$$y(\tau) = \beta_0 + \beta_1 \cdot \frac{1 - e^{-\lambda_1 \tau}}{\lambda_1 \tau} + \beta_2 \cdot \left(\frac{1 - e^{-\lambda_1 \tau}}{\lambda_1 \tau} - e^{-\lambda_1 \tau} \right) + \beta_3 \cdot \left(\frac{1 - e^{-\lambda_2 \tau}}{\lambda_2 \tau} - e^{-\lambda_2 \tau} \right)$$

Where β_0, β_1, β_2, and β_3 determine the shape of the yield curve. The parameter β_0 represents the long-term level of interest rates, capturing the asymptotic yield as maturity increases. The parameter β_1 influences the short-term slope of the curve, while β_2 introduces curvature that allows for a hump-shaped feature over medium-term maturities. The addition of β_3 in the Svensson extension enables a second hump, providing greater flexibility to fit more complex yield curve shapes. The decay parameters λ_1 and λ_2 control the location and steepness of these humps, with λ_1 affecting the influence of the short- and medium-term components, and λ_2 governing the contribution of the second curvature term. Together, these parameters allow the model to flexibly approximate a wide range of yield curve shapes observed in financial markets. We estimate the Nelson-Siegel Svensson curve by following the approach of Gilli et al. (2010). The optimisation involves minimising the sum of residuals of observed yields to the yields of the rate curve generated by the parameters that are to be optimised.

3.3 Panel Data regression model

A panel data regression as in Pietsch and Salakhova (2022) was conducted, with greenium (calculated as the yield spread in each pair of matched bonds) as depend variable. The model takes the following form:

$$y_{i,t} = \beta_0 + \beta_1 \, \text{is\_green}_{i,t} + X_{i,t}\gamma + M_t\delta + \varepsilon_{i,t} \tag{1}$$

Among the explanatory variables included in $X_{i,t}$ are *days to maturity*, *modified duration*, *log of issuance volume*, and *coupon rate*. The vector M_t captures the following macroeconomic controls: 3-month Euribor rate, the 10-year Bund yield, and the VIX volatility index. Assuming all bond characteristics are accounted for with issuer fixed affects and the macroeconomic controls are well specified, identification of the greenium through the coefficient β_1 is provided.

4 Overview of Data

All computer code employed in this analysis, as well as the majority of the data collected, is hosted on our dedicated GitHub repository. Our dataset is derived from publicly available bond information on the Börse Frankfurt website,[2] with more than 35,000 bonds listed on the exchange.

4.1 Bond Price Data

Börse Frankfurt's dedicated pages for green and conventional bonds were scraped at regular intervals to compile time series of daily prices, which included bond names, last prices, trading volumes, coupons, currencies, and yield-to-maturity (YTM) where available for all green bonds and a selection of the 2,000 most actively traded conventional bonds. Table 1 illustrates a typical example of the price data structure.

Name	WKN	Last Price	Date/Time	Volume (Euro)
Deutschland 2.5% 23/25	BU2200	99.98	27.12.24 16:06	996,799
Türkei 6.75% 10/40	A1AR3B	90.45	27.12.24 17:00	874,269
USA 1.125% 21/28	A3KVAX	89.00	27.12.24 17:08	853,474
Deutschland 1% 15/25	110238	99.21	27.12.24 13:47	620,060

Name	+/- %	Coupon	YTM
Deutschland 2.5% 23/25	0.00	2.50%	-
Türkei 6.75% 10/40	0.02	6.75%	7.88%
USA 1.125% 21/28	0.08	1.13%	-
Deutschland 1% 15/25	0.01	1.00%	2.26%

Table 1: Bond Price Data

4.2 Bond Market Data

In addition to the daily price data, a single cross-sectional sample of bid-ask spreads for the 1,000 most actively traded bonds was collected. Each scraping iteration required approximately 1.5 hours, thus limiting the frequency with which these observations could be gathered. Table 13 presents an example of the bid-ask spread dataset, displaying the bid price, ask price, and both absolute and relative spreads. Consequently, our subsequent analyses of intra-day liquidity rely on the last price observed on Börse Frankfurt's main website, which is generally reported in the "ask" column.

4.3 Bond Metadata

In addition, we undertook a large-scale web scraping procedure to capture metadata on approximately 35,000 bonds listed on the Frankfurt exchange. This comprehensive dataset allowed us to identify and exclude callable bonds, which are priced differently owing to their embedded option features. Without corresponding option-adjusted spread (OAS) data, including callable instruments in our analysis could introduce distortions stemming from their atypical convexity

[2] https://www.boerse-frankfurt.de/anleihen/green-bonds

characteristics. Table 2 outlines the primary metadata variables acquired from Börse Frankfurt, subsequently cleaned via automated procedures.

Variable	Description
URL	Bond listing link
Letzter Preis	Last recorded price
Veränderung zum Vortag	Change from previous day (%)
Letzter Handel	Last trade date/time
Geld	Bid price
Brief	Ask price
Kupon	Coupon rate (%)
Emittent	Issuer
Branche	Sector/Industry
Fälligkeit	Maturity date

Table 2: Overview of Bond Data Variables

4.4 Data Wrangling and Cleaning

The data collection process follows a modular approach, with scripts scheduled to execute automatically at predetermined intervals. Below, we outline the principal steps undertaken to compile our final dataset:

— **Web scraping of green and conventional bonds and creation of the bond dictionary**

We collected real-time price data from Börse Frankfurt for every listed green bond, as well as for the 2,000 most actively traded conventional bonds, for nearly every hour between 25/12/2024 and 04/02/2025. We then gathered the unique URLs of green bonds alongside those of conventional bonds issued by the same entities. This process yielded a consolidated "bond dictionary," including core identifiers such as ISINs and indicating whether each bond was green.

— **Filtering**

We applied a series of filters to produce a more focused dataset. Bonds maturing in 2025, as well as perpetual instruments or bonds lacking a specified maturity date, were removed. Only bonds issued in 2020 or later were retained. We excluded callable bonds from our sample, as their embedded call option introduces non-linear pricing dynamics that affect convexity and valuation. Without access to an option-adjusted spread (OAS), their inclusion could bias yield comparisons by conflating optionality with credit and liquidity risk. While some studies, such as Pietsch and Salakhova (2022), address this by using OAS-based metrics, callable instruments accounted for only a marginal share of our initial dataset, making their exclusion methodologically sound. Furthermore, we removed bonds issued by supranational entities—including the EIB, ESM, and ESFS—given their unique status in the market. These issuers benefit from strong institutional backing and enhanced liquidity, often serving as pricing benchmarks. Their yields may therefore reflect structural premiums unrelated to credit or green premia, potentially distorting the comparability of conventional and green bonds. Excluding callable and supranational bonds, and appropriately matching otherwise similar instruments, ensures that our comparisons of yield differentials focus primarily on credit risk, maturity, and market liquidity rather than optionality or institutional credibility.

— **Merging with static bond data and final data selection**

We enhanced our bond dictionary with descriptive and static features such as coupon rates, issuance volumes, and sector classifications. The static data was extracted and cleaned using a VBA macro (Static Data Cleaning Macro). We subsequently merged the price and static datasets to form a single analytic sample, focusing on bonds issued by 35 corporate entities. After matching, 288 unique bonds remained, of which 100 were green. Restricting the sample to euro-denominated instruments produced a final dataset of 5,948 observations, underpinning the empirical analyses presented in this paper.

Name	**WKN**
Volkswagen Leasing GmbH 4,75% 23/31	A3514V
Volkswagen Leasing GmbH 4,625% 23/29	A3514U
Volkswagen International Finance N.V. 4,125% 22/25	A3LA6A
Volkswagen International Finance N.V. 4,375% 22/30	A3LA6C
Volkswagen International Finance N.V. 4,25% 23/29	A3LFX2
Volkswagen International Finance N.V. 7,5%	A3LMPT
Volkswagen International Finance N.V. 7,875%	A3LMPU
Volkswagen International Finance N.V. 0,875% 20/28	A282U1
Volkswagen International Finance N.V. 3,125% 22/25	A3K61G
Volkswagen International Finance N.V. 4,25% 22/28	A3LA6B
Volkswagen International Finance N.V. 1,25% 20/32	A282U2
Volkswagen International Finance N.V. 3,75% 22/27	A3K61H
Volkswagen International Finance N.V. 3,875% 23/26	A3LFX1
Volkswagen Leasing GmbH 4,5% 23/26	A3514T

Table 3: Example List of Green Bonds - Volkswagen

5 Results

In this section we present and interpret our empirical findings on the yield differentials between green and conventional bonds. We begin by discussing descriptive evidence derived from our matching approach and daily yield-to-maturity (YTM) differentials. We then turn to panel regressions designed to control for additional covariates and potential sources of omitted-variable bias. Throughout, we highlight how methodological choices—particularly in matching—affect the estimates of the greenium.

5.1 Descriptive Analysis of YTM Differentials

Figures 1 and 2 illustrate the evolution of average YTM differences (green minus conventional) over time, using one-to-one and one-to-many matching methods, respectively.[3] In both cases, a greenium (i.e. negative YTM differences) is evident on many days, consistent with parts of the literature (Pietsch and Salakhova 2022). However, the magnitude and statistical reliability of these differences vary based on how matched samples are constructed.

One-to-One Matching. Under the one-to-one approach, each green bond is paired with a single conventional bond deemed most similar on observed characteristics (e.g. coupon, seniority, days to maturity). As shown in Figure 1, the weighted average YTM difference across the sample is generally below zero, indicating that green bonds tend to have slightly lower

[3] We refer to differences as measured in percentage points or basis points (bps), depending on scale. Negative values indicate lower yields on green bonds relative to their conventional counterparts.

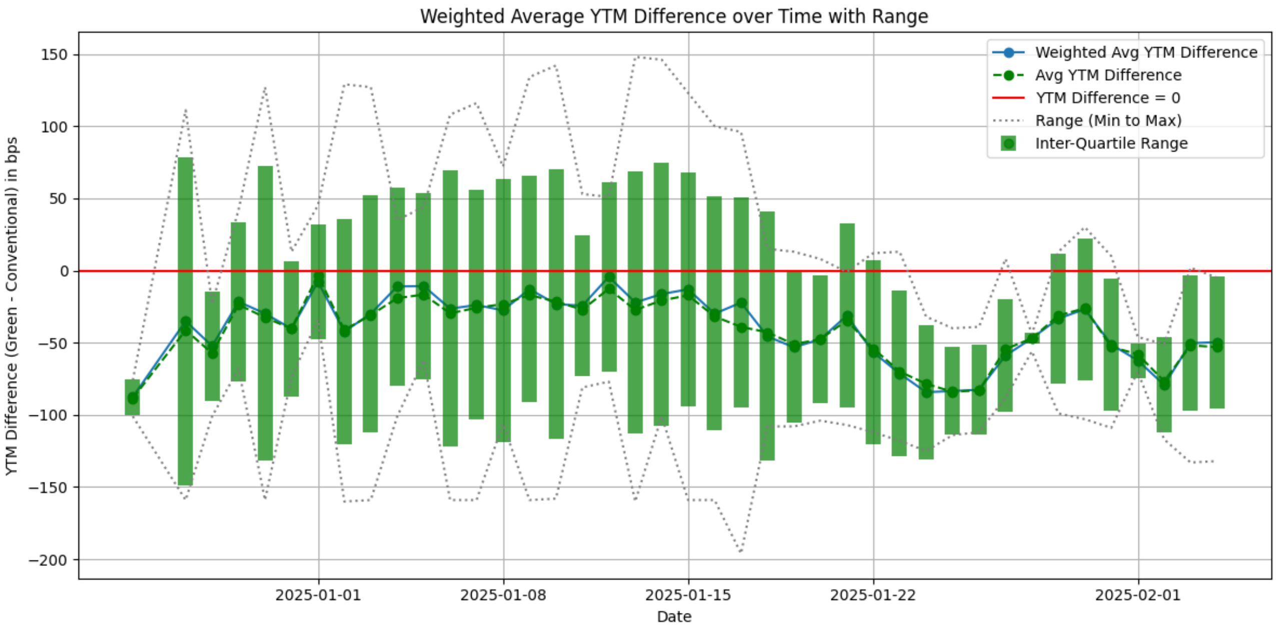

Figure 1: Weighted average YTM difference over time using a **one-to-one** matching method - Plot shows the arithmetic mean and the weighted mean, with the interquartile range (0.25-0.75) and the whole range. We observe a strong greenium (negative YTM difference) here for most of the observations periods, with some periods displaying a smaller greenium in terms of absolute values. The size of our results suggests that we overestimate the yield differences of green and conventional bonds when compared to the existing literature.

yields than conventional bonds. Table 6, which provides daily summary statistics of this difference, shows that the greenium fluctuates from approximately -0.05 to -0.90 percentage points across the observation window with the a mean greenium of -20.14 bps and -25.21 bps for the weighted and simple mean respectively (Table 4). These results align with previous findings in the literature, suggesting that investors may be willing to accept a modest yield penalty in order to hold green bonds, reflecting either reputational benefits or compliance with sustainability mandates.

One-to-Many Matching. When we expand our methodology to allow one green bond to match with multiple conventional bonds, as illustrated in Figure 2 and Table 7, the average yield differential diminishes in magnitude and is more frequently centred around zero. In certain instances, the difference even becomes slightly positive (indicating marginally higher yields for green bonds), although these periods tend to be less frequent. The weighted and simple mean greenium was -3.14 bps and -7.93 bps respectively. The one-to-many matching method exhibited a lower standard deviation in both the weighted average and simple mean YTM differences compared to the other methods. This weakening of the greenium can arise because a single green bond's yield is re-used multiple times, effectively "overweighting" green bond yields and bonds that are observed frequently, which are also the bonds that are most liquid[4]. As a result, any idiosyncratic features of particularly liquid issuers that issue a large number of bonds dominate the aggregated estimate (see Table 3 as an example). Consequently, although the broader data sample increases, the reliability of inferences concerning the greenium suffers as identification becomes more difficult.

[4]This is due to our data collect, we collected data of all green bonds and the 2000 highest volume traded bond overall. We therefore oversample the most traded bonds on Börse Frankfurt relative to other bonds, with these bonds coming from larger and on average, more credit worthy issuers.

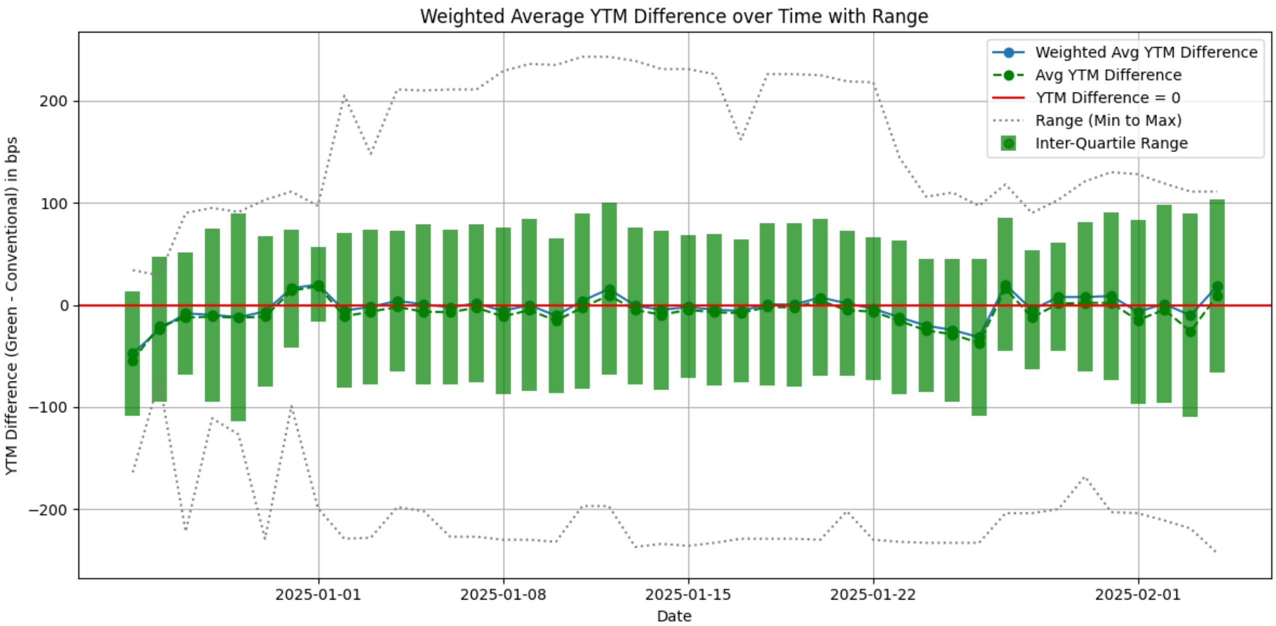

Figure 2: Weighted average YTM difference over time using a **one-to-many** matching method - Plot shows the arithmetic mean and the weighted mean, with the interquartile range (0.25-0.75) and the whole range. We observe a slight greenium (negative YTM difference) here for most of the observations periods, with some periods of a negative greenium (positive YTM difference). Compared to the One-to-One Matching method (Figure: 1) the greenium is much smaller in magnitude and closer to existing literature, suggesting an overestimation and bad matching behaviour in the one-to-one matching case.

Table 4: Overview of Mean YTM Differences (Greenium Estimates)

Method	**Weighted Mean Greenium**	**Mean Greenium**
One-to-One Matching	-0.2014	-0.2521
Winsorized One-to-One Matching	-0.1636	0.1962
One-to-Many Matching	-0.0314	-0.0793

5.2 Panel Regression Results

To investigate more rigorously both the existence and size of the greenium, we estimate a series of panel regressions incorporating standard control variables and issuer-level fixed effects. These regressions include macroeconomic determinants such as the three-month Euribor rate (`Euribor_3m`), the ten-year German government bond yield (`Bund_10yr`), and the VIX index (`VIX`), alongside bond-level characteristics including days to maturity, coupon, and modified duration. Table 5 summarises two principal model specifications in accordance with Pietsch and Salakhova (2022), one of which explicitly isolates the effect of being a green bond.

The estimated coefficient for `is_green` remains close to zero and does not achieve statistical significance after issuer-specific fixed effects and other covariates are introduced. In particular, Table 5 indicates a point estimate of approximately 0.0032 (i.e. 0.32 basis points), a magnitude that is neither economically meaningful nor statistically different from zero in contrast to our results with the matching methods.

The remaining covariates generally align with expectations. A higher three-month Euribor rate and an elevated ten-year Bund yield both exert an upward pressure on corporate bond yields, as these variables capture prevailing monetary conditions and long-term interest rate

movements, respectively. The VIX enters insignificantly, implying that day-to-day volatility may not strongly affect bond yields in this context. Consistent with standard bond-pricing theory, higher coupons and longer durations are associated with incrementally higher yields.
Overall, these panel regression outcomes may suggest that once a sufficiently set of controls is introduced, the previously observed green bond discount may not hold at a statistically significant level. Several explanations are plausible. First, it is possible that unobserved heterogeneity, specifically among issuers, inflates the greenium in simpler specifications but becomes absorbed by fixed effects in these regressions. Second, any genuine yield advantage of green bonds could be overshadowed by confounding differences in issuer credit quality or sector affiliation not fully captured in the matched sample. Finally, it is possible that the greenium predominantly manifests in narrower segments of the market, such as newly issued securities or specific industries, and thus does not generalise sufficiently to be detected in this broader panel setting and dataset.
Collectively, the results underscore the importance of methodological design and the inclusion of robust issuer-level controls when testing for a greenium. They also illustrate that panel approaches—while capturing more variation—can conflict with findings derived from stricter matching procedures, particularly if the sample is subject to self-selection or unmeasured issuer-specific attributes. In section 5.4, we consider how further refinements to both the sample and model specification might reconcile these differing perspectives.

5.3 Nelson-Siegel-Svensson Approach

Figure 3 shows individual bond YTM compared to the respective day's ECB yield curve. For most maturities we observe a positive spread to the ECB NSS curve which is to be expected. To visualise the difference in spreads we use a smoothing process to estimate a general trend in the yield spread. This was done by applying smoothing splines, which allow for a flexible yet structured approximation of the data while mitigating the influence of noise and outliers. No clear and consistent spread is observed. In the maturity period between 2.5 and 10 years we observe a negative greenium, with it being positive for shorter maturities. Clumping is observed due to the autocorrelation of YTM throughout time which would be removed by looking at only one specific day as done in Figure 4.
In Figure 10 we compare the NSS curve implied by our data set for green and conventional bonds to the ECB curve. For smaller maturities we observe the NSS curve estimation not working well due to filtering out most bonds that have short maturities [5]. The lower yield if the conventional NSS curve is caused by an imbalance in our data set for bonds maturing in less than 1 year, with YTM for conventional bonds skewed downwards compared with green bond yields. Looking at maturities greater than 2.5 years however, we see a slight but consistent spread between green and conventional bonds. The NSS curves reflect the greenium observed in Figures 1 and 2.

5.3.1 Newey-West Adjusted t-Test

To determine whether the differences in yield to maturity (YTM) between green and conventional bonds, as well as the Nelson-Siegel-Svensson implied yields provided by the European Central Bank (ECB), are statistically significant, we employ the Newey-West adjusted t-test. This approach accounts for the presence of autocorrelation and heteroskedasticity in the data by adjusting the standard errors, ensuring that statistical inference remains valid despite serial correlation.

[5] See the Section 4 and the GitHub created for the project. During the data cleaning we removed any bonds maturing in 2025 due to these often having low liquidity and low volumes traded.

Table 5: Comparison of Panel Regression Specifications

Variable	Specification (1)	Specification (2)
is_green	–	0.0032
	–	(0.0344)
days_to_maturity	0.0001***	0.0001***
	(3.88e-05)	(4.087e-05)
modified_duration	70.786***	70.606***
	(22.883)	(23.700)
log_emissions_volume	0.0365	0.0364
	(0.0255)	(0.0256)
Coupon	0.0296**	0.0296**
	(0.0123)	(0.0124)
Euribor_3m	0.3173***	0.3188***
	(0.0521)	(0.0506)
Bund_10yr	0.8685***	0.8682***
	(0.0345)	(0.0341)
VIX	-0.0004	-0.0004
	(0.0015)	(0.0015)

Variable	Specification (1) p-value	Specification (2) p-value
is_green	–	0.9249
days_to_maturity	0.0021	0.0034
modified_duration	0.0020	0.0029
log_emissions_volume	0.1530	0.1549
Coupon	0.0159	0.0173
Euribor_3m	0.0000	0.0000
Bund_10yr	0.0000	0.0000
VIX	0.8008	0.8107

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

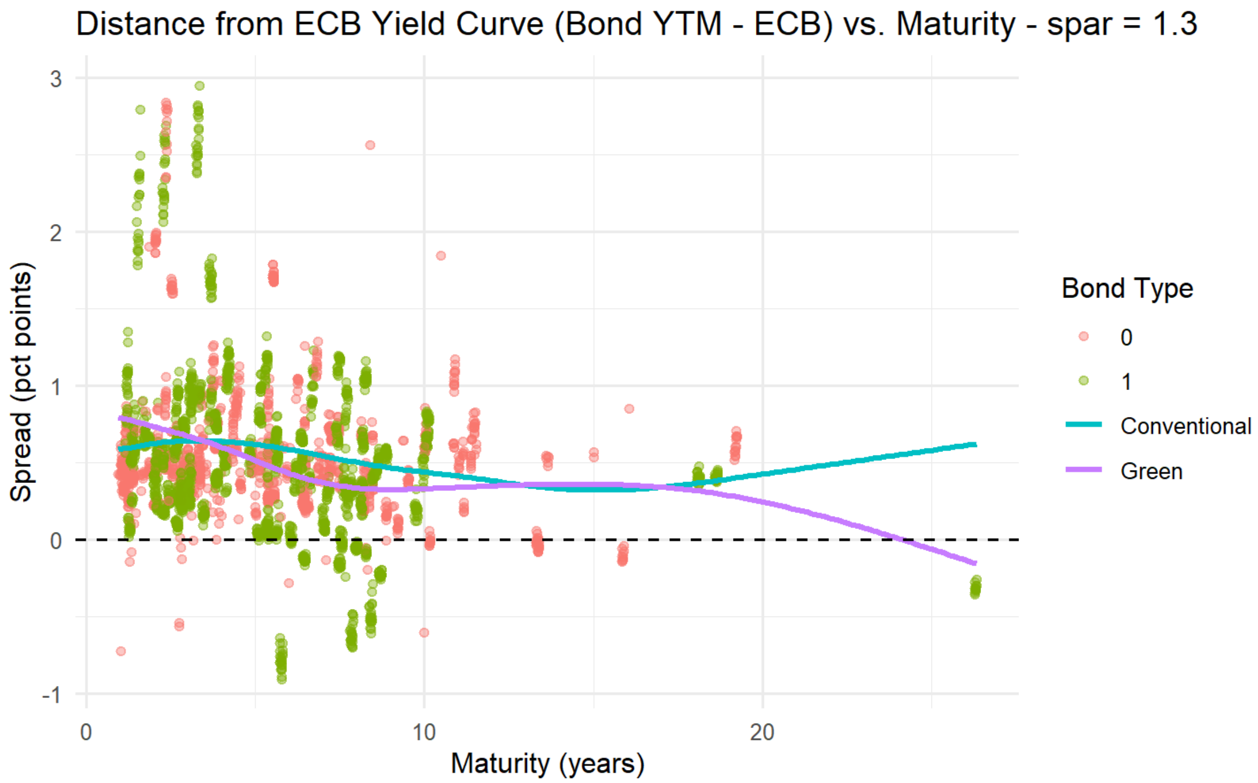

Figure 3: Bond Spread to ECB Yield Curve - Averaging across bond yields and correcting for the ECB yield does not yield clear results. The coloured points shows the spread of the YTM of individual bonds to the ECB implied Nelson-Siegel-Svensson curve for the corresponding years to maturity. We take the last price of a given day and the corresponding YTM

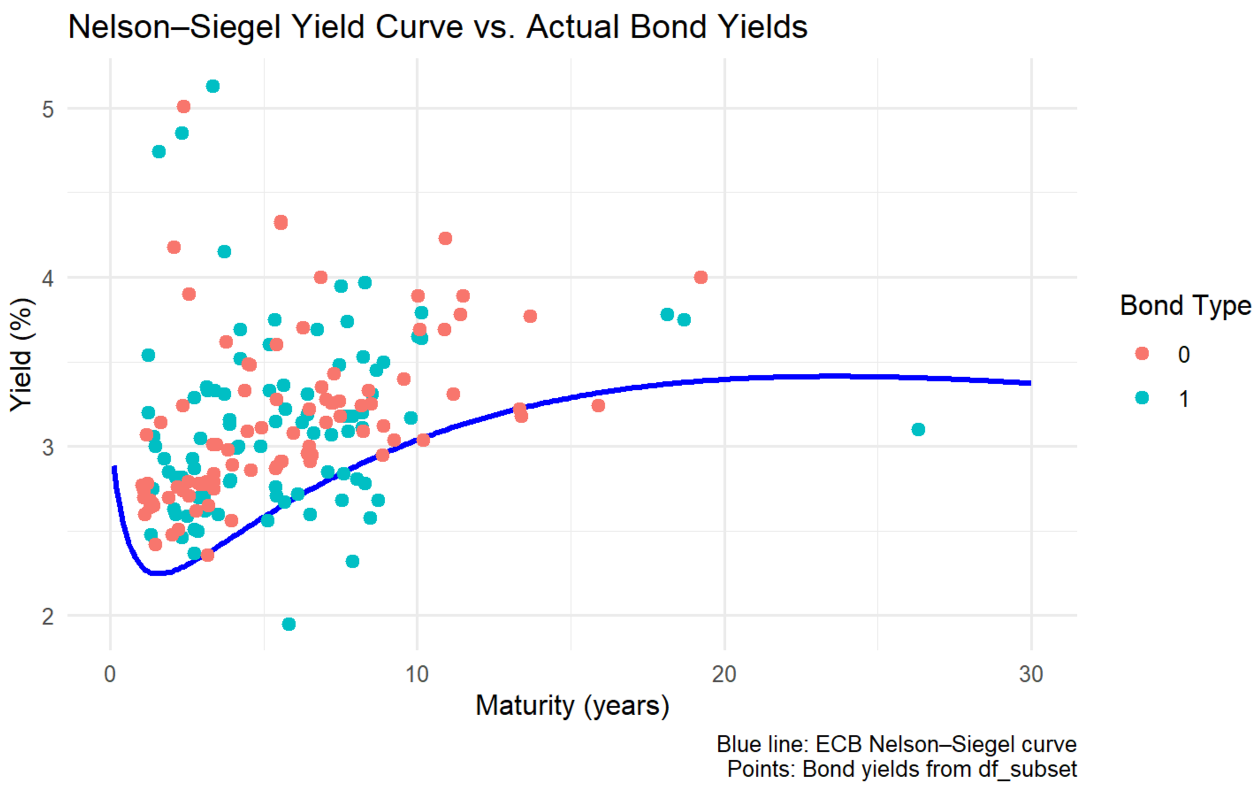

Figure 4: Plot comparing the Nelson-Siegel Yield Curve implied by the ECB to the bond yields observed in our data

The results, presented in Table 12, indicate that the intercept is statistically significant at the 0.001 level. Furthermore, the coefficient for *is_green* is negative and statistically significant at the 5% level ($p = 0.0321$), suggesting that, on average, green bonds exhibit a lower difference compared to their non-green counterparts. The use of Newey-West standard errors enhances the robustness of these findings relative to standard ordinary least squares (OLS) estimates. This method is particularly advantageous when analysing time-series or panel data, where residual correlation can otherwise lead to misleading statistical inferences.

5.4 Discussion of Methodological Trade-Offs

Our findings demonstrate that the manner in which green and conventional bonds are matched exerts a decisive influence on estimates of the greenium. In particular, a strict one-to-one matching procedure reveals a moderate negative yield differential, consistent with prior evidence from studies such as Pietsch and Salakhova (2022). By contrast, one-to-many matching, which expands the sample by reusing certain green bonds with multiple conventional bonds, yields an estimate of the greenium that is closer to zero. This divergence highlights the importance of tailoring the matching design carefully, thereby reducing the risk of over-weighting particular issuers or bond characteristics.

Our results imply that several refinements could address these methodological challenges. First, restricting repeated use of the same conventional bond to match multiple green bonds would prevent a single highly liquid conventional issue from unduly shaping aggregate results. Second, adopting alternative distance metrics, such as option-adjusted spreads, may better capture bond-specific features, including embedded options or varying credit profiles.

Finally, the discrepancy between matched-pair analysis and panel regression estimates underlines the complexity of identifying a greenium in real-world contexts. Even robust matching designs may fail to capture issuer-level heterogeneity that influences bond pricing. On the other hand, once issuer-specific factors and macroeconomic variables enter the panel regression, residual within-issuer variation may be insufficient to detect a systematic green discount. From a policy standpoint, these observations suggest that the greenium, if present, is likely modest in scale and highly sensitive to modelling choices. Careful research design, attentive to both matching practices and potential confounders, thus remains essential for accurately gauging whether—and to what extent—green bonds enjoy a yield benefit.

6 Robustness Checks

6.1 YTM Difference over Time

A key methodological concern involves ensuring that bond prices are observed sufficiently close in time so as not to conflate legitimate yield divergences with day- or hour-specific market movements. Ideally, bonds in a matched pair should be traded on the same day or within a short time window (for instance, two hours). Allowing for broader time spans can artificially amplify or diminish yield differentials, particularly in volatile markets. To account for this effect we ensured that our matching method emphasises a small intra-day time discrepancy. Nevertheless, we saw no significant changes with a lower intra-day time discrepancy penalty in the matching method.

We further investigate whether winsorizing our data significantly alters the magnitude of the estimated greenium. As shown in Figures 9 and related plots, removing extreme values does not substantially modify the observed trends. While minor fluctuations emerge in certain intervals, the overarching conclusion—that a negative greenium appears stable—remains intact.

In addition, the irregular distribution of observations across dates can influence both matching quality and average yield differentials. Figure 8 displays the number of matched pairs over time, illustrating pronounced spikes and troughs in sample size. During periods with sparse data, yield estimates exhibit wider variance, reinforcing the importance of consistent data collection. As coverage expands, average yield differentials tend to stabilise, further suggesting that a robust sample is crucial to obtaining reliable inferences.

6.1.1 OLS Estimates on Matched Subsamples

To reconcile the negligible greenium effect in our panel regressions with the negative yield differentials given by daily matches, we perform supplemental Ordinary Least Squares (OLS) estimations on the one-to-one matched dataset. These models incorporate additional covariates, notably `Matching_Distance`, `Coupon_diff`, and `days_to_maturity_diff`, to better understand which factors most strongly drive the yield gap between matched pairs of green and conventional bonds.

In these OLS regressions, `Matching_Distance` emerges as both statistically and economically significant: closer matches tend to exhibit more pronounced negative yield differentials, supporting the notion that a rigorous matching procedure can isolate a greenium. With standard errors clustered at the issuer level, the significance of several parameters diminishes. Overall, these findings emphasise the importance of carefully specifying both the matching algorithm.

6.2 Panel Regression Results

Our Panel Regressions do not consider alternative specifications, particularly with regard to omitted variables such as bond seniority or external reviews. At present, we lack detailed information in these areas; nonetheless, the introduction of issuer-level fixed effects partially addresses potential confounders, mitigating some forms of time-invariant heterogeneity. Crucially, we have opted to cluster standard errors by issuer to account for serial dependence in yield data. This approach yields more conservative (and thus likely more accurate) inference by widening standard error estimates.

It is worth noting that adjusting the sampling frequency could further temper autocorrelation problems: while daily data allows us to track yield movements at a relatively granular level, lower-frequency observations (e.g. weekly or monthly) might reduce noise and serial dependence, though at the cost of less immediate pricing information.

6.3 Nelson–Siegel–Svensson Curves

Finally, we revisit the Nelson–Siegel–Svensson fits to assess whether our results hold at various maturity ranges. As displayed in Figure 3, the spline-based smoothing suggests that data constraints—for instance, a scarcity of observations below two-year maturities and above ten-year maturities—can skew fitted curves. In some cases, just a handful of bonds drive the shape of the yield curve, exacerbating measurement errors or anomalies in YTM calculations (e.g. if coupon payments or day-count conventions diverge from assumptions).

As a result, the observed greenium at certain maturities must be interpreted with caution. A more extensive dataset spanning a broader range of maturities, along with more robust YTM calculations, would likely yield deeper insights. Overall, the Nelson–Siegel–Svensson approach still largely supports a tentative negative yield differential, but highlights the risk that inadequate coverage at the short and long ends of the yield curve may hamper definitive conclusions.

7 Extensions

Repeat analysis with more data about green bond certification as in Pietsch and Salakhova (2022). Particularly if a specific green bond certification is the most important one. This would allow one to analyse whether investors have grown more attentive and aware to external certifications in recent years. Comparing the different methodologies presented in this paper with additional certification data would add to the discussion surround the effectiveness of external green bond certifications. The addition of issuer level CO_2 data to the bond data could warrant further investigation. CO_2 emissions might act as a good proxy for the believability of green bonds and whether the emission of green bonds coincides with CO_2 reductions. Additionally, CO_2 data would allow for a stratified analysis to see if green bonds from "best in sector" issuers show a stronger greenium, if any, with Fatica and Panzica (2021) finding that only issuers with certified green bonds decreased emissions whilst Ehlers et al. (2020) find no decreasing carbon intensity.

8 Conclusion

In concluding this study of yield differentials between green and conventional bonds, our results emphasise the profound influence of methodological design on the estimation of any "greenium." First, our one-to-one matching procedure uncovers a moderate negative yield differential, averaging around 20 to 25 bps, suggesting that green bonds may trade at a slight premium or experience lower yields. By contrast, the one-to-many matching strategy yields a much smaller spread—on the order of 3 to 8 bps—underscoring how the repeated use of the same green bond can attenuate or even obscure differences in pricing.
Second, when we control for issuer-specific heterogeneity and broader macroeconomic conditions in panel regressions, the estimated greenium becomes both economically and statistically negligible. This discrepancy suggests that issuer-level distinctions—such as creditworthiness, sector classification, or balance-sheet characteristics—can overshadow a supposed green effect once they are robustly modelled. In other words, any unconditional yield advantage arising from a bond's green status may be too slight to detect in settings with strong fixed effects or highly variable issuer attributes.
Third, our Nelson–Siegel–Svensson estimations exhibit yield curve shapes that align with a negative greenium at certain maturities but do not confirm it uniformly across all segments of the curve. In this sense, the yield-curve analysis corroborates a smaller greenium, which appears contingent upon particular maturity ranges or market conditions. While such evidence reinforces the notion that green characteristics can matter, it likewise indicates that their influence varies across the term structure and may remain modest overall.
From a methodological perspective, these outcomes highlight the importance of refining matching algorithms and restricting time discrepancies in data. Additionally, caution is warranted in interpreting panel regressions that rely on relatively limited intra-issuer variation, especially when more granular data on external certifications, governance practices, or climate performance is unavailable.
Finally, to clarify whether yield disparities genuinely reflect a commitment to environmental objectives, future studies might examine external reviews, issuer-level carbon emissions, or compliance with recognised sustainability frameworks. Such extensions would help determine whether any yield premium or discount is more directly attributable to sustainability attributes or whether it instead derives from unobserved factors unrelated to climate commitments. In sum, our findings suggest that the greenium is negative—averaging roughly -20 basis points under a strict matching method, yet narrowing substantially under looser or more comprehensive matching. This underscores not only the importance of careful research design but also

the nuanced and context-specific nature of pricing ”green” in contemporary bond markets.

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A Appendix

A.1 matching

The selection of matching features includes coupon rate, days to maturity, emission year, and the transformed time variable. These features are standardised by subtracting the mean and dividing by the standard deviation, ensuring that differences in scale across variables do not unduly influence the matching process.
To refine the matching further, a differential weighting scheme is applied to certain features. The coupon rate is down-weighted by a factor of 0.5 to reduce its influence, given that coupon structures may differ systematically between green and conventional bonds. Additionally, the time variable is weighted according to an adjustable parameter, allowing for greater or lesser emphasis on temporal proximity between bond issuances.
Once the features are normalised and weighted, the Euclidean distance between each green bond and each conventional bond is calculated, forming a pairwise distance matrix. The Euclidean distance is computed as follows:

$$d(i,j) = \sqrt{\sum_k \left(\frac{x_{i,k} - x_{j,k}}{\sigma_k} \right)^2} \tag{1}$$

where $x_{i,k}$ and $x_{j,k}$ represent the standardised values of feature k for green bond i and conventional bond j, respectively, and σ_k denotes the standard deviation of feature k across the sample.
With the distance matrix constructed, the Hungarian algorithm is applied to determine the optimal one-to-one assignment of green and conventional bonds that minimises the aggregate matching cost. The Hungarian algorithm, a combinatorial optimisation method, guarantees a globally optimal pairing that minimises the sum of distances between matched pairs.
The output of the matching process consists of a structured dataset in which each green bond is paired with its most similar conventional counterpart based on the defined criteria. The matched dataset includes bond identifiers, financial attributes such as coupon rate, days to maturity, yield to maturity, last price, and modified duration, as well as the computed matching distance, which quantifies the degree of similarity between the paired observations.
This matching methodology offers several advantages. By restricting matching within the same company, issuer-specific factors that could confound the analysis are controlled for, thereby improving comparability. Additionally, the incorporation of a temporal dimension ensures that matched pairs correspond as closely as possible in issuance timing, mitigating distortions arising from market-wide interest rate fluctuations. The standardisation of features ensures that differences in scale across variables do not bias the matching, while the Hungarian algorithm guarantees an optimal assignment, reducing potential selection bias.
Despite these strengths, certain limitations warrant further consideration. Endogeneity concerns may arise if unobserved factors influence both bond characteristics and the probability of a bond being green. Alternative distance metrics, such as Mahalanobis distance, or propensity score matching techniques could be explored as robustness checks. Moreover, in cases where the number of green and conventional bonds issued by a company is imbalanced, some observations may remain unmatched, potentially leading to sample selection issues.
Overall, this methodology provides a rigorous framework for matching green and conventional bonds, facilitating a robust empirical analysis of yield differentials and liquidity effects. By leveraging an optimised assignment approach and incorporating key financial and temporal features, this matching procedure enhances the validity of comparisons and contributes to the broader empirical literature on the pricing dynamics of green bonds.

A.1.1 K-Prototypes Matching Procedure

In addition to the Hungarian-based matching method described above, a further approach was employed that adapts the k-prototypes algorithm of Huang et al. (1997) and Huang (1998) to a one-to-one matching context. Whereas the Hungarian method (Kuhn 1955) relies on Euclidean distance and is thus most naturally suited to numerical variables, the k-prototypes methodology allows for a dissimilarity measure that jointly considers both numerical and categorical bond attributes. Specifically, the total distance between a green bond g and a conventional bond c is given by:

$$d(g,c) \;=\; \sum_{i=1}^{n} \omega_i \left(g_i - c_i\right)^2 \;+\; \sum_{j=n+1}^{m} \omega_j \, \delta(g_j,\, c_j), \tag{2}$$

where g_i and c_i denote the numerical variables (such as nominal amount or duration), g_j and c_j are categorical variables (for instance, seniority or currency), and ω_i and ω_j represent the relative importance (weights) assigned to each variable. The function $\delta(g_j, c_j)$ is an indicator that equals 1 if the categorical variables differ and 0 if they match, thereby penalising any mismatch in qualitative attributes.

In its original form, the k-prototypes algorithm is designed for clustering observations containing both numeric and categorical features. In this study, however, the distance measure has been adapted for one-to-one bond matching. Instead of partitioning observations into k clusters, each green bond is compared against all available conventional bonds, and the conventional bond yielding the smallest k-prototypes distance is selected as its match. This approach preserves the flexibility to weight certain variables more heavily than others, which is especially beneficial when particular bond characteristics are deemed more crucial for comparability. For instance, if seniority is considered a decisive feature, a large weight can be assigned to the corresponding categorical mismatch term, effectively ruling out conventional bonds that differ in seniority from the green bond.

Ultimately, as we match categorical variables (currency, year of issuance, issuer, removed callable bonds) before running the k-prototypes algorithm, we effectively run a k-means algorithm as no categorical variables are left to match. This ensures that the matching process remains issuer-specific and maturity-year-specific, thereby controlling for issuer-level credit differences and aligning the temporal horizon of green and conventional bonds. By focusing on bonds from the same issuer and with identical maturity years, the method controls for variations in credit risk profiles and mitigates distortions arising from structural differences in term-to-maturity.

The final outcome of this matching procedure is a sample of green and conventional bond pairs that are highly comparable across multiple dimensions, both quantitative and qualitative. In the subsequent analysis, the results of this k-prototypes matching are contrasted with those obtained via the Hungarian algorithm. While the Hungarian approach is well-suited to purely numerical attributes and offers a globally optimal assignment in terms of Euclidean distance, the k-prototypes method provides a more nuanced perspective by explicitly accounting for categorical variables. This distinction is particularly relevant in settings where features such as seniority, currency, or debt type are expected to exert a significant influence on bond pricing. By comparing the outcomes of these two methodologies, it is possible to assess the robustness of the matching results and to determine whether the inclusion of categorical variables alters the conclusions regarding yield differentials or liquidity effects in the green bond market.

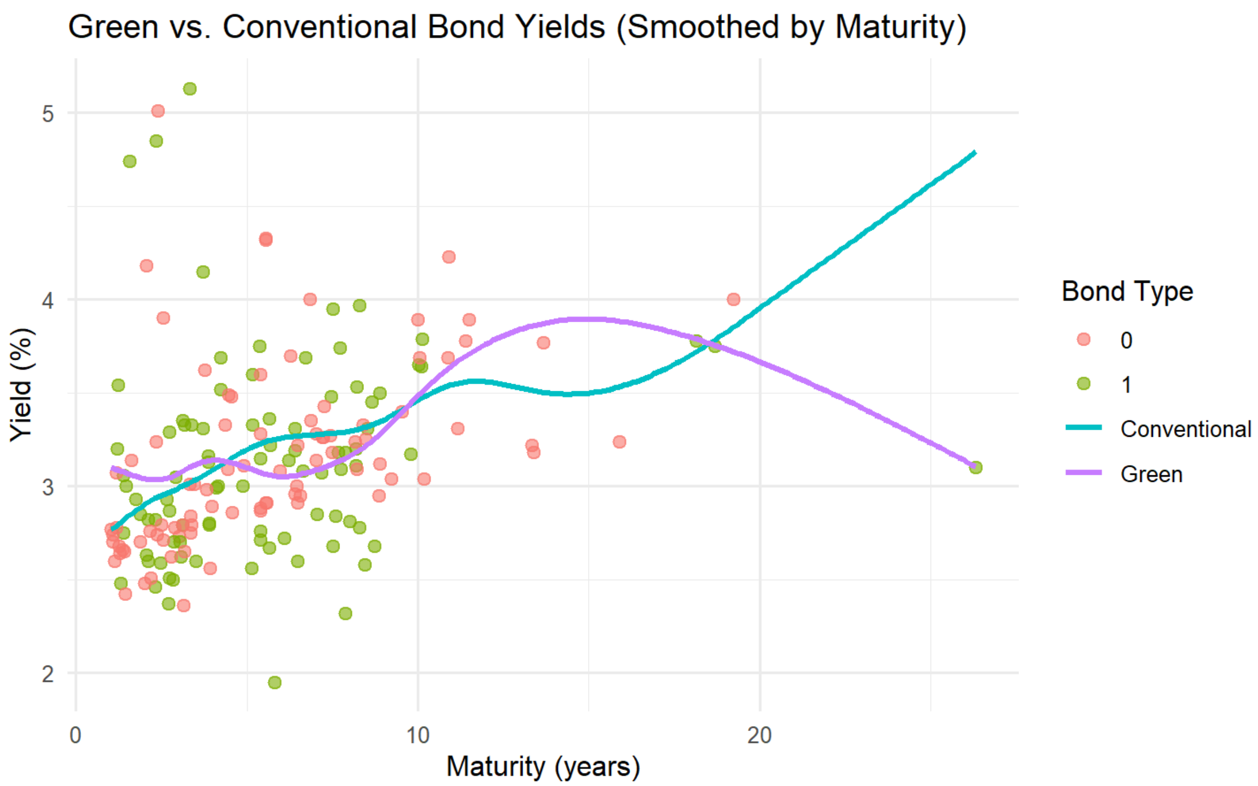

Figure 5: Comparing Green and Conventional Bond yields - Plotting average bond YTM as estimated by splines, spar = 1.3

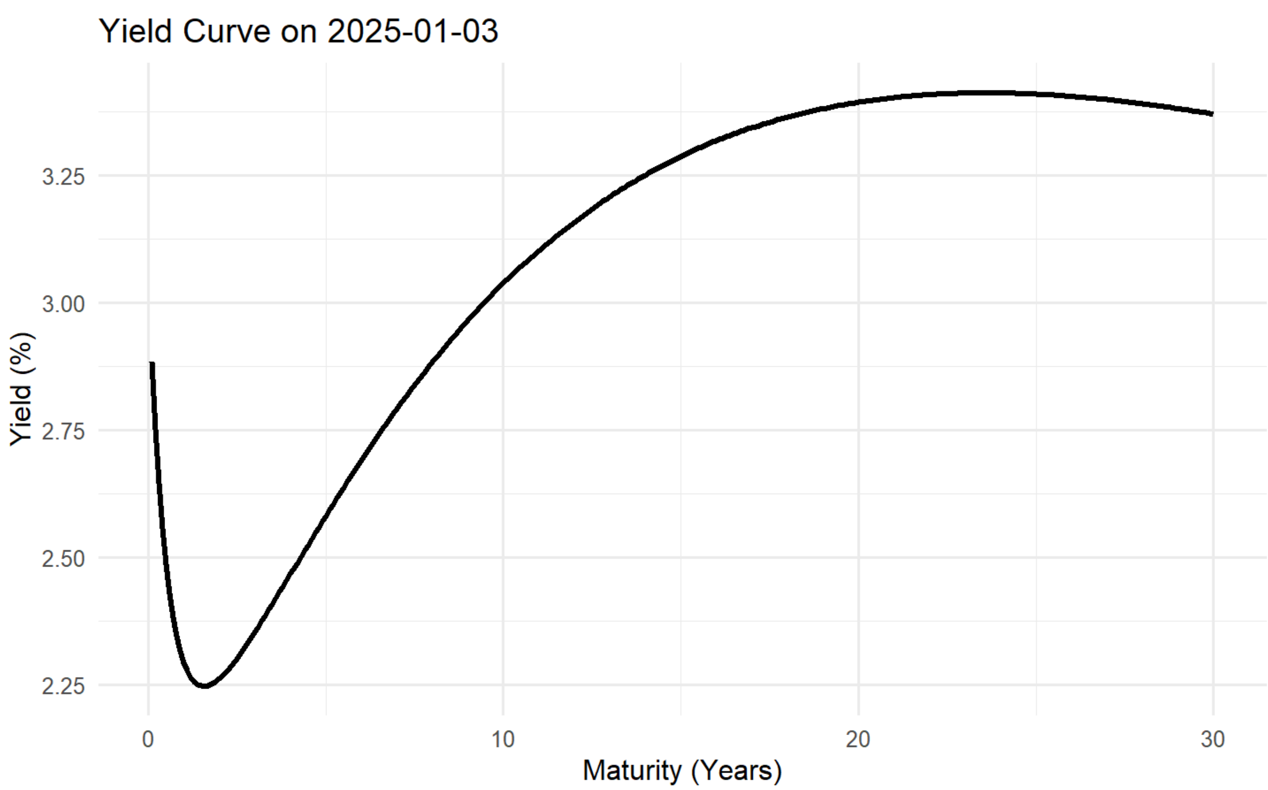

Figure 6: Eurozone Yield Curve - constructed through an weighted average of eurozone sovereign debt and using the Nelson-Siegel parameters implied by the Svensson method to plot the yield Curve for 03/01/2025

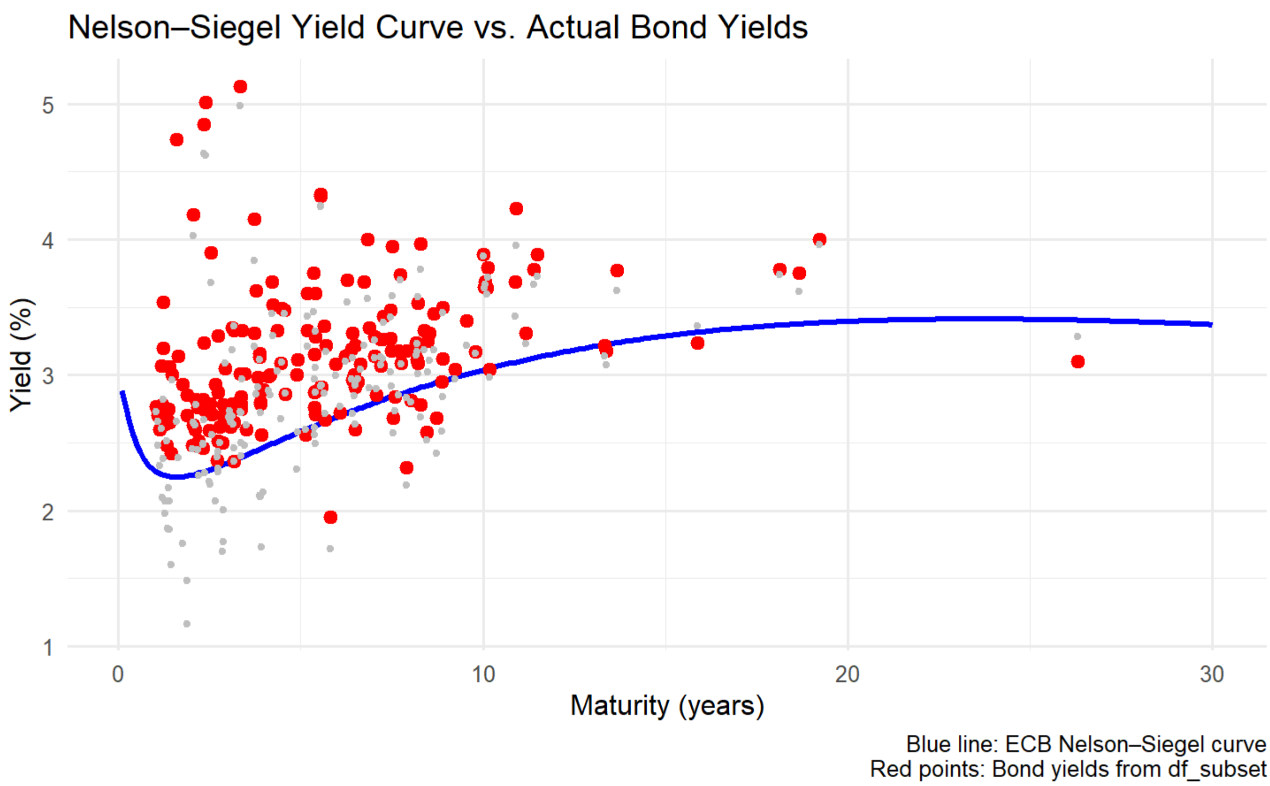

Figure 7: Same as Figure 4 just with a different YTM calculation - Our results to not change significantly compared to the original method

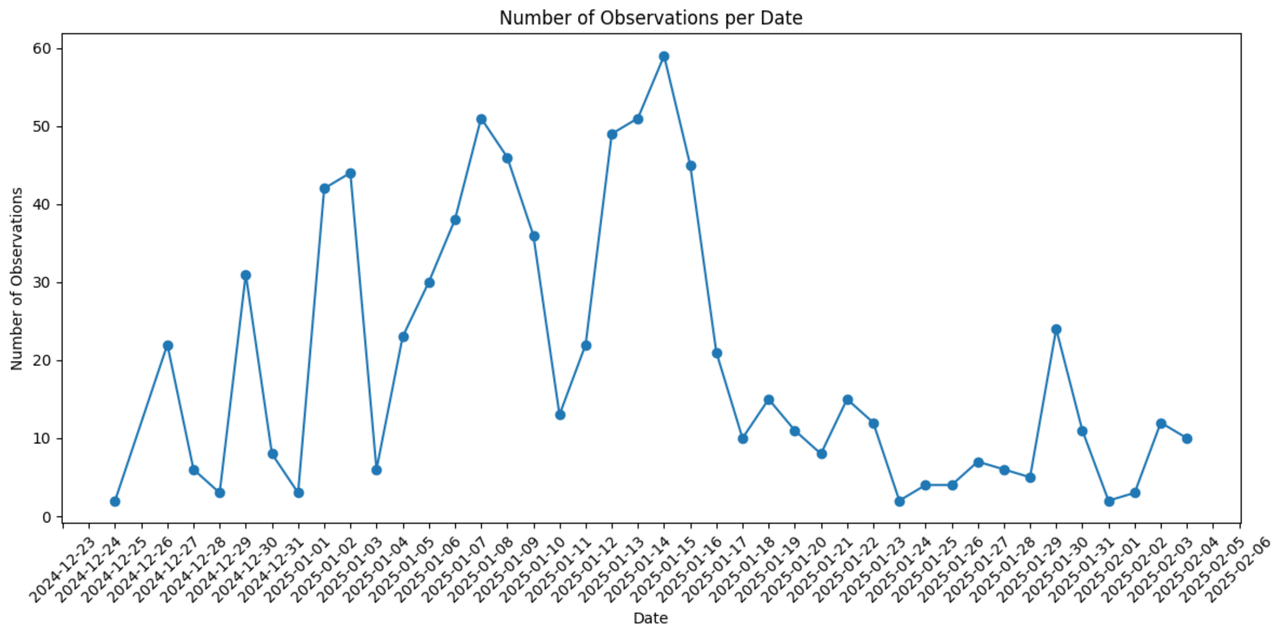

Figure 8: Number of matched bond pairs observed per date used in the YTM difference graphs (Figures 1, 2).

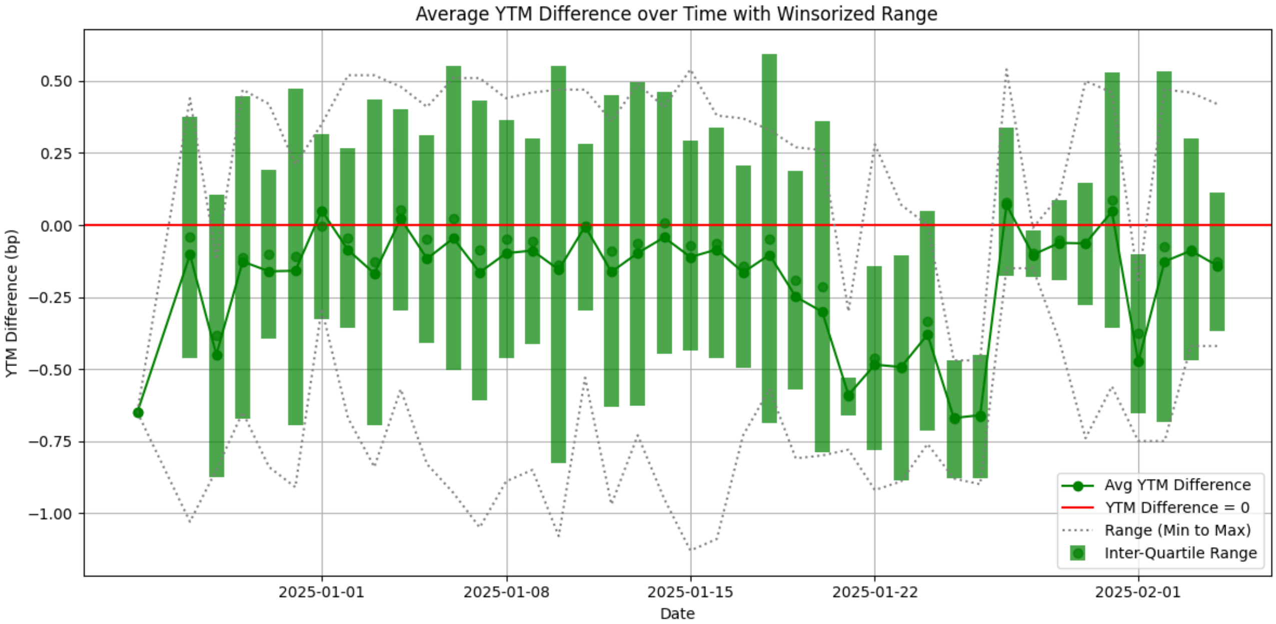

Figure 9: Average YTM Difference over time when removing the lowest and highest 5% of YTM differences from our matched dataset using the one-to-one matching method

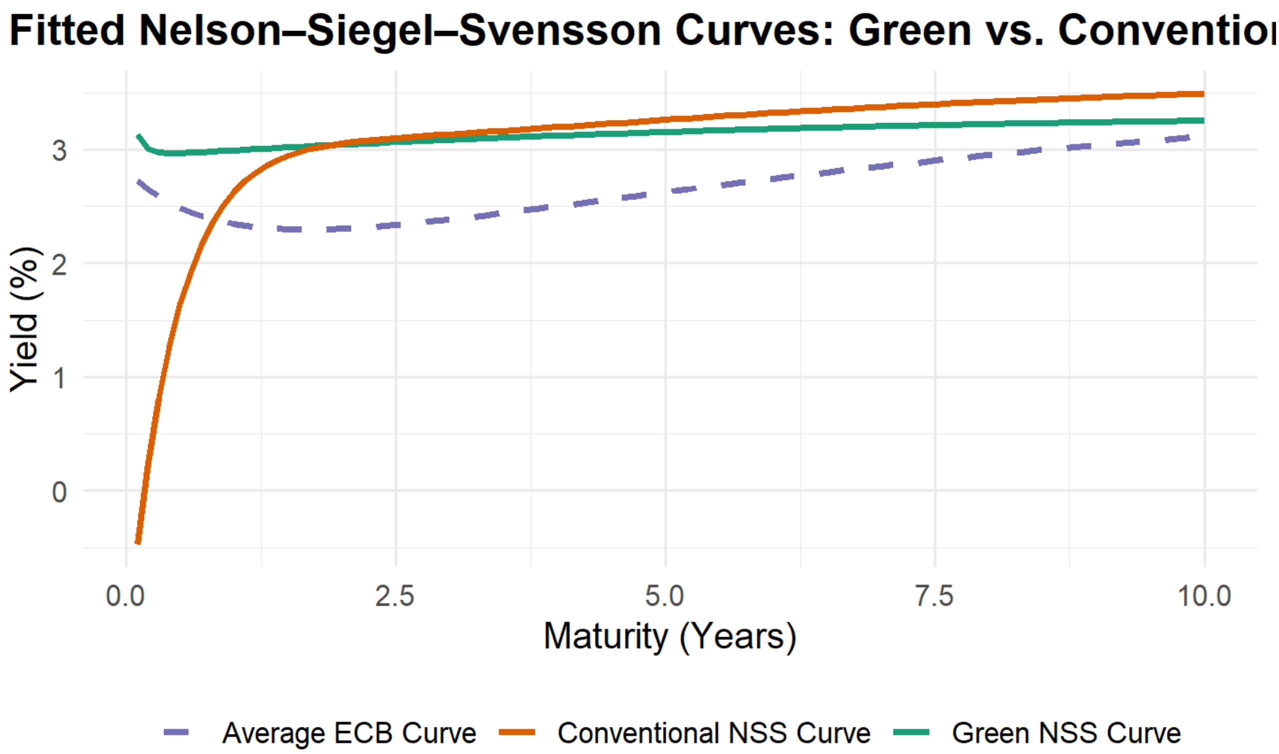

Figure 10: Comparison of Green and conventional bond YTM implied Nelson-Siegel Svensson curve to the ECB implied curve

A.2 Figures

A.3 DAG plot

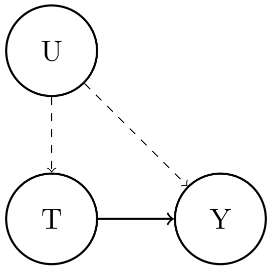

Figure 11: Directed Acyclic Graph (DAG) illustrating the effect of an unmeasured confounder on estimating the Average Treatment Effect (ATE) and Average Treatment on the Treated (ATT) that the treatment (T) has on outcome (Y). U represents the unmeasured confounder that can introduce bias.

A.4 Tables

A.4.1 Daily Descriptive Statistics of YTM Difference Graphs

A.4.2 OLS Regression Results for Matched Bonds

Tables 8, 9, 10 below present Ordinary Least Squares (OLS) estimates from three regressions relating the yield differential (`YTM_diff`) between matched green and conventional bonds to various explanatory variables. Since each bond pair may be observed at multiple points in time, serial correlation (autocorrelation) within an issuer over time can arise, leading to downward-biased standard errors when relying on conventional OLS. To address this, we cluster standard errors by the issuer's "Company" identifier, thereby allowing for arbitrary correlation of errors within the same issuer.

Comment on Autocorrelation. Because our dataset comprises pairs of matched bonds recorded on multiple dates and times, yields associated with the same issuer may exhibit serial dependence (autocorrelation). Standard OLS assumes that error terms are independent across observations. When this assumption is violated, conventional (non-robust) standard errors become unreliable. Clustering by issuer (i.e. the `Company` variable) accommodates within-group correlation, ensuring that the inference (e.g. hypothesis tests) remains valid despite potential autocorrelation within each issuer's time series of yield observations. The intercept term gives the average difference in yield to maturity between the pairs of green and conventional bonds

A.5 Nelson-Siegel Curve Results

A.6 Data

All data and the entire code base is available on our GitHub.
We include Macro variables, M_t: Vix data: 10 year Bund yield 3m euribor daily yields

Table 6: Daily Stats Results (One-to-One Matching)

pair_date	weighted_mean	mean	min	max	quant75	quant25
2024-12-25 00:00:00	-0.876141	-0.885000	-1.010000	-0.760000	-0.822500	-0.947500
2024-12-27 00:00:00	-0.350255	-0.413182	-1.590000	1.110000	0.130000	-1.005000
2024-12-28 00:00:00	-0.523487	-0.573333	-1.010000	-0.230000	-0.337500	-0.717500
2024-12-29 00:00:00	-0.216167	-0.236667	-0.680000	0.420000	-0.015000	-0.565000
2024-12-30 00:00:00	-0.298073	-0.325806	-1.590000	1.270000	0.140000	-0.880000
2024-12-31 00:00:00	-0.403480	-0.402500	-0.740000	0.130000	-0.187500	-0.655000
2025-01-01 00:00:00	-0.078453	-0.033333	-0.340000	0.450000	0.120000	-0.275000
2025-01-02 00:00:00	-0.422288	-0.411667	-1.600000	1.290000	-0.010000	-0.792500
2025-01-03 00:00:00	-0.299811	-0.308182	-1.590000	1.270000	0.135000	-0.685000
2025-01-04 00:00:00	-0.110554	-0.191667	-1.010000	0.350000	0.187500	-0.500000
2025-01-05 00:00:00	-0.107714	-0.166522	-0.620000	0.440000	0.150000	-0.495000
2025-01-06 00:00:00	-0.264337	-0.296667	-1.590000	1.080000	0.185000	-0.770000
2025-01-07 00:00:00	-0.239018	-0.258158	-1.590000	1.160000	0.190000	-0.605000
2025-01-08 00:00:00	-0.276152	-0.232745	-1.060000	0.720000	0.205000	-0.705000
2025-01-09 00:00:00	-0.128620	-0.169783	-1.590000	1.340000	0.257500	-0.527500
2025-01-10 00:00:00	-0.232463	-0.215556	-1.580000	1.420000	0.225000	-0.712500
2025-01-11 00:00:00	-0.243826	-0.270769	-0.810000	0.530000	-0.030000	-0.520000
2025-01-12 00:00:00	-0.043419	-0.126818	-0.770000	0.510000	0.190000	-0.467500
2025-01-13 00:00:00	-0.221357	-0.273469	-1.600000	1.480000	0.220000	-0.690000
2025-01-14 00:00:00	-0.162881	-0.207255	-1.010000	1.460000	0.240000	-0.670000
2025-01-15 00:00:00	-0.130532	-0.172034	-1.590000	1.230000	0.240000	-0.570000
2025-01-16 00:00:00	-0.299169	-0.318444	-1.590000	1.000000	0.140000	-0.670000
2025-01-17 00:00:00	-0.222223	-0.390476	-1.960000	0.960000	0.060000	-0.670000
2025-01-18 00:00:00	-0.456935	-0.428000	-1.080000	0.150000	0.012500	-0.850000
2025-01-19 00:00:00	-0.531749	-0.510667	-1.080000	0.130000	-0.250000	-0.775000
2025-01-20 00:00:00	-0.476715	-0.475455	-1.040000	0.080000	-0.285000	-0.725000
2025-01-21 00:00:00	-0.311573	-0.346250	-1.070000	-0.010000	-0.020000	-0.657500
2025-01-22 00:00:00	-0.566837	-0.540000	-1.120000	0.120000	-0.230000	-0.865000
2025-01-23 00:00:00	-0.713930	-0.700000	-1.180000	0.130000	-0.532500	-1.107500
2025-01-24 00:00:00	-0.843009	-0.785000	-1.250000	-0.320000	-0.552500	-1.017500
2025-01-25 00:00:00	-0.834770	-0.840000	-1.140000	-0.400000	-0.722500	-1.027500
2025-01-26 00:00:00	-0.825920	-0.830000	-1.120000	-0.390000	-0.712500	-1.022500
2025-01-27 00:00:00	-0.589431	-0.544286	-0.880000	0.080000	-0.435000	-0.825000
2025-01-28 00:00:00	-0.469607	-0.470000	-0.560000	-0.440000	-0.440000	-0.480000
2025-01-29 00:00:00	-0.333262	-0.312000	-0.990000	0.130000	-0.020000	-0.470000
2025-01-30 00:00:00	-0.267686	-0.261250	-1.030000	0.300000	-0.010000	-0.502500
2025-01-31 00:00:00	-0.512743	-0.529091	-1.090000	0.100000	-0.300000	-0.755000
2025-02-01 00:00:00	-0.622545	-0.580000	-0.700000	-0.460000	-0.520000	-0.640000
2025-02-02 00:00:00	-0.792596	-0.766667	-1.170000	-0.510000	-0.565000	-0.895000
2025-02-03 00:00:00	-0.503787	-0.518333	-1.330000	0.020000	-0.227500	-0.697500
2025-02-04 00:00:00	-0.496243	-0.531000	-1.320000	-0.050000	-0.210000	-0.667500

Table 7: Daily Stats Results (One-to-Many Matching Method)

pair_date	weighted_mean	mean	min	max	quant75	quant25
2024-12-25 00:00:00	-0.475721	-0.540909	-1.640000	0.340000	-0.175000	-0.785000
2024-12-26 00:00:00	-0.242104	-0.210000	-0.740000	0.290000	0.070000	-0.640000
2024-12-27 00:00:00	-0.082945	-0.123204	-2.220000	0.900000	0.267500	-0.330000
2024-12-28 00:00:00	-0.097344	-0.115400	-1.110000	0.950000	0.302500	-0.547500
2024-12-29 00:00:00	-0.120774	-0.124375	-1.270000	0.910000	0.410000	-0.605000
2024-12-30 00:00:00	-0.064538	-0.115442	-2.290000	1.030000	0.310000	-0.425000
2024-12-31 00:00:00	0.162279	0.138644	-0.990000	1.110000	0.497500	-0.080000
2025-01-01 00:00:00	0.200747	0.183901	-1.990000	0.970000	0.390000	0.020000
2025-01-02 00:00:00	-0.055281	-0.110986	-2.290000	2.050000	0.320000	-0.440000
2025-01-03 00:00:00	-0.018723	-0.066468	-2.280000	1.480000	0.370000	-0.390000
2025-01-04 00:00:00	0.039765	-0.019820	-1.980000	2.110000	0.400000	-0.290000
2025-01-05 00:00:00	0.005120	-0.066997	-2.020000	2.100000	0.330000	-0.450000
2025-01-06 00:00:00	-0.023379	-0.070970	-2.270000	2.110000	0.340000	-0.420000
2025-01-07 00:00:00	0.015171	-0.027541	-2.270000	2.110000	0.410000	-0.360000
2025-01-08 00:00:00	-0.058230	-0.113270	-2.300000	2.290000	0.330000	-0.490000
2025-01-09 00:00:00	-0.001306	-0.050306	-2.300000	2.360000	0.360000	-0.480000
2025-01-10 00:00:00	-0.105632	-0.155264	-2.320000	2.350000	0.250000	-0.510000
2025-01-11 00:00:00	0.038785	-0.026144	-1.970000	2.430000	0.430000	-0.430000
2025-01-12 00:00:00	0.156623	0.094498	-1.970000	2.430000	0.530000	-0.310000
2025-01-13 00:00:00	-0.007394	-0.049867	-2.370000	2.390000	0.350000	-0.420000
2025-01-14 00:00:00	-0.048515	-0.095687	-2.340000	2.310000	0.340000	-0.440000
2025-01-15 00:00:00	-0.019191	-0.047977	-2.360000	2.310000	0.320000	-0.380000
2025-01-16 00:00:00	-0.048124	-0.072839	-2.330000	2.260000	0.310000	-0.430000
2025-01-17 00:00:00	-0.057119	-0.078420	-2.290000	1.620000	0.310000	-0.390000
2025-01-18 00:00:00	0.006206	-0.019408	-2.290000	2.260000	0.392500	-0.400000
2025-01-19 00:00:00	0.002592	-0.025336	-2.290000	2.260000	0.400000	-0.400000
2025-01-20 00:00:00	0.073443	0.042817	-2.300000	2.250000	0.440000	-0.327500
2025-01-21 00:00:00	0.015223	-0.052348	-2.020000	2.190000	0.370000	-0.342500
2025-01-22 00:00:00	-0.037219	-0.065563	-2.300000	2.180000	0.290000	-0.405000
2025-01-23 00:00:00	-0.121514	-0.157383	-2.320000	1.440000	0.240000	-0.510000
2025-01-24 00:00:00	-0.203165	-0.250282	-2.330000	1.060000	0.100000	-0.550000
2025-01-25 00:00:00	-0.245809	-0.287626	-2.330000	1.100000	0.090000	-0.610000
2025-01-26 00:00:00	-0.316440	-0.374129	-2.330000	0.970000	0.045000	-0.720000
2025-01-27 00:00:00	0.199216	0.160937	-2.040000	1.180000	0.552500	-0.100000
2025-01-28 00:00:00	-0.048031	-0.124056	-2.040000	0.900000	0.140000	-0.445000
2025-01-29 00:00:00	0.077047	0.012486	-2.000000	1.030000	0.370000	-0.160000
2025-01-30 00:00:00	0.077350	0.020532	-1.680000	1.210000	0.410000	-0.320000
2025-01-31 00:00:00	0.086707	0.019385	-2.030000	1.300000	0.460000	-0.360000
2025-02-01 00:00:00	-0.067794	-0.150383	-2.040000	1.280000	0.330000	-0.570000
2025-02-02 00:00:00	0.010317	-0.046514	-2.110000	1.190000	0.480000	-0.490000
2025-02-03 00:00:00	-0.103480	-0.259022	-2.190000	1.110000	0.385000	-0.612500
2025-02-04 00:00:00	0.183498	0.088642	-2.430000	1.110000	0.580000	-0.270000

Table 8: OLS Regression without Clustering (Non-Robust Standard Errors)

Variable	Coefficient	Std. Err.	t-stat	p-value
const	-0.0846	0.035	-2.431	0.015
Matching_Distance	-0.1365	0.016	-8.626	0.000
Coupon_diff	0.0450	0.012	3.869	0.000
days_to_maturity_diff	-0.00003	0.00001	-2.591	0.010

Observations = 812; $R^2 = 0.095$; F-statistic = 28.19 (p ¡ 0.001).

OLS without robust or clustered standard errors may underestimate true SEs if observations within the same issuer are correlated.

Table 9: OLS Regression with Clustered Standard Errors by Issuer

Variable	Coefficient	Std. Err.	z-stat	p-value
const	-0.0846	0.165	-0.511	0.609
Matching_Distance	-0.1365	0.054	-2.543	0.011
Coupon_diff	0.0450	0.047	0.955	0.340
days_to_maturity_diff	-0.00003	0.00006	-0.571	0.568

Observations = 812; $R^2 = 0.095$; F-statistic = 4.03 (p = 0.017).

Standard errors are clustered at the issuer level, mitigating serial correlation.

Table 10: OLS Regression with Modified Duration and Clustered SEs

Variable	Coefficient	Std. Err.	z-stat	p-value
const	-0.0810	0.183	-0.443	0.658
Matching_Distance	-0.1391	0.067	-2.062	0.039
Mdur_diff	0.1230	0.074	1.662	0.097
Coupon_diff	0.0590	0.061	0.964	0.335
days_to_maturity_diff	-0.0002	0.00006	-2.628	0.009

Observations = 743; $R^2 = 0.127$; F-statistic = 8.90 (p ¡ 0.001).

Including modified duration captures an additional aspect of bond risk.

SEs are clustered by issuer. Autocorrelation is partially accounted for.

is_green	avg_diff
0	0.5602
1	0.5192

Table 11: Average difference by green bond classification compared to ECB based Nelson-Siegel-Svensson curve. This table is just the average over all maturity's of figure 3

Variable	Estimate	Std. Error	t-value	p-value
Intercept	0.5602	0.0156	35.98	¡ 2e-16 ***
is_green	-0.0411	0.0191	-2.14	0.0321 *

Table 12: Newey-West Adjusted t-test Results of whether or not the spreads are statistically significantly different

URL	Time	Bid	Ask	Spread Abs./Rel.
xs2893176862	13.01.25 10:11:21	101.01	102.05	1.04 / 1.03%
us900123cg37	13.01.25 10:13:27	82.45	82.86	0.41 / 0.50%
gb00bpcjd880	13.01.25 10:05:05	99.08	99.16	0.08 / 0.08%

Table 13: Sample of Bond Spread Data