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Abstract

Since 2007, the green bond market has grown to about 3% of the global bond universe. We provide the first evidence on green bond liquidity based on trading activity, using unique Euroclear data on daily trading volumes and frequency from 2020 to 2025. These measures are especially relevant in relatively small markets, where more common proxies may provide an incomplete picture of liquidity. Our dataset allows us to directly compare green bonds with conventional bonds. We find that green bonds do not suffer from a systematic liquidity disadvantage relative to conventional bonds. Instead, they exhibit higher aggregate trading volumes, driven by more frequent trading rather than larger transaction sizes. These differences persist during periods of market stress. Within the green bond universe, third-party certification is associated with higher trading volumes through more intensive trading, while bonds financing more common project types trade more frequently than those funding niche projects.

Keywords: Green bonds, Bond liquidity, Trading activity, Market stress, Certification

JEL Classification: G11 , G23 , Q56

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1 Introduction

Since the first green bond issuance in 2007, the green bond market has grown rapidly. According to Jena and Vuppuluri (2025), cumulative green bond issuances have surpassed USD 3 trillion and account for approximately 3% of global fixed-income markets in 2025. Green bonds are defined by the fact that the proceeds raised at issuance fund environmental and/or climate-related projects. Many policy makers view the market of green bonds as an important contribution to the transition towards a low-carbon economy (OECD 2017). The academic literature has mostly focused on why companies issue green bonds and whether the pricing of such instruments is favourable. The seminal paper by Flammer (2021) shows that companies issue green bonds as a credible signal for their envionmental commitment, while the funding advantage from green bonds is very small at best. While liquidity in corporate bond markets is well studied (see, for example, Bao et al. 2011; Bessembinder et al. 2018; Dick-Nielsen et al. 2012), green bond market liquidity has hardly been studied and is the focus of our study.

This paper studies the liquidity of green bond markets using a unique dataset allowing the analysis of actual traded volumes, trading activities and frequencies - liquidity dimensions that standard databases do not provide. The database is provided by the Euroclear central securities depository (CSD), the globally largest CSD and most important CSD for green bonds.[1] With the dataset, we can overcome a classical problem of liquidity analysis in fixed income markets: since they are over the counter markets (OTC), the absence of a central market place means that data are generally not available and most research uses quotations from individual dealers, which are not necessarily representative of the market as a whole. We can capture the market at a place where it is centralised, namely a the point of settlement. We study a matched sample of green and comparable conventional bonds drawn from the Bloomberg Global Aggregate Index.

Liquidity is a central feature of financial markets, as it facilitates portfolio rebalancing and supports market functioning, particularly during periods of stress (Foucault et al. 2013; Guéant 2019; Perraudin 2017). In the context of green bonds, liquid secondary markets are especially important to sustain investor participation and confidence in a relatively small and growing market. By affecting investors' willingness to hold and trade these securities, liquidity also shapes pricing conditions and, ultimately, the development of this market. Several features of the green bond market suggest that green bond liquidity may differ from that of comparable conventional bonds, both in

[1] In February 2026, green bonds under custory at Euroclear represent about EUR 976 billion, corresponding to roughly 35% of the global green bond market.

normal times and in periods of market stress. Green bonds are often held by investors with long investment horizons, may involve higher information costs, and are issued in a relatively small and fragmented market, all of which can reduce secondary-market liquidity. In addition, bond-specific characteristics, such as third-party certification and the types of projects financed, may further shape secondary-market liquidity.

We contribute to the literature on green bond markets in several ways. First, thanks to our unique data set, we are able to examine several dimensions of liquidity, including trading volume, trading activity, the number of trades, and average trade size. These dimensions have been identified as relevant in the literature and studied in the context of the US corporate bond market using the Trade Reporting and Compliance Engine database, but not yet for green bonds (see, for example, Friewald et al. 2012; Goldstein et al. 2007; O'Hara and Zhou 2021). Second, we examine how green bond liquidity behaves during periods of heightened market stress, when liquidity conditions matter most. Third, we investigate whether bond-level design features that are specific to green bonds, such as third-party certification and similarities in project profiles, affect liquidity. Taken together, our study offers the first detailed assessment of key activity-based dimensions of green bond liquidity that are not captured by bid–ask spreads, including the volume, frequency, and intensity of trading.

Our results provide a nuanced picture of green bond liquidity. Contrary to our main hypothesis, we find that green bonds exhibit higher trading activity than comparable conventional bonds. This difference is driven by the extensive margin: green bonds trade on a larger share of days, but individual trades tend to be smaller. We show that this higher trading frequency is closely related to a broader investor base. Turning to market stress, we find no evidence that green bonds experience a relative contraction in trading activity during periods of heightened volatility. Instead, their trading remains frequent but continues to occur in smaller transactions. Finally, we document substantial heterogeneity within the green bond universe: certified bonds and those financing more common project types are more actively traded. Overall, these findings suggest that green bond liquidity is characterized by more frequent but less concentrated trading, reflecting a broader and more dispersed investor base.

The remainder of the paper is organized as follows. Section 2 reviews the related literature, discusses the economic mechanisms underlying green bond liquidity, and develops the research hypotheses. Section 3 describes the data, the matching procedure, the construction of variables, and summary statistics. Section 4 presents the empirical methodology. Section 5 reports the main empirical results, and Section 6 concludes.

2 Literature review and research hypotheses

Liquidity can be defined as the ability to trade large amounts quickly, at low cost, and without moving prices (Pástor and Stambaugh 2003). Liquid markets facilitate investor portfolio rebalancing by enabling securities to be traded rapidly and with limited frictions. In contrast, when liquidity is low, investors may face delays, higher transaction costs, or price concessions when attempting to buy or sell securities, making portfolio adjustments more costly. This can amplify market stress and increase the costs to the real economy (Guéant 2019; Perraudin 2017). Since liquidity is a desirable characteristic of a security, it can affect asset prices at the time of issuance through investors' expectations about future tradability, thereby influencing issuers' cost of funding and their ability to raise capital (Bond et al. 2012).

Liquidity is a multifaceted concept: Sarr and Lybek (2002) identify five dimensions of liquidity, namely tightness, immediacy, depth, breadth, and resiliency. Tightness refers to transaction costs, such as the difference between buy and sell prices. Immediacy captures the speed at which trade orders can be executed. Depth refers to the presence of abundant orders across a range of price levels at which a security trades. Breadth, in turn, reflects the availability of numerous and large orders close to the prevailing price.[2] Finally, resiliency characterizes a market's ability to quickly absorb order imbalances through the rapid arrival of new orders. These five dimensions are to some extent overlapping, and it is not easy to map them cleanly into data. We turn to this in the next subsection.

2.1 Different measures of liquidity and their conceptual underpinning

Among the most commonly used liquidity proxies is the bid–ask spread. According to the market microstructure literature (Duffie et al. 2005; Stoll 2003), bid–ask spreads are set by liquidity providers, or dealers, who intermediate between buyers and sellers by temporarily holding securities on their balance sheets. These spreads compensate dealers for the expected costs of providing liquidity, including inventory-holding costs, order-processing costs, and adverse selection costs.

Inventory-holding costs arise because dealers are exposed to price fluctuations while holding securities before offsetting their positions (Ho and Stoll 1981). Because this exposure decreases with trading activity, bid–ask spreads are endogenously related to

[2] In this sense, breadth can be viewed as a more restrictive dimension of liquidity than depth, as it pertains only to orders located near the prevailing price. Note, however, that a security may exhibit high breadth but low depth if orders are concentrated close to the prevailing price.

trading intensity: securities that trade more actively tend to exhibit lower spreads, which in turn facilitate further trading (Demsetz 1968; Tinic and West 1974). In addition, spreads compensate for order-processing costs, such as trading, clearing, and operational expenses, and for adverse selection costs, arising when dealers trade with better-informed investors. Beyond these cost components, bid–ask spreads also reflect dealer behavior and market structure. In particular, spreads are influenced by the degree of competition among dealers, with spreads approaching the expected marginal cost of liquidity provision as competition increases (Bollen et al. 2004). Moreover, when dealers act more as brokers and primarily match buyers and sellers without taking positions on their own balance sheets, their inventory exposure is reduced, allowing them to quote tighter spreads, although liquidity may be smaller, as matching might take longer. Several studies argue that the relatively low bid–ask spreads observed in the post-2008 period are consistent with a shift in this direction (Bessembinder et al. 2018; Choi et al. 2022; Perraudin 2017).

Besides reflecting a range of dealer-specific costs and market structure factors, bid–ask spreads also face important empirical limitations, particularly in bond markets. Because these markets operate largely over the counter, trading occurs bilaterally and transaction prices are not immediately or fully observable to all participants, unlike in centralized markets such as stock exchanges (De Renzis et al. 2018; Harris and Piwowar 2006). As a result, bid and ask prices are often observed as dealer quotes rather than as prices from executed transactions. These quoted spreads may therefore not correspond to realized trading costs or may be posted even when no trade takes place (Guéant 2019; Jankowitsch et al. 2011; O'Hara et al. 2018), leading them to provide only an incomplete measure of liquidity. This limitation is particularly relevant when trading activity is low or infrequent, as quotes may remain unchanged over extended periods.

Taken together, bid–ask spreads capture important aspects of liquidity, but they may not fully reflect how actively securities are traded in bond markets. This limitation is likely to be particularly relevant for green bond markets, which are smaller on average and may have less secondary-market trading activity. In such environments, dealer quotes may be less closely tied to recent transactions and may instead reflect dealers' expectations about intermediation costs and risks rather than actual trading conditions (O'Hara et al. 2018).

Measures based on observed transactions therefore provide valuable complementary information, as they capture both the ease with which counterparties can be found (number of trades) and the volume of transactions. In this sense, they shed light on several dimensions of liquidity identified in the literature, including immediacy and, more indirectly, aspects related to depth and breadth (Guéant 2019; Sarr and Lybek 2002). High-frequency transaction data are particularly well suited, as they allow the analysis of trading activity at a granular level and over short time intervals. These considerations motivate our focus on daily trading volume, trading frequency, number of transactions and average trade size, which are directly observable in our Euroclear data and allow us to assess dimensions of liquidity that are especially relevant in bond markets and that have not been studied before.

2.2 Potential sources of liquidity differences between green and conventional bonds

In this paper, our objective is to understand whether green and conventional bonds exhibit systematic liquidity differences. A growing but still limited literature has examined this question, with mixed results. Using bid–ask spreads, Bachelet et al. (2019) document higher liquidity for green bonds issued by institutional issuers and for certified green corporate bonds, a finding confirmed by Molino et al. (2023), who also show that the relative liquidity of green bonds improves during periods of market turbulence. Other studies based on bid–ask spreads reach less conclusive results: Cotugno et al. (2025) find no overall difference, although they report higher liquidity for green bonds in Europe, while Belloni et al. (2020) and Mazzacurati (2021) report either no difference or a liquidity disadvantage for green bonds. Using trading-based measures at the quarterly level, such as bond turnover and the number of trades, Larcker and Watts (2020) find no systematic difference between green and conventional bonds in the US municipal bond market.

Taken together, these findings suggest that the relationship between the green label and liquidity is not straightforward. Understanding the underlying mechanisms is therefore key. In principle, several factors may explain liquidity differences associated with the green label.

First, demand for green bonds is often driven by investors seeking to comply with internal sustainability targets or mandates (Sangiorgi and Schophol 2021). Once these bonds are acquired, such investors may be less inclined to trade them frequently, as selling green assets could make it more difficult to maintain targeted sustainability exposures. This concern is reinforced by the relatively small size of the green bond market, which represents only about 3% of the global bond universe (Jena and Vuppuluri 2025) and limits the availability of close green substitutes. Consistent with this interpretation, primary-market demand for green bonds has been shown to be relatively strong (Harrison 2023), suggesting that investors seek to secure green exposure at issuance rather than through secondary-market trading.

Second, while all bonds involve uncertainty related to issuer performance, green bonds introduce an additional layer of uncertainty related to the credibility and future recognition of their environmental benefits. Investors must assess how proceeds are allocated, monitored, and reported, which can be particularly demanding when underlying projects are complex or innovative (Febi et al. 2018). Moreover, disclosure practices and external reviews may vary across issuers, further complicating assessment (Cochu et al. 2016). This complexity is amplified by the evolving nature of green taxonomies and reporting requirements, as activities considered green today may not necessarily remain so over time (Deschryver and de Mariz 2020). As a result, green bonds are associated with higher information costs and greater scope for adverse selection than conventional bonds, which may reduce some investors' willingness to trade these securities frequently in the secondary market (Goldstein et al. 2007). At the same time, these information frictions need not affect all green bonds uniformly. Bonds that provide clearer signals regarding the environmental use of proceeds or credibility may face lower information costs, resulting in higher trading activity relative to other green bonds.

Third, green bonds differ not only in reporting frameworks and external review practices but also in the types of projects they finance. Sangiorgi and Schophol (2021) show that investors tend to favour specific project categories, such as renewable energy, clean transport, and low-carbon buildings. This heterogeneity can fragment trading across narrower sub-segments of the green bond market rather than concentrating activity within a unified green bond universe. As a result, this segmentation may reduce trading activity for green bonds overall by limiting the pool of potential counterparties for any given bond. At the same time, green bonds financing more common project types may attract a broader set of investors and therefore trade more frequently than bonds linked to more niche or less widely demanded project categories (Chan et al. 2007; Mosk and de Vette 2025).

These mechanisms point to potential differences in secondary-market trading activity, including trading frequency, volumes, and the structure of trading across bonds. We examine these dimensions in the empirical analysis through four testable hypotheses.

2.3 Research hypotheses

First, based on the above mechanisms, our first hypothesis is that green bonds tend to have lower secondary-market trading activity than comparable conventional bonds.

H1. Green bonds are less traded than comparable conventional bonds.

Second, beyond average trading differences, a large body of work emphasizes that liquidity risk becomes particularly important during periods of market stress. Models of liquidity and asset pricing show that when volatility rises and funding conditions tighten, investors become more sensitive to trading frictions and liquidity premia increase sharply (Vayanos 2004; Acharya et al. 2010). Reflecting these concerns, regulatory frameworks such as the Basel III liquidity standards explicitly stress the importance of asset liquidity under adverse market conditions, highlighting that liquidity should remain reliable precisely during stress episodes (BIS 2013).

The mechanisms discussed for our first hypothesis may, therefore, have important implications when market conditions deteriorate. In normal times, liquidity is abundant and intermediation capacity is ample, allowing a wide range of securities to trade with limited frictions. During periods of market stress, however, dealer intermediation declines (Brunnermeier and Pedersen 2009; O'Hara and Zhou 2021) and some investor groups reduce trading activity simultaneously (Shleifer and Vishny 1997). When this occurs, trading becomes more difficult and less reliable, increasing the risk of liquidity dry-ups as investors reallocate toward safer and more liquid assets (Acharya et al. 2010; Beber et al. 2009).

These dynamics are likely to affect green bonds more strongly if the frictions associated with the green label already reduce trading in normal times. This implies that any liquidity differences between green and conventional bonds may become more pronounced when market stress increases. In particular, mandate-constrained demand in a relatively small market, higher information costs, and fragmented trading may limit the ability to reallocate green bond holdings smoothly when market conditions deteriorate. As a result, green bonds may be more exposed to liquidity dry-ups during periods of market stress.

H2. The trading disadvantage of green bonds relative to comparable conventional ones widens with market stress.

Third, when it comes to assessing the credibility of a green bond, issuers often rely on process-based frameworks designed to improve transparency and reduce information asymmetries. One of the most influential frameworks is the ICMA Green Bond Principles (GBP), a set of voluntary guidelines that outline market best practices. The GBP recommend disclosure on four elements: the use of proceeds, the project evaluation and selection process, the management of proceeds, and ongoing reporting. Disclosure regarding the use of proceeds appears particularly important to investors, with Sangiorgi and Schophol (2021) reporting that nearly 80% of investors would not purchase a green bond if the intended allocation of funds was not clear to them.

Process-based frameworks such as the GBP, however, do not evaluate whether the financed projects meet specific environmental criteria. This has increased the relevance of third-party certification schemes that verify that proceeds are directed towards activities with demonstrable environmental benefits. Although such certification imposes additional administrative and compliance costs on issuers, it reduces adverse selection risks and helps mitigate greenwashing concerns (Bachelet et al. 2019; Flammer 2021). Consistent with this mechanism, certified green bonds have been shown to send stronger credibility signals, as reflected in stronger stock-market reactions for issuing firms around bond issuance (Flammer 2021), higher bond prices (Baker et al. 2019; Kapraun et al. 2021; Larcker and Watts 2020), and smaller bid–ask spreads (Molino et al. 2023). We may therefore expect certified green bonds to be more actively traded in secondary markets.

H3. Certified green bonds are more traded than non-certified green bonds.

Fourth, the heterogeneity in project types may also have implications for liquidity differences within the green bond universe. As illustrated in Table 1, green bonds are used to finance a wide range of project categories. While some bonds finance projects within a single category, many fund projects spanning several categories, highlighting substantial heterogeneity in project profiles across green bonds. When multiple green bonds finance similar types of projects, they are more likely to attract overlapping investor groups, increasing the likelihood that buyers and sellers meet in secondary markets. By contrast, bonds linked to more unique project profiles may face a narrower set of potential counterparties. This suggests that green bonds whose project profiles are more similar to those of other green bonds may exhibit higher secondary-market trading activity.

Table 1: Distribution of project types among green bonds

	Number	%
Renewable Energy	1,327	81.21
Energy Efficiency	1,042	63.77
Clean Transportation	1,007	61.63
Green Buildings	887	54.28
Sustainable Water	544	33.29
Circular Economy	471	28.82
Pollution Control	392	23.99
Biodiversity	319	19.52
Climate Change Adaptation	317	19.40
Natural Resources Management	311	19.03
Non-Renewable Energy	24	1.47

The table reports the distribution of project types for the 1,635 green bonds included in the Bloomberg Global Aggregate Index as of June 30, 2025, for which project-type information is available. Non-renewable energy projects financed by green bonds consist of projects related to nuclear energy.

H4. Green bonds that fund more common project types are more traded than green bonds that fund more niche project types.

3 Data

3.1 Matching approach

To study whether green bonds trade differently from otherwise similar conventional bonds, we rely on a one-to-one matching between green and conventional bonds.[3] The matching approach is widely used in the green bond literature (see, for example, Larcker and Watts 2020; Zerbib 2019) and allows us to isolate the role of the green label by comparing each green bond with a nearly identical conventional counterpart.

Our sample starts from all corporate and government-related bonds included in Bloomberg's Global Aggregate Index as of June 30, 2025. This index is a flagship benchmark for global investment-grade debt across twenty-seven currency markets and includes bonds from both developed and emerging markets, subject to minimum par amount requirements (Bloomberg 2025). The total number of bonds amounts to 25,560, among which 1,642 are classified as green. Bloomberg's green classification framework is aligned with the Green Bond Principles and requires information on use

[3]Given constraints on data access that limit the number of bonds for which information can be retrieved, we rely on one-to-one matching to balance match quality and sample coverage. Using a higher matching ratio, that is, matching each green bond to multiple conventional bonds, would therefore mechanically reduce the number of green bonds that can be included in the analysis.

of proceeds, the project selection process, the management of proceeds, and reporting (Bloomberg 2024).

Before implementing the matching procedure, we apply several filters to the initial sample. First, following Baker et al. (2019) and Larcker and Watts (2020), we restrict the analysis to fixed-rate bullet bonds. Second, as in Boutabba and Rannou (2022), we exclude Rule 144A bonds, whose secondary market liquidity may be limited due to investor eligibility restrictions. Third, since our goal is to compare green bonds with strictly conventional bonds, we remove from the non-green universe all bonds classified as social, sustainability, or sustainability-linked bonds. Fourth, we exclude the bonds for which daily trading data from Euroclear LiquidityDrive data are not available.

Next, for each green bond, we follow the literature and identify all conventional bonds that share the same issuer, currency, rating, and callable bond features. We further require conventional bonds to have been issued by the same Central Security Depository (CSD). Since exact matching on issue date, maturity at issuance, and size would drastically reduce the number of observations, in the spirit of Kapraun et al. (2021) and Zerbib (2019), we require potential matches to have an issue date I no more than two years before or after the green bond's issue date, a maturity at issuance M that is not more than two years shorter or longer than that of the green bond, and an issue amount S between one-half and twice the green bond's issue amount.

When more than one conventional bond satisfies these criteria, we retain the conventional bond that minimizes the Euclidean distance[4] to the green bond, defined as:

$$\text{Distance} = \sqrt{(\Delta_I)^2 + (\Delta_M)^2 + (\Delta_S)^2}$$

where the Δ variables represent the normalized differences between green and conventional bonds, namely $\Delta_I = |I_g - I_c|/24$, $\Delta_M = |M_g - M_c|/24$, $\Delta_S = |\log(S_g/S_c)|/\log 2$, such that the maximum difference along each dimension equals one.

This procedure yields a final sample of 880 bonds, corresponding to 440 green–conventional pairs from 254 distinct issuers.[5]

3.2 Data, variables and sample composition

We next gather the variables used in our analysis. For each bond in our final sample, and for our period of interest running from July 1, 2020 to June 30, 2025, we retrieve

[4] We rely on a Euclidean distance rather than propensity score matching or a Mahalanobis distance because the limited variability and strong correlations across these characteristics lead to weak overlap and convergence issues for these alternative approaches. This choice is of limited importance for our results, as any remaining differences along these dimensions are explicitly controlled for in the regression analysis.

[5] Euroclear LiquidityDrive was decommissioned shortly after the data were downloaded, preventing any further expansion of the sample.

variables from several sources. First, bond characteristics, including ISIN, issue date, maturity date, bond size in euro, issuer name, currency, rating, and callable bond features, are obtained from Bloomberg. From the same source, we also collect green-related information such as the existence of third-party verification and the type of projects financed by green bonds.

Second, trading variables are sourced from Euroclear's LiquidityDrive, which provides aggregated transaction and holding data for securities settled within the Euroclear group. LiquidityDrive captures secondary-market activity and excludes other operations such as primary-market transactions, instructions related to other Euroclear services, bilateral repo instructions, client intra-family instructions, central bank instructions, and technical movements related to Euroclear internal accounts (Euroclear 2024). As a Central Securities Depository, Euroclear records trades that take place between participant accounts, including custodians, broker-dealers, investment managers, and market infrastructures (Schmiedel et al. 2006; Van Cayseele and Wuyts 2007). Accordingly, the observed trading activity reflects inter-participant market activity, while transactions occurring within a given participant account (for example, between investors using the same custodian) or outside Euroclear's settlement perimeter fall outside the scope of the database.

In this context, the number of trades corresponds to the number of transactions between participant accounts. Holdings volume corresponds to the free-float amount[6] of the bond held in participant accounts settled within the Euroclear group on a given date, that is, positions recorded in accounts maintained at Euroclear and its affiliated CSDs. The number of holders corresponds to the number of distinct participant accounts holding the bond.

Importantly, LiquidityDrive offers broad and consistent coverage across bond types and regions and uniquely allows identification of the number of distinct participant accounts holding a given bond, making it particularly well suited for analyzing relative trading activity in secondary bond markets. From this dataset, we obtain daily measures of trading volume in euros, number of trades, holdings volume in euros, and number of holders.[7]

Third, daily macrofinancial variables, including the one-year risk-free rate, the yield curve slope (proxied by the difference between the ten-year and the two-year risk-free

[6]Following Euroclear's definition, holdings free-float excludes positions held by central banks or by collateral takers within the Euroclear group, as these positions are not freely tradeable and therefore do not contribute to secondary-market liquidity.

[7]For confidentiality reasons, LiquidityDrive does not report the number of daily trades or holders when these numbers are below three. In such cases, we set the number of trades equal to zero when trading volume is zero and to 1.5 otherwise. The same procedure applies to the number of holders.

rates), and the CBOE Volatility Index VIX, are retrieved from the Federal Reserve Economic Data (FRED).

In addition to the variables directly obtained from these data sources, we construct a measure of project-profile similarity for green bonds. To compute this measure, we use the green bonds from the initial sample for which project-type information is available, which consists of 1,635 bonds. The distribution of project types among these bonds is reported in Table 1. For each green bond i in our final sample, we calculate a score based on the share of other green bonds in this set that finance at least one project type financed by bond i:

$$PPSimilarity_i = \frac{1}{N_{TOT} - 1} \sum_{j \neq i} \mathbf{1}\{\mathcal{P}_i \cap \mathcal{P}_j \neq \varnothing\},$$

where $\mathcal{P}_i$ denotes the set of project types financed by bond i and N_{TOT} is the total number of green bonds over which the comparison is performed, namely 1,635. An illustrative example of the construction of this score is provided in Appendix A.

We next describe the composition of the final sample along key categorical dimensions. Table 2 reports the distribution of bonds by issuer category, currency, rating, and callable status. Because green and conventional bonds were matched along these variables, the distributions are identical in the green and conventional subsamples. We observe that about 63% of the bonds were issued by corporates, with roughly half of these issued by financial institutions. Regarding government-related bonds, the vast majority were issued by local authorities or government agencies, around 5% were issued by supranational entities, and slightly less than 3% were issued by sovereign states. In terms of currency, the euro is the dominant currency, with close to 60% of the bonds. Just under 30% were issued in US dollars, and the remaining 10% were issued in other currencies. Turning to ratings, a bit less than one quarter of the bonds are rated AAA or AA, with the two categories equally represented. Bonds rated A and BAA account for 35% and 40% of the sample, respectively. Finally, with respect to callability, about 60% of the bonds are callable.

Overall, the composition of the matched final sample closely mirrors that of the initial green sample described in Appendix C. In particular, local government issuance and euro-denominated bonds remain strongly represented.

Table 3 provides the distribution of green bonds according to the existence of third-party certification and across project-profile similarity buckets. Regarding certification, the proportion of certified bonds amounts to 4%, while 88% of the bonds are

Table 2: Distribution of bonds in the final sample

	Number	%
Panel A. Issuer category		
Corporates - Financial institutions	290	32.95
Corporates - Non-financial institutions	264	30.00
Government - Local authorities & Agencies	256	29.09
Government - Supranationals	46	5.23
Government - Sovereign & Treasuries	24	2.73
Panel B. Currency		
EUR	516	58.64
USD	258	29.32
Other	106	12.05
Panel C. Rating		
AAA	114	12.95
AA	104	11.82
A	306	34.77
BAA	356	40.45
Panel D. Callable status		
Callable	524	59.55
Non-callable	356	40.45

The table shows the distribution of the final sample of 880 bonds by issuer category, currency, rating and callable status

not certified. For the remaining bonds, certification information is missing. Concerning project-profile similarity, consistent with the fact that many bonds finance several project types and that some project types are financed by a large share of green bonds, we find that the majority of bonds in the sample - namely, 64% - have a high project-profile similarity score. Bonds with moderate-high and moderate scores account for 26% and 9% of the sample, respectively, and only 1% of the bonds have a score below 50%.

3.3 Summary statistics

To characterize bond liquidity, we examine the daily trading volume and decompose it into three components. The first component, trading activity, is defined as a dummy variable that takes the value one if a bond trades on a given day and zero otherwise. The two remaining components are the number of trades conditional on trading and the average trade size. We also consider trading volume at the intensive margin, defined as the product of the number of trades and the average trade size. Daily trading volume and its components are linked through the following identity:

Table 3: Distribution of green bonds in the final sample

	Number	%
Panel A. Third-party certification		
Certified	18	4.09
Non-certified	387	87.95
Missing	*35*	*7.83*
Panel B. Project-profile similarity		
High ($\geq$ 90%)	283	64.32
Moderate-high (70-90%)	113	25.68
Moderate (50-70%)	40	9.09
Low (< 50%)	4	0.91

The table shows the distribution of the 440 green bonds of the final sample according to the existence of third-party certification and across project-profile similarity buckets.

$$\text{TradingVolume}_{i,t} = \text{TradingActivity}_{i,t} \times \text{Number of Trades}_{i,t} \mid \text{TradingActivity}_{i,t} = 1 \times \text{Average Trade Size}_{i,t}.$$

To mitigate the influence of issuance-related trading, we exclude observations from the first month following issuance for each bond.

Table 4 reports summary statistics for the trading and control variables for green and conventional bonds. On average, green bonds have lower total trading volume than conventional bonds, driven by both a lower number of trades and a smaller average trade size. The same pattern holds for trading volume at the intensive margin. By contrast, green bonds trade on a slightly larger share of days, as reflected in higher trading activity. In terms of bond characteristics, green and conventional bonds are similar with respect to age, size, holdings volume, and number of holders. Most trading and holdings variables are strongly right-skewed, with medians well below means and a small number of very large observations, which leads us to use logarithmic transformations in the regression analysis.

3.4 Time variation in trading activity

Figures 1 to 4 show the time evolution of daily trading volume and its components for green and conventional bonds over the sample period, using 20-day moving averages. Green bonds have lower total trading volumes than conventional bonds throughout most of the sample period, with the difference particularly visible during periods of elevated market activity, such as in 2022 and 2023 (Figure 1).

Table 4: Summary statistics for green and conventional bonds

	Mean	sd	min	p25	p50	p75	Max	Obs
Trading volume (M€)								
Green	6.29	52.12	0.00	0.00	0.00	1.30	4,455.68	333,206
Conventional	10.60	102.82	0.00	0.00	0.00	1.20	9,284.82	334,239
Trading activity								
Green	0.49	0.50	0	0	0	1	1	333,206
Conventional	0.48	0.50	0	0	0	1	1	334,239
Trading number								
Green	5.36	6.58	1.5	1.5	3	6	240	164,770
Conventional	5.60	8.19	1.5	1.5	3	6	251	159,074
Trade size (M€)								
Green	1.50	5.43	0.00	0.16	0.38	0.89	236.27	164,770
Conventional	2.20	10.40	0.00	0.15	0.40	1.04	612.10	159,074
Trading volume (IM, M€)								
Green	12.73	73.56	0.00	0.40	1.30	4.60	4,455.68	164,770
Conventional	22.27	148.17	0.00	0.40	1.40	5.20	9,284.82	159,074
Age (years)								
Green	2.34	1.68	0.09	0.99	2.01	3.36	9.03	333,206
Conventional	2.46	1.78	0.09	1.01	2.08	3.59	9.44	334,239
Size (B€)								
Green	1.13	3.33	0.12	0.50	0.64	1.00	46.44	333,206
Conventional	1.23	3.80	0.12	0.50	0.64	1.00	48.55	334,239
Holdings volume (M€)								
Green	250.92	422.55	0.00	19.32	171.88	314.80	8,286.83	333,206
Conventional	245.17	371.50	0.00	14.42	170.40	327.74	5,562.79	334,239
Holders number								
Green	37.20	28.34	0	8	36	58	153	333,206
Conventional	34.03	26.80	0	7	33	54	162	334,239

The table reports summary statistics for trading and control variables for green and conventional bonds. Trading variables include total trading volume, trading activity, the number of trades conditional on trading, average trade size, and trading volume at the intensive margin (IM). Control variables include bond age, issue size, holdings volume, and the number of holders.

This difference is driven by the intensive margin. Green bonds tend to have fewer trades and smaller average trade sizes over time (Figures 3 and 4). At the same time, green bonds trade on a larger share of days across most of the sample period (Figure 2), consistent with stronger trading along the extensive margin.

These observations are consistent with the summary statistics reported in Table 4 and indicate that the differences in trading between green and conventional bonds are persistent over time rather than driven by short-term fluctuations

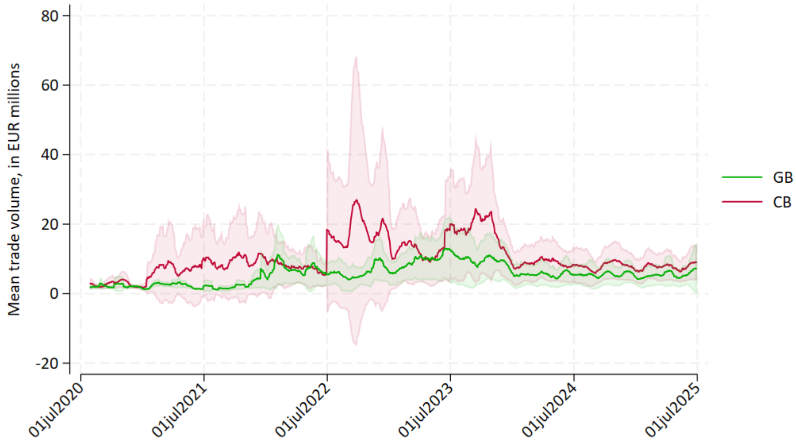

Fig. 1: Trading volume for green and conventional bonds, 20-days moving average.

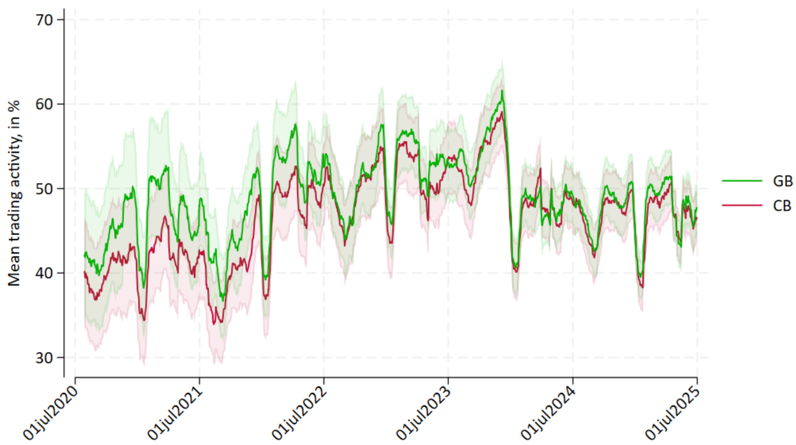

Fig. 2: Trading activity for green and conventional bonds, 20-days moving average.

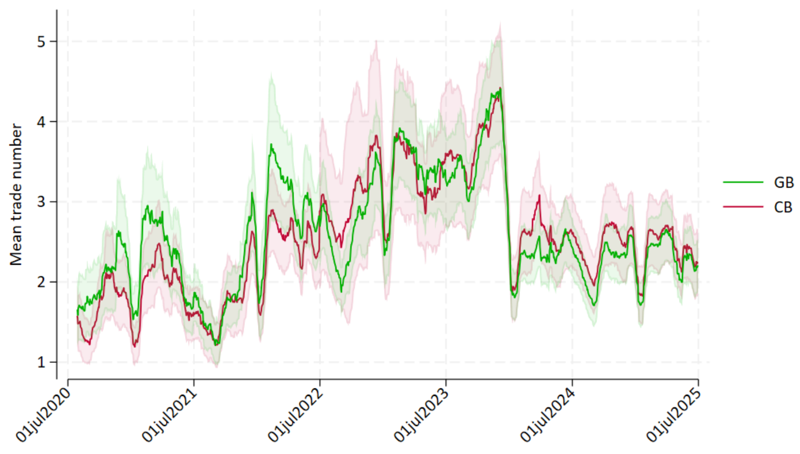

Fig. 3: Trading number for green and conventional bonds, 20-days moving average.

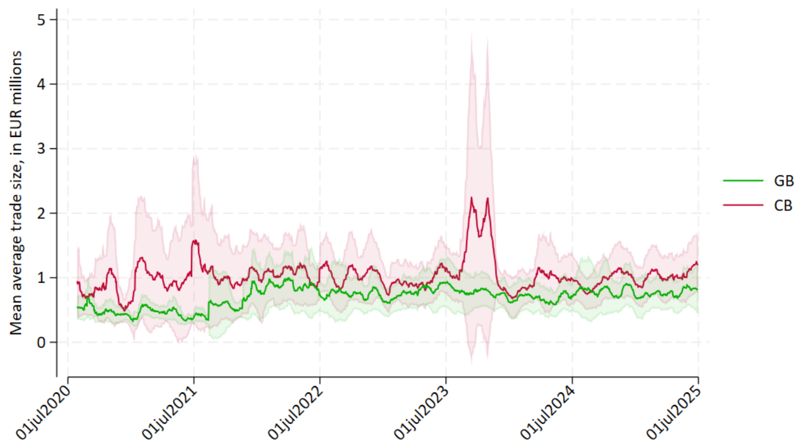

Fig. 4: Average trading size for green and conventional bonds, 20-days moving average.

4 Methodology

Building on the matched-pair construction and on the descriptive evidence presented in Section 3, we estimate panel regressions with pair and date fixed effects to assess whether the green character of a bond affects its secondary-market trading. Our baseline specification is:

$$Trading_{it} = \beta_0 + \beta_1\, GB_i + \theta' Z_{it} + \lambda_t + \gamma_p + \varepsilon_{it}.$$

where i indexes bonds, t indexes days, and p indexes matched pairs.

The dependent variable $Trading_{it}$ corresponds to one of five trading measures: total trading volume, trading activity, the number of trades conditional on trading, average trade size, and trading volume conditional on trading. All volume-based measures are expressed in logarithms.[8] The variable of interest, GB_i, is a dummy equal to one if the bond is green.

The vector Z_{it} includes a set of bond-level control variables. Consistent with Bachelet et al. (2019), we control for bond characteristics that are not exactly matched within pairs, namely bond age and issue size, both in logarithms. Controlling for these variables is particularly important because they are well-established determinants of liquidity. Younger bonds and bonds with larger issue sizes have been shown to be more liquid, reflecting stronger investor attention and greater market depth (Houweling et al. 2005; Sarig and Warga 1989). We also include the holdings volume in Euroclear accounts, expressed in logarithms, to control for differences in bonds' presence within the Euroclear settlement system. Pair fixed effects γ_p absorb all time-invariant differences at the matched-pair level, while date fixed effects λ_t control for common market conditions. Standard errors are clustered at the matched-pair level.[9]

Mechanically, the inclusion of matched-pair fixed effects implies that this specification is equivalent to estimating the relationship between within-pair differences in trading outcomes and within-pair differences in the corresponding covariates, after controlling for common time effects.[10]

To examine whether liquidity differences vary with market stress, we modify the baseline specification by replacing date fixed effects with a set of time-varying macroeconomic controls W_t. These include the one-year risk-free rate and the yield curve

[8] All variables that enter the regressions in logarithmic form are transformed using $\log(1 + x)$, to ensure that observations with zero values are retained in the sample.

[9] This regression and the following ones are estimated in Stata using the `reghdfe` command (Correia and Constantine 2014), which allows for the inclusion of multiple high-dimensional fixed effects and implements cluster-robust standard errors.

[10] As a consistency check, we also estimate the model by expressing all variables in within-pair differences. The results are identical and are available upon request.

slope, proxied by the difference between the ten-year and two-year risk-free rates. We additionally include the S&P 500 volatility index (VIX), a widely used measure of market-wide uncertainty and investor risk aversion derived from option-implied volatility. Unlike the other macroeconomic controls, the VIX is introduced separately because it is the variable of interest capturing market stress. It enters the regression both directly and interacted with the green bond dummy to assess whether differences in trading between green and conventional bonds vary with market stress. The corresponding specification is:

$$Trading_{it} = \beta_0 + \beta_1 \, GB_i + \beta_3 \, VIX_t + \beta_4 GB_i \times VIX_t + \zeta' W_t + \theta' Z_{it} + \gamma_p + \varepsilon_{it}.$$

Next, we focus on green bonds only and examine whether green-specific characteristics are associated with differences in liquidity. In particular, we consider the role of third-party certification and project-profile similarity. Unlike the baseline specifications, this analysis exploits cross-sectional variation across green bonds and therefore restricts the sample accordingly. The estimated specification is:

$$Trading_{it} = \beta_0 + \beta_1 \, V_i + \theta' Z_{it} + \delta' X_i + \lambda_t + \varepsilon_{it}.$$

The variable of interest, V_i, alternatively captures a dummy equal to one if the green bond is certified or the project-profile similarity score described in Section 3. Since green bonds are not matched with each other in this specification, we additionally include a set of time-invariant control variables X_i, capturing differences in issuer category, bond currency, bond rating, and callable status. Standard errors are clustered at the issuer level.

5 Results

This section presents the empirical results. We first test the liquidity differences in terms of trading between green and conventional bonds (H1), then assess how these differences vary with market stress (H2). We next examine heterogeneity within green bonds by studying the role of third-party certification (H3) and project-profile similarity (H4).

5.1 Baseline results (H1): green vs conventional

Our first hypothesis, H1, predicts that green bonds are less liquid and, more specifically, less traded than their conventional counterparts. Table 5 reports the results from the baseline specification. Focusing on the first column, we find the opposite result. Green bonds have higher secondary-market trading volume than comparable conventional bonds. The coefficient on GB_i is positive and statistically significant, indicating that, all else equal, green bonds trade in larger total amounts. In economic terms, the estimate implies that daily trading volume is approximately 34 percent[11] higher for green bonds relative to their matched conventional counterparts.

Table 5: Differences in trading between green and comparable conventional bonds

VARIABLES	Trading volume	Trading activity	Trading number	Trade size	Trading volume (IM)
GB_i	0.294***	0.024***	0.006	-0.079***	-0.069**
	(0.076)	(0.005)	(0.013)	(0.026)	(0.030)
$Age_{i,t}$	-2.090***	-0.112***	-0.366***	-0.531***	-0.977***
	(0.177)	(0.012)	(0.027)	(0.062)	(0.070)
$Size_i$	2.497***	0.156***	0.213***	0.364***	0.630***
	(0.308)	(0.021)	(0.047)	(0.104)	(0.131)
$Hold_{i,t}$	0.055*	0.003*	0.081***	0.211***	0.309***
	(0.028)	(0.002)	(0.019)	(0.048)	(0.060)
Pair FE	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES
Observations	667,445	667,445	323,841	323,841	323,841
R-squared	0.490	0.453	0.411	0.318	0.381

The table reports the results of the baseline specification. The dependent variable is, in turn, the logarithm of trading volume, a dummy variable equal to one if a bond is traded on a given day, the logarithm of the number of trades conditional on trading activity, the logarithm of the average trade size, and the logarithm of trading volume conditional on trading activity. GB_i is a dummy variable equal to one if the bond is green. $Age_{i,t}$ denotes the logarithm of the age of the bond (in years), $Size_i$ corresponds to the logarithm of the bond size, and $Hold_{i,t}$ represents the logarithm of the bond holdings at Euroclear. Standard errors clustered at the pair level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Decomposing total trading volume into its components shows that green bonds trade on a larger number of days, as reflected in the positive and significant coefficient on trading activity, our variable taking the value of 1 when there is trading. By contrast, conditional on trading, green bonds display a similar number of transactions but significantly smaller average trade sizes as can be seen in regression result columns 3 and 4. Consistent with this, trading volume at the intensive margin is lower for green bonds (last column). The higher total trading volume of green bonds is therefore driven by a the extensive margin that more than compensates for the lower trading

[11] $e^{0.294} - 1 \approx 34\%$.

intensity of green bonds. Green bonds therefore cannot be characterized as inactive securities. Rather, they trade more frequently, but in smaller amounts.

As shown in Tables B1 and B2 in the Appendix, these results are broadly robust when splitting the sample between corporate and government-related bonds and between EUR- and USD-denominated bonds. Across subsamples, the estimated effects remain directionally consistent, although their magnitudes and statistical significance vary. In particular, the difference in average trade size and trading volume at the intensive margin is no longer statistically significant for corporate bonds and USD-denominated bonds.

As a complementary analysis, we next examine whether differences in the investor base help explain the previous findings. To do so, we augment the baseline specification by controlling for the logarithm of the number of holders. The results are reported in Table 6. Once the number of holders is included, the coefficient on GB_i becomes statistically insignificant for trading volume, trading activity, and average trade size. At the same time, the number of holders has a strong and positive effect on both trading activity and total trading volume.

Table 6: Differences in trading between green and comparable conventional bonds controlling for the number of holders

VARIABLES	Trading volume	Trading activity	Trading number	Trade size	Trading volume (IM)
GB_i	0.027	0.005	-0.034***	-0.019	-0.058*
	(0.071)	(0.005)	(0.013)	(0.028)	(0.033)
$Age_{i,t}$	-2.177***	-0.118***	-0.366***	-0.531***	-0.977***
	(0.163)	(0.011)	(0.026)	(0.062)	(0.070)
$Size_i$	1.703***	0.098***	0.129***	0.491***	0.652***
	(0.282)	(0.019)	(0.044)	(0.111)	(0.139)
$Hold_{i,t}$	-0.153***	-0.012***	0.007	0.323***	0.329***
	(0.023)	(0.001)	(0.014)	(0.057)	(0.064)
$Holders_{i,t}$	2.232***	0.162***	0.378***	-0.573***	-0.101
	(0.152)	(0.011)	(0.041)	(0.115)	(0.124)
Pair FE	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES
Observations	667,445	667,445	323,841	323,841	323,841
R-squared	0.495	0.458	0.417	0.321	0.381

The table reports the results of the baseline specification controlling for the number of holders. The dependent variable is, in turn, the logarithm of trading volume, a dummy variable equal to one if a bond is traded on a given day, the logarithm of the number of trades conditional on trading activity, the logarithm of the average trade size, and the logarithm of trading volume conditional on trading activity. GB_i is a dummy variable equal to one if the bond is green. $Age_{i,t}$ denotes the logarithm of the age of the bond (in years), $Size_i$ corresponds to the logarithm of the bond size, and $Hold_{i,t}$ represents the logarithm of the bond holdings at Euroclear. $Holders_{i,t}$ corresponds to the logarithm of the number of holders. Standard errors clustered at the pair level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

These findings suggest that the higher trading frequency of green bonds documented in Table 5 is closely related to their broader investor base. Differences in investor dispersion account for a substantial share of the extensive-margin trading advantage of green bonds. In this sense, green bonds trade more frequently because they are held by a larger number of market participants.

Taken together, the results from Tables 5 and 6 indicate that liquidity differences between green and conventional bonds operate primarily through the extensive margin of trading and are closely linked to differences in investor dispersion. On average over the sample period, green bonds trade on a larger share of days, largely because they are held by a broader set of investors, but individual trades tend to be smaller. This evidence suggests that green bond liquidity is characterized by more frequent but less concentrated trading, a feature that may have important implications for how these securities behave when market conditions vary over time.

5.2 Market stress (H2): interaction with VIX

To test H2, we interact the green bond dummy with the VIX index, which captures time-varying market-wide uncertainty and investor risk aversion. Higher values of the VIX are typically associated with periods of heightened uncertainty, tighter funding conditions, and increased sensitivity to liquidity frictions. As discussed in Section 4, identifying the effect of market stress requires replacing date fixed effects with a set of time-varying financial controls. Table 7 reports the results.

Column (1) of Table 7 reproduces the baseline specification for trading volume from the previous subsection, with the only modification being that date fixed effects are replaced by time-varying macroeconomic controls. The coefficient on GB_i remains positive and statistically significant, and its magnitude is very close to that reported in Table 5, confirming the robustness of results.[12]

Focusing on the remaining columns, the standalone coefficient on the VIX index is positive and statistically significant across all trading measures, reflecting higher trading intensity when volatility rises. This finding is consistent with increased portfolio rebalancing during periods of heightened uncertainty.

Turning to the interaction between the green bond dummy and the VIX index, we find no evidence that green bonds experience a relative decline in total trading volume or trading activity as the VIX increases. The interaction terms are positive but not statistically significant for both measures, suggesting that the extensive-margin trading behavior of green bonds does not deteriorate disproportionately with market

[12] Results for the other trading measures are qualitatively similar and are available upon request.

Table 7: Differences in trading between green and comparable conventional bonds conditional on market stress

VARIABLES	Trading volume	Trading volume	Trading activity	Trading number	Trade size	Trading volume (IM)
GB_i	0.314***	0.160	0.013	-0.018	0.018	-0.001
	(0.075)	(0.125)	(0.009)	(0.023)	(0.049)	(0.062)
VIX_t	0.040***	0.036***	0.002***	0.005***	0.008***	0.013***
	(0.003)	(0.004)	(0.000)	(0.001)	(0.002)	(0.002)
$GB_i \times VIX_t$		0.008	0.001	0.001	-0.004**	-0.003
		(0.006)	(0.000)	(0.001)	(0.002)	(0.003)
$Age_{i,t}$	-2.228***	-2.225***	-0.123***	-0.391***	-0.498***	-0.976***
	(0.150)	(0.149)	(0.010)	(0.022)	(0.047)	(0.053)
$Size_i$	2.569***	2.567***	0.160***	0.274***	0.530***	0.869***
	(0.310)	(0.310)	(0.021)	(0.051)	(0.100)	(0.131)
$Hold_{i,t}$	0.030*	0.030*	0.002	0.009***	0.024***	0.035***
	(0.016)	(0.017)	(0.001)	(0.003)	(0.007)	(0.009)
r_t^F	0.253***	0.252***	0.016***	0.053***	-0.014	0.049**
	(0.051)	(0.051)	(0.003)	(0.008)	(0.018)	(0.020)
YC_t	-0.191*	-0.193*	-0.014**	-0.004	-0.017	-0.027
	(0.102)	(0.102)	(0.007)	(0.016)	(0.037)	(0.041)
Pair FE	YES	YES	YES	YES	YES	YES
Observations	641,253	641,253	641,253	313,783	313,783	313,783
R-squared	0.471	0.471	0.435	0.384	0.309	0.365

The table reports the results of the second specification. The dependent variable is, in turn, the logarithm of trading volume, a dummy variable equal to one if a bond is traded on a given day, the logarithm of the number of trades conditional on trading activity, the logarithm of the average trade size, and the logarithm of trading volume conditional on trading activity. GB_i is a dummy variable equal to one if the bond is green. $Age_{i,t}$ denotes the logarithm of the age of the bond (in years), $Size_i$ corresponds to the logarithm of the bond size, and $Hold_{i,t}$ represents the logarithm of the bond holdings at Euroclear. VIX_t, r_t^f and YC_t denote the level of VIX, the one-year risk-free rate, and the yield curve slope, respectively. Standard errors clustered at the pair level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

stress. By contrast, the interaction term is negative and statistically significant for average trade size, indicating that the increase in trade size associated with higher market stress is more limited for green bonds than for conventional bonds.

To assess whether these results depend on the linear specification of the VIX, we re-estimate the regressions using indicator variables equal to one when the VIX exceeds its 75^{th} and 90^{th} percentiles. The corresponding results are reported in Tables B3 and B4 in the Appendix. In both cases, the high-stress dummy is positive and statistically significant across all trading measures, confirming that trading activity increases during periods of high market stress. The interaction terms between the green bond dummy and the high-VIX indicators remain statistically insignificant for trading volume and trading activity, showing that green bonds do not experience a relative contraction along the extensive margin even during episodes of particularly high volatility. For average trade size, the interaction term remains negative and weakly significant when stress is defined using the 75^{th} percentile, but loses statistical significance at the 90^{th} percentile.

Our findings provide limited support for H2. While we do not find evidence of a relative contraction in trading frequency or total trading volume for green bonds during periods of high volatility, average trade sizes increase less for green bonds than for conventional bonds. This is consistent with the continuation of the more fragmented trading structure documented in the baseline results, rather than with abrupt liquidity dry-ups for green bonds. In other words, even during periods of market stress, green bonds continue to be exchanged through relatively frequent, smaller transactions across a broad set of market participants, which supports the stability of their trading activity.

5.3 Assessing certification effects on green bonds (H3)

We next test H3, which posits that certified green bonds are more liquid than non-certified green bonds. As discussed in Section 2, certification may reduce information asymmetries and greenwashing concerns, thereby facilitating secondary-market trading. To this end, we restrict the sample to green bonds and exploit cross-sectional variation in third-party certification status. Since this specification no longer relies on matched green–conventional pairs, pair fixed effects are replaced by fixed effects for issuer category, currency, rating, and callable status.

Table 8 reports the results. Focusing on total trading volume, certified green bonds are traded in significantly larger amounts than non-certified ones. The coefficient on $Certified_i$ implies that daily trading volume is approximately 189 percent higher for certified green bonds. While this estimate is statistically significant at the 10% level, its magnitude suggests economically meaningful differences in trading activity between certified and non-certified bonds.

Looking at the components of daily trading volume, all of them are higher for certified bonds, although the corresponding coefficients are not statistically significant. By contrast, trading volume at the intensive margin is significantly higher for certified green bonds.

Overall, the evidence points to higher secondary-market trading for certified green bonds. The effect appears to operate primarily through more intensive trading on days when bonds are active, rather than through more frequent trading. While the limited number of certified bonds in the sample calls for caution in interpretation, the findings are consistent with the view that third-party certification reduces information frictions and facilitates larger trades in secondary markets.

5.4 Is project-profile similarity a factor driving liquidity? (H4)

Finally, we examine whether heterogeneity in project profiles across green bonds translates into differences in secondary-market trading, as stated in H4. Specifically, bonds financing more common project types may be easier to trade than those linked to

Table 8: Differences in trading between certified and non-certified green bonds

VARIABLES	Trading volume	Trading activity	Trading number	Trade size	Trading volume (IM)
$Certified_i$	1.062*	0.064	0.069	0.197	0.286**
	(0.574)	(0.041)	(0.062)	(0.140)	(0.120)
$Age_{i,t}$	-1.138***	-0.050***	-0.242***	-0.419***	-0.713***
	(0.288)	(0.019)	(0.036)	(0.081)	(0.094)
$Size_i$	3.692***	0.226***	0.326***	0.255**	0.654***
	(0.363)	(0.029)	(0.032)	(0.118)	(0.121)
$Hold_{i,t}$	0.508***	0.037***	0.116***	0.285***	0.433***
	(0.148)	(0.010)	(0.017)	(0.032)	(0.039)
Issuer category FE	YES	YES	YES	YES	YES
Currency FE	YES	YES	YES	YES	YES
Rating FE	YES	YES	YES	YES	YES
Callable status FE	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES
Observations	293,349	293,349	159,105	159,105	159,105
R-squared	0.392	0.350	0.316	0.227	0.320

The table shows the results of the third specification with $Certified_i$ as variable of interest. The dependent variable is, in turn, the logarithm of trading volume, a dummy variable equal to one if a bond is traded on a given day, the logarithm of the number of trades conditional on trading activity, the logarithm of the average trade size, and the logarithm of trading volume conditional on trading activity. $Certified_i$ is a dummy variable equal to one if the bond is certified by a third party. $Age_{i,t}$ denotes the logarithm of the age of the bond (in years), $Size_i$ corresponds to the logarithm of the bond size, and $Hold_{i,t}$ represents the logarithm of the bond holdings at Euroclear. Standard errors clustered at the issuer level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

more unique project profiles, as they are likely to appeal to a broader set of investors and therefore benefit from a larger pool of potential counterparties. As in the previous subsection, the sample is restricted to green bonds, and pair fixed effects are again replaced by fixed effects for issuer category, currency, rating, and callable status.

We use the project-profile similarity score introduced in Section 3 as the variable of interest. This score captures how common a bond's financed project types are relative to the broader green bond universe. Table 9 reports the results.

Green bonds with more mainstream project profiles trade in significantly higher volumes. Economically, a one–percentage-point increase in the project-profile similarity score is associated with a 2.4% increase in daily trading volume. This effect is statistically significant at the 5% level.

The higher trading volume linked to greater project-profile similarity is driven by the extensive margin. Green bonds with more common project profiles trade on a larger share of days. By contrast, we do not find significant effects on the number of trades or on average trade size, consistent with the absence of a significant effect on trading volume conditional on trading.

These results suggest that green bonds financing more common project types are more likely to trade, but not in larger or more frequent transactions once trading

Table 9: Differences in trading according to the project-profile similarity of green bonds

VARIABLES	Trading volume	Trading activity	Trading number	Trade size	Trading volume (IM)
$PPSimilarity_i$	0.024**	0.002**	-0.001	0.002	0.001
	(0.011)	(0.001)	(0.001)	(0.002)	(0.002)
$Age_{i,t}$	-0.955***	-0.042**	-0.226***	-0.387***	-0.661***
	(0.270)	(0.018)	(0.033)	(0.076)	(0.092)
$Size_i$	3.297***	0.207***	0.318***	0.242**	0.630***
	(0.342)	(0.026)	(0.032)	(0.116)	(0.123)
$Hold_{i,t}$	0.455***	0.034***	0.106***	0.274***	0.412***
	(0.127)	(0.009)	(0.015)	(0.033)	(0.041)
Issuer category FE	YES	YES	YES	YES	YES
Currency FE	YES	YES	YES	YES	YES
Rating FE	YES	YES	YES	YES	YES
Callable status FE	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES
Observations	333,206	333,206	164,770	164,770	164,770
R-squared	0.416	0.376	0.318	0.232	0.324

The table shows the results of the third specification with $PPSimilarity_i$ as variable of interest. The dependent variable is, in turn, the logarithm of trading volume, a dummy variable equal to one if a bond is traded on a given day, the logarithm of the number of trades conditional on trading activity, the logarithm of the average trade size, and the logarithm of trading volume conditional on trading activity. $PPSimilarity_i$ is the project-profile similarity score described in Section 3 in percentage. $Age_{i,t}$ denotes the logarithm of the age of the bond (in years), $Size_i$ corresponds to the logarithm of the bond size, and $Hold_{i,t}$ represents the logarithm of the bond holdings at Euroclear. Standard errors clustered at the issuer level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

occurs. Project-profile commonality therefore appears to facilitate investor participation and counterparty matching in secondary markets, rather than affecting the size or intensity of individual trades.

Our analysis is subject to several data-related scope limitations. Holdings and transactions are observed at the level of Euroclear participant accounts, which prevents identification of ultimate beneficial owners and limits a more granular characterization of investor types. In addition, the sample is restricted to bonds included in the Bloomberg Global Aggregate index and therefore focuses on large, investment-grade securities. While this ensures comparability and coverage of a central segment of the market, the results may not generalize to smaller, lower-rated, or less actively traded green bonds.

6 Conclusion

This paper examines differences in secondary-market trading between green and conventional bonds using a matched-pair design and a unique dataset from Euroclear that provides daily information on transactions and holdings at the participant-account level. This approach allows us to shed new light on green bond liquidity, particularly along the dimensions of trading volume, trading frequency and transaction size.

Our results reject the commonly held hypothesis that green bonds suffer from lower liquidity due to mandate-constrained demand in a relatively small market, as well as higher information costs and fragmented trading. Instead, we find that green bonds trade on a larger number of days than comparable conventional bonds, even though individual trades tend to be smaller. We show that this result is linked to the greater number of investors per green bond issuance holding green bonds.

We further examine whether these liquidity patterns vary with market conditions by interacting the green bond indicator with measures of market stress. While overall trading activity rises during periods of elevated volatility, we find no evidence that green bonds experience a relative contraction in trading frequency or total trading volume as market stress increases. Average trade sizes increase during stress episodes, but this increase is less pronounced for green bonds than for conventional bonds. These results suggest that green bond liquidity does not become disproportionately fragile during adverse market conditions, even though trading continues to be dominated by smaller transactions.

Within the green bond universe, bond-level characteristics are associated with distinct trading outcomes. Certified green bonds exhibit higher trading volumes than non-certified bonds driven by more intensive trading on days when they are active. This suggests that certification mitigates information frictions and facilitates larger transactions. By contrast, project-profile similarity affects liquidity primarily through the extensive margin. Green bonds financing more common project types trade on a larger number of days, but not in larger or more frequent transactions once trading occurs, suggesting that project commonality increases the likelihood of trading without affecting transaction size.

Taken together, the findings suggest that green bonds are not characterized by lower secondary-market trading activity, even during periods of elevated market stress. For investors, this implies that green bonds are not inherently harder to trade than comparable conventional bonds within the segment studied. For issuers, the results show that bond design features affecting investor reach and information, such as third-party certification and the type of financed projects, correspond to differences in secondary-market trading. For regulators, the absence of disproportionate contractions in green bond trading during periods of market stress provides evidence that green bond markets are resilient.

Several avenues for future research emerge from our analysis. Our study focuses on activity-based measures of liquidity, capturing how frequently and how intensively bonds are traded. While these measures provide direct evidence on secondary-market trading, future work could complement this approach by examining other dimensions of liquidity in order to provide a more comprehensive assessment of green bond liquidity. In addition, our sample focuses on bonds included in Bloomberg's Global Aggregate Index, which primarily covers large, investment-grade securities. Extending the analysis to smaller or lower-rated bonds, including speculative-grade instruments, could provide further insights into liquidity patterns in segments of the green bond market that may be less actively traded or more sensitive to market frictions.

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A Construction of the project-profile similarity score: example

The project-profile similarity measure is computed using the subset of green bonds from the initial sample for which project-type information is available ($G = 1,635$). The distribution of project types across these bonds is reported in Table 1.

For each green bond i, the project-profile similarity score is defined as

$$PPSimilarity_i = \frac{1}{N_{TOT} - 1} \sum_{j \neq i} \mathbf{1}\{\mathcal{P}_i \cap \mathcal{P}_j \neq \varnothing\},$$

where $\mathcal{P}_i$ denotes the set of project types financed by bond i.

Consider a green bond financing both Renewable Energy and Biodiversity projects, so that

$$\mathcal{P}_i = \{\text{Renewable Energy}, \text{Biodiversity}\}.$$

Let N_{RE} denote the number of bonds financing Renewable Energy projects and N_{Bio} the number financing Biodiversity projects, as reported in Table 1. Denoting by $N_{RE\cap Bio}$ the number of bonds financing both Renewable Energy and Biodiversity projects (not reported), the number of bonds financing at least one of the two project types is

$$N_{\text{similar}}(i) = (N_{RE} - 1) + (N_{Bio} - 1) - (N_{RE\cap Bio} - 1).$$

Using the values reported in Table 1 and the observed overlap across project types, we obtain

$$N_{\text{similar}}(i) = 1,326 + 318 - 291 = 1,353.$$

The project-profile similarity score of bond i is therefore

$$PPSimilarity_i = \frac{1,353}{1,635 - 1} = 0.8275,$$

or 82.75%.

B Additional results

Table B1: Differences in trading between green and comparable conventional bonds, corporate and government-related bonds

VARIABLES	Trading volume	Trading activity	Trading number	Trade size	Trading volume(IM)
Panel A. Corporates					
GB_i	0.214***	0.018***	0.007	-0.032	-0.021
	(0.077)	(0.006)	(0.014)	(0.019)	(0.024)
$Age_{i,t}$	-2.026***	-0.114***	-0.398***	-0.359***	-0.848***
	(0.190)	(0.013)	(0.029)	(0.038)	(0.055)
$Size_i$	2.020***	0.133***	0.271***	0.052	0.391***
	(0.331)	(0.023)	(0.053)	(0.076)	(0.108)
$Hold_{i,t}$	0.043**	0.002*	0.034***	0.137***	0.179***
	(0.022)	(0.001)	(0.012)	(0.037)	(0.041)
Pair FE	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES
Observations	429,504	429,504	209,149	209,149	209,149
R-squared	0.532	0.501	0.306	0.251	0.288
Panel B. Government-related					
GB_i	0.502***	0.039***	-0.012	-0.167***	-0.177**
	(0.157)	(0.011)	(0.027)	(0.060)	(0.070)
$Age_{i,t}$	-2.208***	-0.109***	-0.296***	-0.823***	-1.178***
	(0.363)	(0.024)	(0.054)	(0.141)	(0.152)
$Size_i$	3.122***	0.190***	0.137*	0.605***	0.777***
	(0.507)	(0.035)	(0.079)	(0.197)	(0.246)
$Hold_{i,t}$	0.068	0.003	0.142***	0.352***	0.522***
	(0.077)	(0.004)	(0.034)	(0.089)	(0.110)
Pair FE	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES
Observations	237,941	237,941	114,692	114,692	114,692
R-squared	0.429	0.371	0.555	0.336	0.438

The table reports the results of the baseline specification, differentiating between corporate and government-related bonds. The dependent variable is, in turn, the logarithm of trading volume, a dummy variable equal to one if a bond is traded on a given day, the logarithm of the number of trades conditional on trading activity, the logarithm of the average trade size, and the logarithm of trading volume conditional on trading activity. GB_i is a dummy variable equal to one if the bond is green. $Age_{i,t}$ denotes the logarithm of the age of the bond (in years), $Size_i$ corresponds to the logarithm of the bond size, and $Hold_{i,t}$ represents the logarithm of the bond holdings at Euroclear. Standard errors clustered at the pair level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B2: Differences in trading between green and comparable conventional bonds, EUR- and USD-denominated bonds

VARIABLES	Trading volume	Trading activity	Trading number	Trade size	Trading volume (IM)
Panel A. EUR					
GB_i	0.392***	0.033***	0.011	-0.097***	-0.079**
	(0.091)	(0.006)	(0.014)	(0.027)	(0.033)
$Age_{i,t}$	-2.630***	-0.135***	-0.387***	-0.508***	-0.976***
	(0.220)	(0.015)	(0.028)	(0.069)	(0.079)
$Size_i$	2.325***	0.133***	0.187***	0.419***	0.651***
	(0.449)	(0.029)	(0.055)	(0.142)	(0.173)
$Hold_{i,t}$	1.130***	0.062***	0.144***	0.253**	0.428***
	(0.215)	(0.012)	(0.039)	(0.107)	(0.129)
Pair FE	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES
Observations	373,217	373,217	252,392	252,392	252,392
R-squared	0.328	0.290	0.394	0.254	0.310
Panel B. USD					
GB_i	0.215*	0.019**	0.019	-0.100	-0.075
	(0.113)	(0.009)	(0.026)	(0.067)	(0.068)
$Age_{i,t}$	-1.579***	-0.098***	-0.342***	-0.537***	-0.973***
	(0.306)	(0.021)	(0.068)	(0.156)	(0.155)
$Size_i$	1.767***	0.130***	0.171***	-0.016	0.204
	(0.428)	(0.032)	(0.057)	(0.206)	(0.233)
$Hold_{i,t}$	0.047**	0.003*	0.019**	0.162***	0.186***
	(0.023)	(0.002)	(0.009)	(0.042)	(0.041)
Pair FE	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES
Observations	219,222	219,222	51,887	51,887	51,887
R-squared	0.442	0.395	0.399	0.342	0.408

The table reports the results of the baseline specification, differentiating between EUR- and USD-denominated bonds. The dependent variable is, in turn, the logarithm of trading volume, a dummy variable equal to one if a bond is traded on a given day, the logarithm of the number of trades conditional on trading activity, the logarithm of the average trade size, and the logarithm of trading volume conditional on trading activity. GB_i is a dummy variable equal to one if the bond is green. $Age_{i,t}$ denotes the logarithm of the age of the bond (in years), $Size_i$ corresponds to the logarithm of the bond size, and $Hold_{i,t}$ represents the logarithm of the bond holdings at Euroclear. Standard errors clustered at the pair level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B3: Differences in trading between green and comparable conventional bonds conditional on market stress - VIX above 75th percentile

VARIABLES	Trading volume	Trading activity	Trading number	Trade size	Trading volume (IM)
GB_i	0.293***	0.024***	0.007	-0.053*	-0.042
	(0.075)	(0.005)	(0.013)	(0.028)	(0.034)
$VIX75_t$	0.242***	0.014***	0.032***	0.083***	0.123***
	(0.049)	(0.003)	(0.008)	(0.021)	(0.023)
$GB_i \times VIX75_t$	0.091	0.008	0.014	-0.054*	-0.036
	(0.070)	(0.005)	(0.012)	(0.028)	(0.033)
$Age_{i,t}$	-2.191***	-0.121***	-0.389***	-0.496***	-0.972***
	(0.149)	(0.010)	(0.022)	(0.047)	(0.053)
$Size_i$	2.558***	0.160***	0.273***	0.529***	0.867***
	(0.309)	(0.021)	(0.050)	(0.100)	(0.131)
$Hold_{i,t}$	0.030*	0.002	0.009***	0.025***	0.036***
	(0.017)	(0.001)	(0.003)	(0.007)	(0.009)
r_t^F	0.224***	0.014***	0.050***	-0.014	0.044**
	(0.051)	(0.003)	(0.008)	(0.018)	(0.020)
YC_t	-0.184*	-0.014**	-0.002	-0.010	-0.017
	(0.101)	(0.007)	(0.016)	(0.037)	(0.041)
Pair FE	YES	YES	YES	YES	YES
Observations	642,057	642,057	313,830	313,830	313,830
R-squared	0.470	0.433	0.383	0.309	0.365

The table reports the results of the second specification. The dependent variable is, in turn, the logarithm of trading volume, a dummy variable equal to one if a bond is traded on a given day, the logarithm of the number of trades conditional on trading activity, the logarithm of the average trade size, and the logarithm of trading volume conditional on trading activity. GB_i is a dummy variable equal to one if the bond is green. $Age_{i,t}$ denotes the logarithm of the age of the bond (in years), $Size_i$ corresponds to the logarithm of the bond size, and $Hold_{i,t}$ represents the logarithm of the bond holdings at Euroclear. $VIX75_t$ is a dummy variable equal to one if the level of VIX is above its 75th percentile, equal to 22.05. r_t^f and YC_t denote the one-year risk-free rate and the yield curve slope, respectively. Standard errors clustered at the pair level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B4: Differences in trading between green and comparable conventional bonds conditional on market stress - VIX above 90th percentile

VARIABLES	Trading volume	Trading activity	Trading number	Trade size	Trading volume (IM)
GB_i	0.305***	0.025***	0.009	-0.063**	-0.049
	(0.074)	(0.005)	(0.013)	(0.027)	(0.032)
$VIX90_t$	0.384***	0.022***	0.057***	0.097***	0.169***
	(0.052)	(0.003)	(0.009)	(0.023)	(0.026)
$GB_i \times VIX90_t$	0.104	0.008	0.010	-0.029	-0.016
	(0.079)	(0.005)	(0.014)	(0.031)	(0.039)
$Age_{i,t}$	-2.191***	-0.121***	-0.389***	-0.495***	-0.971***
	(0.149)	(0.010)	(0.022)	(0.047)	(0.053)
$Size_i$	2.558***	0.160***	0.273***	0.528***	0.866***
	(0.309)	(0.021)	(0.050)	(0.100)	(0.131)
$Hold_{i,t}$	0.030*	0.002	0.009***	0.025***	0.036***
	(0.017)	(0.001)	(0.003)	(0.007)	(0.009)
r_t^F	0.205***	0.013***	0.048***	-0.018	0.038*
	(0.051)	(0.003)	(0.008)	(0.018)	(0.020)
YC_t	-0.224**	-0.016**	-0.007	-0.018	-0.031
	(0.103)	(0.007)	(0.016)	(0.037)	(0.041)
Pair FE	YES	YES	YES	YES	YES
Observations	642,057	642,057	313,830	313,830	313,830
R-squared	0.470	0.434	0.383	0.309	0.365

The table reports the results of the second specification. The dependent variable is, in turn, the logarithm of trading volume, a dummy variable equal to one if a bond is traded on a given day, the logarithm of the number of trades conditional on trading activity, the logarithm of the average trade size, and the logarithm of trading volume conditional on trading activity. GB_i is a dummy variable equal to one if the bond is green. $Age_{i,t}$ denotes the logarithm of the age of the bond (in years), $Size_i$ corresponds to the logarithm of the bond size, and $Hold_{i,t}$ represents the logarithm of the bond holdings at Euroclear. $VIX75_t$ is a dummy variable equal to one if the level of VIX is above its 90th percentile, equal to 27.16. r_t^f and YC_t denote the one-year risk-free rate and the yield curve slope, respectively. Standard errors clustered at the pair level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

C An overview of the green bond market

C.1 Green bonds market size

The green bond market has expanded rapidly, now representing around 3% of the global bond market (Jena and Vuppuluri 2025). This number, reported in the main article, is consistent with evidence drawn from Bloomberg's *Green Bond Index* and *Global Aggregate Index*: Using data from January 2018 to June 2025, Figure 1 shows that the *Green Bond Index* grew from approximately €200 billion to nearly €1,800 billion, corresponding to a ninefold increase over a period of seven and a half years. Comparing this growth with that of the overall bond market, as represented by the *Global Aggregate Index*, we find that the share of the *Green Bond Index* increased from around 0.4% to approximately 2.8%.[1]

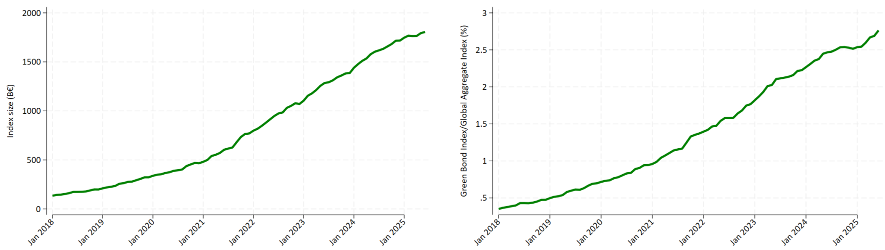

Fig. 1: Evolution of the size of the *Green Bond Index*, in billions of euros (left), and evolution of the ratio of the *Green Bond Index* to the *Global Aggregate Index*, in percentage (right).

The development of the share of the *Green Bond Index* could reflect an increase in the relative number of green bonds issued or a relative increase in their average size. To disentangle these effects, Figure 2 presents the number of *Green Bond Index* constituents as a share of the *Global Aggregate Index*, as well as the average size (or amount outstanding) of green bonds relative to that of the bonds in the *Global Aggregate Index*. The figure indicates that the relative growth of green bonds is driven by both channels, with the increase in the relative number of constituents playing a more prominent role. Between 2018 and 2025, the share of green bonds in terms of numbers rises from slightly below 1% to more than 6% of the *Global Aggregate Index*. With respect to the average amount outstanding, although the relative size of green bonds increases modestly - from around 38% to approximately 44% over the period

[1]The *Green Bond Index* differs in its components from the green bonds included in the *Global Aggregate Index*, as the former also includes bonds with less than one year remaining to maturity (Bloomberg 2024).

- they remain substantially smaller than the average bond included in the *Global Aggregate Index*.

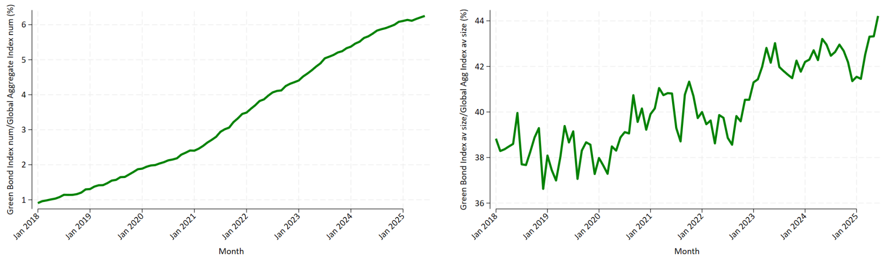

Fig. 2: The ratio of the number of *Green Bond Index* constituents to the number of *Global Aggregate Index* constituents, in percentage (left), and the ratio of the average size of *Green Bond Index* constituents to those of the *Global Aggregate Index*, in percentage (right).

Overall, Bloomberg data indicate a significant expansion of the green bond market between 2018 and 2025, both in absolute terms and relative to the global bond market. This growth particularly driven by the increasing number of bonds available on the market, reflecting a growing interest in green debt instruments.

C.2 Issuer types and issuance currencies

To compare green and conventional bonds in terms of issuer types and issuance currencies, we focus on corporate and government-related bonds included in Bloomberg's *Global Aggregate Index* as of June 30, 2025. To ensure a clean comparison between green and strictly conventional bonds, we exclude all bonds classified as social, sustainability, or sustainability-linked bonds. This leaves us with 24,326 bonds, among which 1,639 are green and 22,687 are conventional.

When it comes to the distribution of issuer types, Figure 3 shows that they are relatively similar, even though the corporate sector takes a larger share of the number of issues in conventional bonds than in green bonds while government agencies and local government in particular play a more important role in green bond markets.

Green bonds are predominantly issued in EUR currency with the US$ following as a distant second. This stands in big contrast to conventional bond markets, where the US$ clearly dominates (Figure 4).

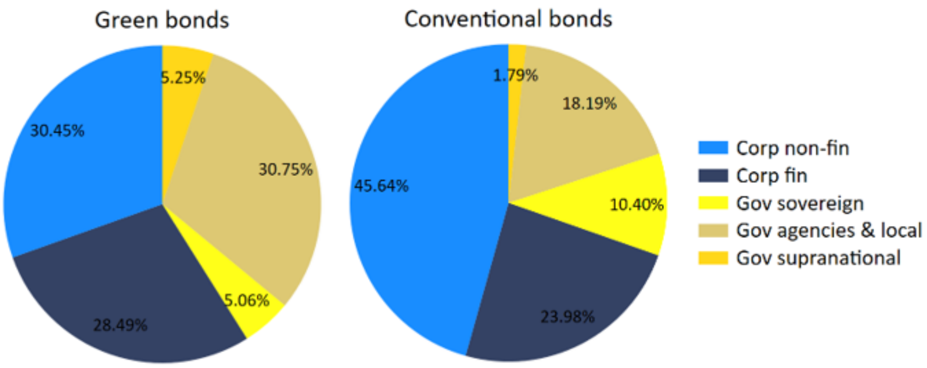

Fig. 3: Distribution of green and conventional bonds by issuer type (%age of the number of bonds). Source: Bloomberg's Global Aggregate Index as of June 30,2025. Exclusion of securitized, social, sustainable and sustainability-linked bonds.

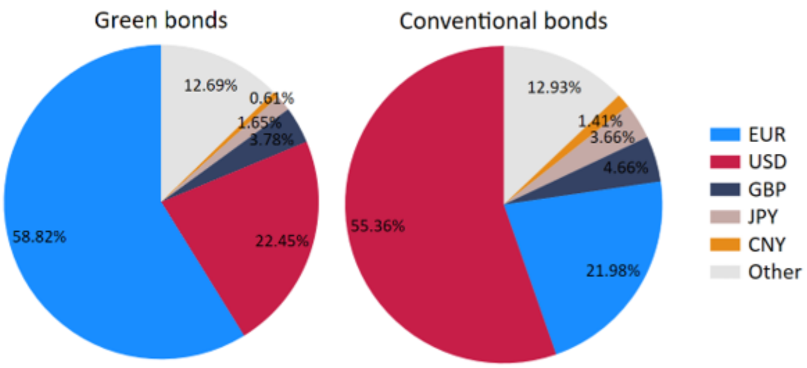

Fig. 4: Distribution of green and conventional bonds by currency (%age of the number of bonds). Source: Bloomberg's Global Aggregate Index as of June 30,2025. Exclusion of securitized, social, sustainable and sustainability-linked bonds.

C.3 Central Secutities Depositories

Post trade settlement and deposit of green bonds is dominated by Euroclear Bank and Clearstream Banking SA (Figure 5).

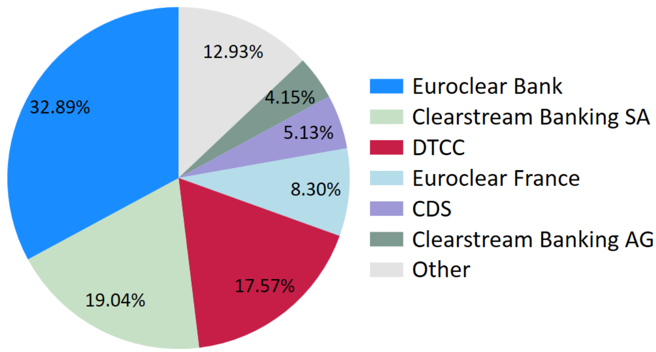

Fig. 5: Distribution of green bonds by Central Securities Depository (%age of the number of bonds). Source: Bloomberg's Global Aggregate Index as of June 30,2025. Exclusion of securitized, social, sustainable and sustainability-linked bonds.

C.4 Green Eurobonds and other green bonds

Finally, we want to study whether the specific "Eurobond" format is prevalent in the green bond market. According to Euroclear, "The Eurobond market has grown to become one of the largest debt markets in the world. With an outstanding value of over EUR 13.2 trillion, more than 12,000 legal entities from over 130 countries have issued Eurobonds to date. It's used by all types of issuers, from governments and supranational organisations to financial institutions and corporations, offering access to a diverse international investor base through a single access point – the International Central Securities Depositories (ICSDs)."[2] One key benefit of Eurobonds is that issuers can raise capital in over 50 currencies and under 85 governing laws, while investors can access them through a leading ICSD like Euroclear, according to information from Euroclear.

Figures 6 and 7 show the volume and number of green bonds in the eurobond format as well as other format. For corporate and government-related bonds altogether, the total amount issued via green Eurobonds has been lower than via other bonds.

However, in terms of the number of bonds, green Eurobond issuance has recently started exceeding the number of other green bonds.

[2]https://www.euroclear.com/newsandinsights/en/Format/Articles/understanding-eurobonds-a-financial-history-journey.html

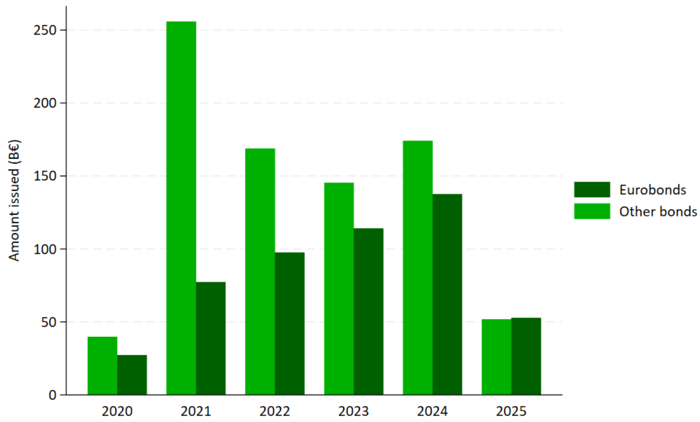

Fig. 6: Amount issued by green Eurobonds and other green bonds (EUR billions). Source: Bloomberg's Global Aggregate Index as of June 30,2025. Exclusion of securitized, social, sustainable and sustainability-linked bonds.

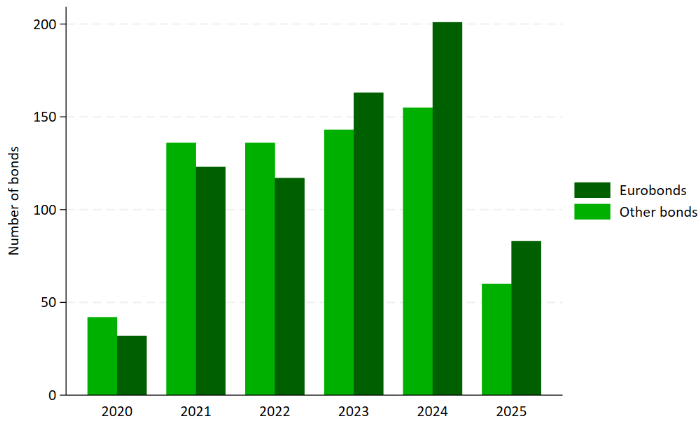

Fig. 7: Number of green Eurobonds and other green bonds issued. Source: Bloomberg's Global Aggregate Index as of June 30,2025. Exclusion of securitized, social, sustainable and sustainability-linked bonds.

One reason why the Eurobond format does not dominate the green bond market could be the relatively strong issuances of green bonds by governments. We therefore focusing on corporate bond issuances only in Figures 8 and 9. The figures reveal that the total amount issued in green corporate Eurobonds has started exceeding the one for other green bonds, both in terms of amounts as well as the number of bonds.

Figure 10 also shows that the average amount issued by bond is larger for corporate green Eurobonds than other corporate bonds.

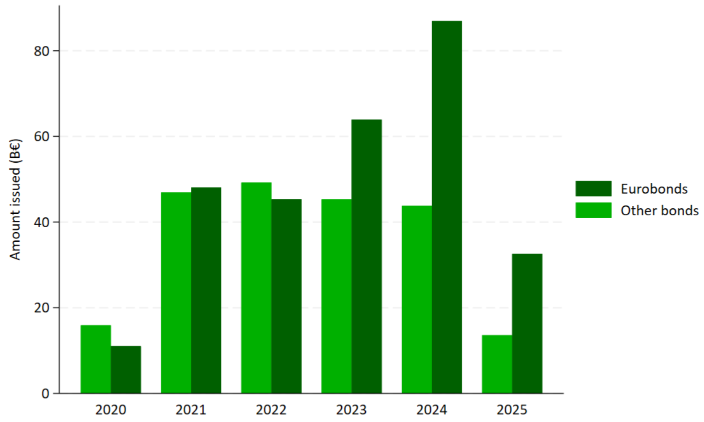

Fig. 8: Amount issued by corporate green Eurobonds and other corporate green bonds (EUR billions). Source: Bloomberg's Global Aggregate Index as of June 30,2025. Exclusion of securitized, social, sustainable and sustainability-linked bonds.

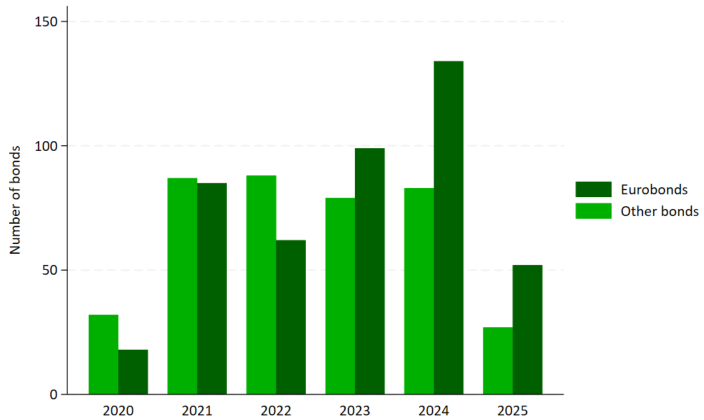

Fig. 9: Number of corporate green Eurobonds and other corporate green bonds issued. Source: Bloomberg's Global Aggregate Index as of June 30,2025. Exclusion of securitized, social, sustainable and sustainability-linked bonds.

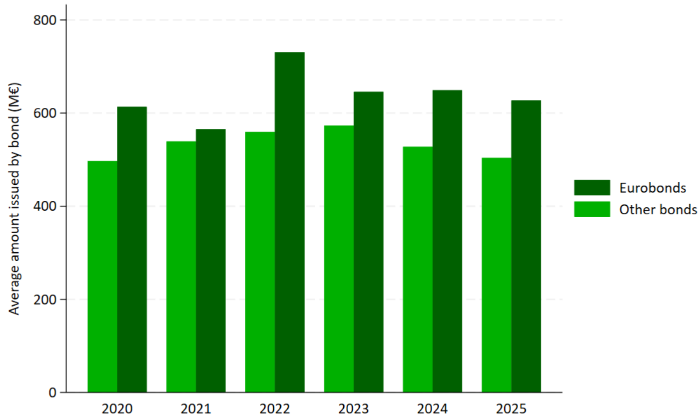

Fig. 10: Average amount issued by corporate green Eurobonds and other corporate green bonds (EUR millions). Source: Bloomberg's Global Aggregate Index as of June 30,2025. Exclusion of securitized, social, sustainable and sustainability-linked bonds.