Chapter 6

Green Bonds and Market-Based Investor Sentiment: A Quantile Coherence Approach

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Abstract

The growing interest in sustainable investment instruments in financial markets necessitates an in-depth examination of the sensitivities these assets exhibit toward risk factors. The aim of this study is to empirically investigate the dependency structure between the green bond index and the global volatility indicators - the VIX (equity market volatility), OVX (oil market volatility), and MOVE (bond market volatility) indices. In the analysis process, the Quantile Coherence approach developed by Baruník and Kley was employed in order to simultaneously evaluate the relationship among the variables both across different frequencies (short and long term) through the implicit components and under different market conditions (bear and bull markets). The findings obtained from the research indicate that, although the dependency between green bond returns and the volatility indices remains generally weak, it exhibits a pronounced heterogeneity and asymmetry depending on frequency and market conditions. Notably, the dependencies with the MOVE index are considerably more pronounced and longer-term compared to those with the VIX and OVX, revealing that risks originating from the broader bond market exert a more persistent and profound influence on the green bond market. In contrast, it is striking that the analyzed imaginary components are generally statistically insignificant. This demonstrates that volatility shocks do not exhibit a delayed transmission to the green bond market, and that the interaction in question occurs largely on a simultaneous (instantaneous) basis. The findings suggest that the green bond market is dynamic, changing with frequency and market conditions in response to external volatility shocks, yet it displays a

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limited dependency mechanism. In this respect, the study offers implications for investors and policymakers regarding portfolio diversification and risk management.

1. Introduction

Within the classical distinction, risk and uncertainty differ in terms of their measurability. Risk is a phenomenon that can be quantified through probability calculations and is therefore manageable, whereas uncertainty is generally regarded as more difficult to measure and has limited predictability. Nevertheless, in modern financial markets, it is possible to indirectly quantify the effects of uncertainty through investors' immediate reactions, volatility indices, and market-based indicators. Uncertainty indices vary depending on their characteristics and the measurement methodologies employed. For example, Baker et al. (2016) developed the Economic Policy Uncertainty Index based on the frequency of newspaper coverage (Aharon et al., 2025). The authors expanded this index along three main dimensions: historical, cross-country, and specific policy categories. Similarly, Gavrilidis (2021) introduced the Climate Policy Uncertainty Index to the literature. Within the scope of this index, climate-related uncertainties are captured through news texts focusing on issues such as emission regulations, global climate strikes, and leaders' statements on climate policies.

On the other hand, some uncertainty and risk indicators are considered reflections of investor psychology. At this point, the concept of investor sentiment, which underlies irrational behaviour in financial markets, becomes important. As also emphasised by Barberis et al. (1998), the limited insight provided by earlier studies into the nature of mispricing in markets and the absence of a model for expectation formation made the empirical investigation of investor sentiment necessary. In this context, the rise of green bond markets has made it even more important to measure and analyse these irrational elements that cannot be integrated into traditional financial models.

This study aims to offer a comparative analysis of various indicators used to measure investor sentiment in green bond markets. It also seeks to empirically evaluate how irrational investor behaviour affects price formation and market efficiency. In this context, market volatility indicators have long been considered crucial indicators of investor sentiment and financial stability (Gürbüz, 2026). In particular, the extreme fluctuations observed in energy markets provide a critical setting for understanding how shifts in sentiment arising from investors' cognitive biases, such as information asymmetry and herd psychology, affect market dynamics. With the growing importance of environmental, social, and governance factors in green bond markets, investors' sustainability-oriented perceptions and their effects on bond pricing and returns have introduced a new dimension of research.

Although no consensus has yet emerged in the literature on the choice of a sentiment proxy, selecting an index that matches the market's characteristics has been a widely adopted approach among researchers. In this context, this study aims to examine the dependence between appropriate sentiment indicators and market responses by taking into account the distinctive structure of green bond markets and the existing literature. By quantitatively assessing the effects of investor sentiment on price discovery and risk premium formation in green bond markets, this analysis offers a new perspective on market efficiency.

In portfolio management, directly measuring sentiment toward financial instruments is highly time-consuming. For this reason, sentiment indices constructed through indirect methods have attracted considerable attention. In this respect, the Volatility Index (VIX) calculated by the CBOE has emerged as one of the most widely used sentiment indicators in the literature (Feldman, 2010; Lıutvınavičıus et al., 2017; Baker et al., 2020; Aharon, 2020; Huang et al., 2020). VIX is preferred as a sentiment proxy because it reduces the complexity investors face (Chang et al., 2018:2) and provides a rapid measure of expectations. Similarly, the MOVE index, which measures the volatility of U.S. 10-year Treasury bonds, reflects market expectations of volatility in the bond market. In this study, another reason for including the MOVE index alongside VIX is the ability of the two indices to predict each other and their high correlation (Zhou, 2014:217). Therefore, the joint use of VIX and MOVE enables a more consistent assessment of the green bond market's sensitivity to both general financial stress and bond-market-specific fluctuations. In this context, the inclusion of the CBOE Crude Oil Volatility Index (OVX) in the model is particularly important for the study's design. OVX is not merely an indicator of oil market volatility but also represents a systematic risk channel that may affect financial markets through energy costs, inflation expectations, global risk appetite, and the relative attractiveness of the energy transition. The critical role of crude oil in the real economy, the predictive power of oil price volatility (Chen, 2018: 837), and its strong forecasting performance when incorporated into empirical models (Haugom, 2014: 13) make it necessary to consider OVX as an indicator of investor sentiment in this study.

Another reason for using OVX in this study is that the green bond market serves as a strategic instrument for financing the energy transition. Since green bonds finance renewable energy, energy efficiency, and sustainable infrastructure projects, volatility in the oil market and the associated perception of risk may exert an indirect yet meaningful influence on the green bond market. In other words, uncertainty in the oil market may affect not only conventional energy assets but also the green bond market through expectations regarding the energy transition and changes in risk appetite (Gökgöz et al., 2025). For this reason, OVX is considered not only a commodity market-based volatility indicator for green bond markets but also an indirect proxy for financial risks associated with the energy transition. In this study, the joint use of VIX, MOVE, and OVX in analysing the sensitivity of the green bond market enables empirical assessment of which risk channel the green bond market is more sensitive to across equity, bond, and energy markets.

The relationship between investor sentiment and traditional financial markets is well established in the literature. The need to address this issue from the perspective of green bond markets constitutes the main motivation of this study. Although the share of fossil fuels has declined in recent years, oil remains the primary source of energy, with a share exceeding 30%. In contrast, renewable energy sources make up about 8% of primary energy consumption. However, with the population growing and energy demand increasing, it is crucial to address the global challenges of protecting the environment and reducing fossil fuel use. As a result, investors are increasingly focusing their attention on clean energy markets rather than traditional energy markets (Zhang et al., 2021). Increasing R and D expenditures, reducing carbon intensity, and promoting investment in clean energy channels are of vital importance for clean energy, which forms the core of environmentally friendly global energy supply security (He et al., 2018:305). Green bonds, one of the most important financial instruments supporting the transition to clean energy, are instruments whose proceeds are used directly for environmental purposes. This market is issued to finance areas such as renewable energy, energy efficiency, and sustainable resource use (Liaw, 2020). Green bonds are not only a safe haven but also a strategic instrument that accelerates the decarbonization process (Zhu et al., 2025:815). Indeed, as of 2025, within the global green economy, which has reached 7.9 trillion dollars, the green bond market has maintained a strong trajectory with a size of 2.9 trillion dollars (Dai et al., 2025:3).

In conclusion, the current and future potential of green bonds makes it necessary to examine these markets from the perspective of investor sentiment. Understanding the relationship between these variables can guide stakeholders by providing critical insights to facilitate the transition to sustainable energy, make climate policies more implementable, optimise investment decisions, and develop effective policies. Nevertheless, although the existing literature has made important contributions by examining the relationship between green bond markets and uncertainty and risk indicators, how this relationship changes across different market conditions and investment horizons remains unclear. In particular, the literature remains limited in jointly addressing not only dependencies at the same quantiles but also asymmetric relationships emerging across quantiles and their patterns across short, medium, and long term frequencies. This study aims to fill this gap. In this context, the dependencies between the green bond index and VIX, OVX, and MOVE are analysed using the Quantile Coherence approach developed by Baruník and Kley (2019). The QC approach enables examination of the dependence structure between variables not only under average market conditions but also across different quantile combinations and time-frequency horizons. In this way, the direction, strength, and possible asymmetries of the dependencies that emerge under both normal and extreme market conditions can be evaluated together.

In this respect, the study seeks to make three main contributions to the literature. First, by examining the dependence between the green bond market and market-based volatility indicators that reflect investor sentiment using the quantile coherence approach, this analysis reveals how this relationship changes across different market regimes and investment horizons. Second, by focusing not only on dependencies at the same quantile levels but also on cross-quantile dependencies, it makes the asymmetric effects of volatility shocks on the green bond market more visible. Third, by comparing stock market fear (VIX), oil market volatility (OVX), and bond market volatility (MOVE) within the same framework, it shows which risk channel is more influential for the green bond market.

The remainder of the study is organised as follows. The next section reviews the literature on investor sentiment and green bond markets. This is followed by the data and methodology section, the empirical findings, and the conclusion section.

2. Literature

Investor sentiment, which gained prominence with the development of behavioural finance, has become increasingly important in the literature. This issue continues to be examined across a wide range of markets, from stock and conventional bond markets to commodity and green financial markets. The main reason for this is the view that investor sentiment has predictive power in empirical models (Haugom, 2014:13; Wang et al., 2022; Bouteska et al., 2024; Bouri et al., 2024). However, no consensus has yet emerged in the literature on the choice of an investor sentiment proxy. Rather than constituting a problem, this can be regarded as a source of richness. Indeed, different investor sentiment proxies should be selected and examined based on market structure, time period, technological conditions, and country-specific dynamics.

The relationship between investor sentiment and green bond markets has been analysed by various authors using different proxies. To provide a basis for our study, we first discuss studies that consider direct investor sentiment proxies, and then review the relationships between this variable and uncertainty and risk indicators.

With the growth of internet use and the increasing popularity of social media and search engines, investor sentiment proxies derived from text-based analyses of social networks have become widespread. In one such study, Piñeiro-Chousa et al. (2021) studied how investor sentiment affects various green bond markets by analysing daily sentiment derived from 18,427 tweets about Green Bonds. Similarly, Bouteska et al. (2024) examined the link between Chinese green bonds and investor sentiment using text-based analysis of millions of posts collected from Chinese online financial forums. Their findings showed that the connection between the variables was more pronounced in the short run than in the long run and that green bonds acted as net receivers of shocks. Huang et al. (2025) conducted a similar study and supported the findings of Bouteska et al. (2024) for the Chinese green bond market. Fu et al. (2024) examined how proxies derived from sentiment data from internet and print media sources, specifically Sina Weibo and the China Important Newspaper Full Text Database, affect the green bond market. These variables are categorised as indirect measures of investor sentiment. In direct measurement approaches, investors are asked about their expectations and views regarding the future through surveys. This method is also frequently considered in the literature. In this regard, the American Association of Individual Investors index is among the most widely used survey-based weekly measures of investor sentiment. Examining the relationship between investor sentiment survey results and the green bond index, Su et al. (2024) found that investor sentiment affects the green bond index and that investors hold an optimistic view of the bond market.

Turning to studies that examine the relationship between investor sentiment and green bond markets within the framework of uncertainty indices, Pham and Cepni (2022) approached the issue from a multidimensional perspective. It focused on the effect of investor attention on green bonds within a behavioural finance framework. The authors found that investor attention in the green bond market is significantly affected by stock, oil, and bond market volatility, as well as economic policy uncertainty. Cao et al. (2024), in contrast, investigated the relationship between U.S. monetary policy uncertainty and another uncertainty index with green bonds. Their findings showed that rising U.S. monetary policy uncertainty adversely affects green bond prices during periods of low market sentiment.

In the context of the effects of uncertainty and risk indices on green bond markets, Wang et al. (2022) investigated the asymmetric causality of EPU and OVX on the time-varying relationship among clean energy, carbon, and green bonds. Using DCC MIDAS and quantile-based methods, the authors found that EPU is a strong predictor of cross-asset correlations, while OVX shows predictive power by significantly affecting them across all market conditions. Adopting a similar perspective, Tian et al. (2022) employed a nonlinear ARDL model to examine the asymmetric effects of CPU, Infectious Disease Equity Market Volatility (IDEMV), OVX, and geopolitical risks (GPR) on green bond prices in the United States, Europe, and China. Their results showed that green bond markets respond heterogeneously to uncertainties, with only the Chinese market exhibiting notable asymmetric effects in the short run, whereas the European and U.S. markets display broader asymmetric effects in the long run.

Pham and Nguyen (2022) examined the effects of VIX, OVX, and EPU on bond returns and showed that the link between green bonds and uncertainty is time-varying and state-dependent. The authors also emphasised that green bonds may serve as a hedging instrument during periods of low uncertainty, as this link weakens under such conditions. In addition, Lee et al. (2022) investigated the connections among oil shocks, geopolitical uncertainty, and green bonds in the case of China by using a structural vector autoregression (SVAR) model. Their findings showed that oil-specific demand shocks significantly affect geopolitical uncertainty and green bond dynamics. In a similar vein, Liu et al. (2025) examined the hedging abilities of sustainable investment indices, namely the Dow Jones Sustainability Index and the S&P Green Bond Index, during periods of uncertainty. The authors noted that OVX and VIX exhibit strong volatility clustering and asymmetric behaviour across market conditions. Kumari and Sharma (2025), for their part, analysed the effects of global and local Indian EPU on the green bond market, together with CPU, MPU, and VIX, using a NARDL model. Their results indicated that global EPU negatively affects green bond returns in the long run and positively in the short run, and that investors tend to liquidate green bonds when uncertainty rises due to risk aversion. Finally, Shi and Guo (2025) examined the correlation between green and conventional bond markets and four uncertainty indices, namely EPU, GPR, VIX, and OVX, from a multifractal perspective. Their results showed that green bonds generally exhibit a more risk-averse structure than conventional bonds. Similarly, Bouri et al.

(2024) analysed the effects of three global risk factors, GPR, EPU, and OVX, on the returns of commodity, Islamic equity, and green bond markets across different time horizons. Their findings revealed that PEU and OVX generate volatility across all financial markets and serve as predictors of market returns.

Taken together, the literature suggests that investor sentiment and uncertainty indicators generally have a meaningful effect on green bond markets, and that these effects vary across market conditions and investment horizons, while also exhibiting asymmetric patterns. Nevertheless, the dependence of green bond markets on uncertainty indicators and investor sentiment has generally been assessed in a one-dimensional manner, and studies that jointly analyse dependence structures across different market conditions and time horizons remain limited. Therefore, examining the relationship between green bond markets and market-based sentiment indicators not only through average effects but also under different market conditions and investment horizons is important for positioning this study within the literature. The place of this study in the literature is shaped at this point. In light of the existing literature, VIX and OVX stand out in this study as appropriate market-based indicators reflecting investor sentiment due to their pronounced effects on green bond markets (Pham and Nguyen, 2022; Wang et al., 2022; Bouri et al., 2024; Shi and Guo, 2025; Kumari & Sharma, 2025; Liu et al., 2025). The MOVE index complements this framework by representing bond-market-specific volatility. By considering VIX, OVX, and MOVE simultaneously, this study examines the responses of the green bond market to stock market, energy market, and bond market risk channels through the QC approach. In doing so, it aims to contribute to the literature in both variable selection and the methodological framework.

3. Data and Methodology

3.1. Data

In this study, we analyse the dependencies among the green bond index, global uncertainty, oil price volatility, and bond market volatility. As the green bond index, we use the S&P Green Bond U.S. Dollar Select Index (GB), which measures the performance of green bonds; VIX for global uncertainty; OVX for oil price volatility; and MOVE for bond market volatility. The analysis uses daily return data[3] covering the period from 17 June 2019[4], the initial

3 We obtain the data for GB from www.spglobal.com and the volatility series from investing.com.

4 Although GB was first issued on 17 June 2019, the starting date of the dataset was subsequently extended to 1 May 2009

issuance date of GB, to 31 October 2025. Table 1 presents the descriptive statistics of the return series.

Table 1. Descriptive Statistics

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	ADF
GB	0.007688	0.016111	1.105086	-1.563934	0.245014	-0.472883	6.71297	1001.34	-33.0007
VIX	0.007599	-0.675678	55.41096	-44.24487	7.845525	1.171504	9.785155	3514.64	-43.9901
OVX	-0.001137	-0.44346	85.76998	-62.22508	7.144078	1.832135	28.01279	43589.66	-41.9845
MOVE	-0.022249	-0.176025	37.20052	-29.88781	5.011287	0.422186	8.2437	1924.113	-17.5108

The descriptive statistics illustrate that GB and VIX have positive average returns, whereas OVX and MOVE have negative average returns. While VIX and OVX exhibit the highest standard deviations, GB has the lowest. All series are non-normally distributed according to the Jarque-Bera test and exhibit fat-tailed characteristics, with kurtosis values greater than 3. The ADF test, which examines unit root properties, indicates that all series are stationary in levels. Figure 1 presents time-series plots of the return series.

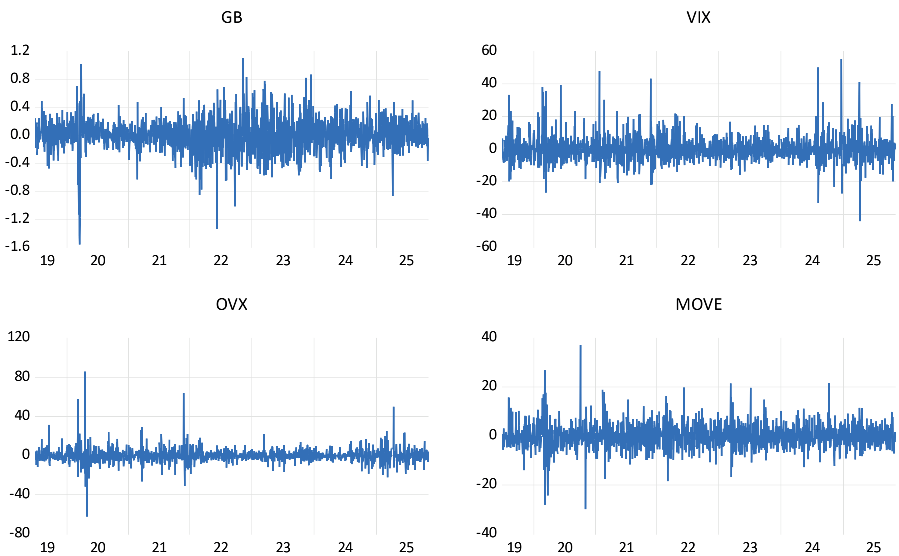


Figure 1. Time Series Plots of Return Series

The plots show that all series vary over time and exhibit outlying observations in certain periods. These outlying observations coincide with periods associated with globally significant economic events. Sharp increases in the volatility of all series are observed in March 2020, which marks the onset of the COVID-19 pandemic. In addition, changes in the volatility of all series can be observed during the initial phase of the Russia-Ukraine War in February 2022 and during the period of the Trump tariff measures in March and April 2025.dir.

3.2. Methodology

To examine the dependencies among the green bond index, VIX, OVX, and MOVE, we employ the QC approach developed by Baruník and Kley (2019). QC reveals the dependence structure between two time series across different quantiles and frequencies. In this way, it allows the dependencies between the series to be analysed under different market conditions and across different investment horizons. It also allows capturing asymmetry in dependence by identifying dependencies at different frequencies when one series rises while the other falls, or vice versa.

$$\nabla^{\mathrm{ij}}\left(r:\tau_{\mathrm{i}},\tau_{\mathrm{j}}\right)=\frac{q^{\mathrm{ij}}\left(r:\tau_{\mathrm{i}},\tau_{\mathrm{j}}\right)}{\sqrt{q^{\mathrm{ii}}\left(r:\tau_{\mathrm{i}},\tau_{\mathrm{j}}\right)q^{\mathrm{jj}}\left(r:\tau_{\mathrm{i}},\tau_{\mathrm{j}}\right)}} \tag{1}$$

Equation 1 is defined for $-\pi<r<\pi$ and $\left(\tau_i,\tau_{\mathrm{j}}\right)\in[0,1]$. Here, $\left(\tau_i,\tau_{\mathrm{j}}\right)\in[0,1]$ and q^{jj} correspond to the quantile spectral densities associated with $i(t)$ and $j(t)$, whereas q^{ij} refers to the cross-spectral density term. These components, namely q^{ii}, q^{jj}, and q^{ij}, are derived from the matrices of quantile cross covariances $\tilde{\mathrm{A}}_n\left(\tau_i,\tau_{\mathrm{j}}\right)=\left(\gamma_n^{\mathrm{ij}}\left(\tau_{\mathrm{i}},\tau_{\mathrm{j}}\right)\right)_{\mathrm{ij}=1,\ldots,k}$ (Baruník and Kley, 2019; Gaies et al., 2024):

$$\gamma_n^{\mathrm{ij}}\left(\tau_{\mathrm{i}},\tau_{\mathrm{j}}\right)=\operatorname{cov}\left(I\left\{\mathrm{i}(t+n)\le f_{\mathrm{i}}\left(\tau_{\mathrm{i}}\right)\right\},I\left\{\mathrm{j}(t+n)\le f_{\mathrm{j}}\left(\tau_{\mathrm{j}}\right)\right\}\right) \tag{2}$$

$I\{S\}$ stands for the indicator function, with $n\in\mathbb{Z}$ and $\left(\tau_i,\tau_{\mathrm{j}}\right)\in[0,1]$. Changes in the lag parameter m convey information about how the dependence structure evolves across the series. Equation 3 defines the quantile cross-spectral density kernel, and Equation 4 specifies the dependence between i and j.

$$q\left(r:\tau_i,\tau_j\right)=\left(q^{\mathrm{ij}}\left(r:\tau_i,\tau_j\right)\right)_{\mathrm{i,j}=1,..k} \tag{3}$$

$$q^{ij}\left(r:\tau_{\mathrm{i}},\tau_{\mathrm{j}}\right)=(2\pi)^{-1}\sum_{k=-\infty}^{\infty}\gamma_n^{\mathrm{ij}}\left(\tau_{\mathrm{i}},\tau_{\mathrm{j}}\right)e^{-xn\omega} \tag{4}$$

Values of $\left|\nabla^{ij}\left(r:\tau_{\mathrm{i}},\tau_{\mathrm{j}}\right)\right|$ approaching -1 or +1 indicate a strong dependence between the variables. In this study, we focus on the median quantile 0.50, the two tail quantiles 0.95 and 0.05 at the same quantile levels for both series, and the cross-tail quantiles 0.05-0.95 and 0.95-0.05. We also present the dependence patterns across short-term (one-week), medium-term (one-month), and long-term (one-year) frequencies.

4. Empirical Results

We use the QC method to examine the dependencies of the green bond index with VIX, OVX, and MOVE. This method enables the identification of dependencies between the green bond index and VIX, OVX, and MOVE at the same and cross quantiles, and across different time frequencies. We report the results for the same quantile levels, lower 0.05-0.05, median 0.5-0.5, and upper 0.95-0.95 and for the cross quantile levels 0.05-0.95 and 0.95-0.05 in Figures 2 and 3. For each variable pair, we present the Real (Re) and Imaginary (Im) components separately across different quantile levels. While Re shows the strength of comovement between variables across different quantiles and time frequencies, Im reveals the lead-phase effect and shows which variable moves first across these quantiles and time frequencies. In this way, it allows the dependence structure under different market conditions to bear, normal, and bull and across different investment horizons to be observed, together with the lead-lag responses of the variables across market states. In addition, the relationships at opposite quantiles reveal the degree of comovement when one variable is declining, and the other is rising, and indicate which variable responds earlier across different time horizons, thereby capturing asymmetric relationships under extreme conditions.

Figures 2 and 3 present the QC results for the green bond index relative to VIX, OVX, and MOVE. The graphs in the left panel display the Re component at different quantile levels and time frequencies, whereas those in the right panel display the Im component at the same levels and frequencies. The x axis indicates the degree of comovement across weekly, monthly, and yearly cycles and across different frequencies for Re, while for Im, it shows which variable responds first. Positive values indicate the green bond index, and negative values indicate the volatility series. The y axis defines different time-frequency domains. Since the observation period is daily, the reciprocal of the value on the y axis gives the number of days for example, 0.2 on the y axis corresponds to 5 days.

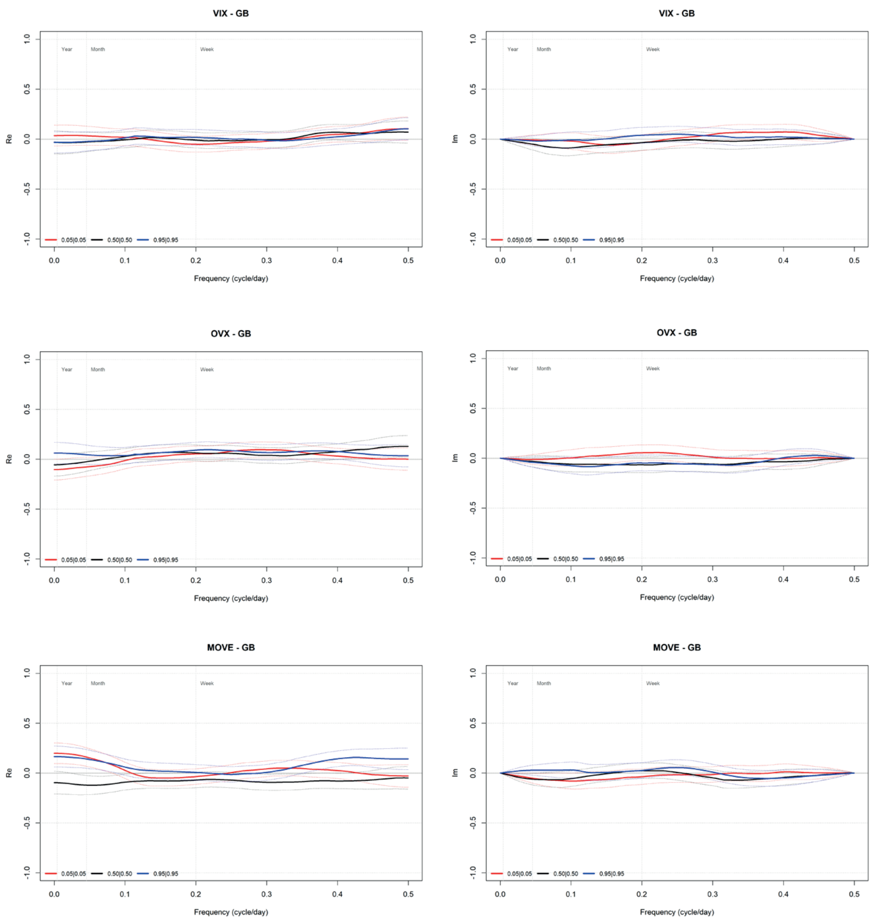
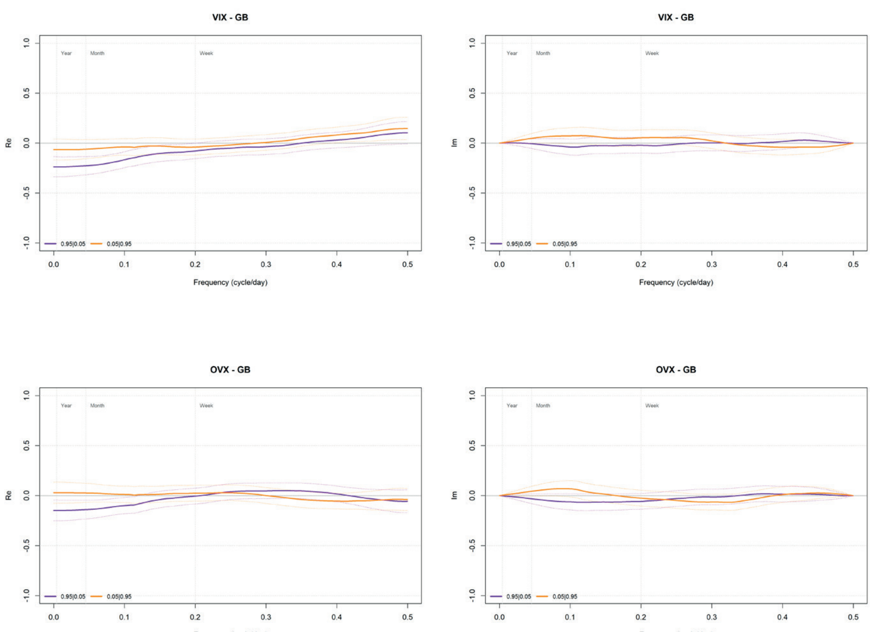


Figure 2. Dependence between GB and Volatility Indices at the Same Quantile Levels

The QC graphs show that the dependencies between GB and the volatility indices are generally weak. While the Re components indicate that the dependence with VIX and OVX remains close to zero across all quantile levels, the dependencies at higher frequencies are relatively stronger. This finding suggests that the effects of shocks are more immediate rather than persistent. The dependencies with OVX are positive at high frequencies, whereas at low frequencies they turn negative except at the upper quantile level 0.95. The positive association between increases in oil price volatility and the green bond index in the long run indicates that green bond indices are sensitive to systematic risks originating from energy markets. The dependencies with MOVE, by contrast, vary across both quantile levels and frequencies. At the median quantile level 0.5, the dependence with MOVE is more negative than at the tail quantiles 0.05 and 0.95. At the upper quantile level 0.95, the dependencies at both high and low frequencies, as well as the low frequency dependencies at the other quantile levels 0.05 and 0.5, are statistically significant. This finding shows that the dependence of the green bond index on MOVE is more pronounced in the long run and is also clearer than the dependencies observed with the other volatility indices considered. In addition, the positive dependencies at the upper quantile level indicate that extreme volatility in the bond market may suggest that shifting toward the green bond index to avoid risk and diversify bond containing portfolios could have the potential to serve as an effective risk management strategy. The Im components show that lead-lag relationships vary across quantiles and frequencies and that although the green bond index generally appears to lead, these effects are statistically insignificant. This finding indicates that there is no delayed transmission of uncertainty shocks from the volatility indices to the green bond index. Figure 3 presents the QC results for conditions in which the green bond index is in decline (0.05) while the volatility indices are in an upward phase (0.95), and vice versa.



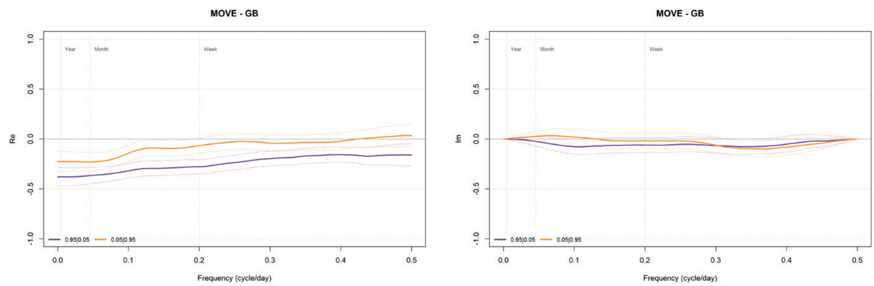


Figure 3. Dependence between GB and Volatility Indices at Cross Quantile Levels

The QC findings at cross quantiles display stronger dependence than those at the same quantile levels. However, these dependencies vary with market upturns and downturns, as well as across investment horizons. The dependence on VIX shifts from positive to negative across high and low frequencies. Under conditions in which VIX is rising while GB is in a downward phase, 0.95-0.05, the negative dependence at low frequencies and over the long-term investment horizon is statistically significant. Under market conditions in which VIX is declining while GB is in an upward phase, 0.05-0.95, the positive dependence at high frequencies is significant. This finding indicates that shocks associated with rising market uncertainty and increases in the VIX are reflected in declines in the green bond index over the long run, whereas the dependence observed during periods of declining market uncertainty is more short-lived and manifests as increases in the green bond index. The dependence between increases in OVX and declines in green bonds is negative in the long run, indicating that green bond indices are more sensitive to oil price shocks than during tranquil periods. In addition, the Re components show that the dependence of increases and decreases in MOVE with decreases and increases in green bonds is negative and statistically significant in the long run. This finding supports the results obtained at the same quantiles and underlines that the dependence between MOVE and green bond indices is more pronounced than that observed for the other volatility indices. The negative relationship observed when MOVE declines while GB is in an upward phase also suggests that bond market investors' shift toward GB may serve as an effective portfolio diversification strategy. As with the same quantile levels, the Im components are statistically insignificant.

The findings show that although the dependence between green bond returns and volatility indices is generally weak, it contains clear heterogeneity and asymmetry depending on frequency and market conditions. In particular, the fact that the dependence on MOVE is more pronounced and more persistent than that on the other volatility indices indicates that bond market-related risks have a more lasting effect on the green bond market. By contrast, the generally insignificant Im components suggest that volatility shocks are not transmitted to the green bond market with a lag and that the relationship is largely contemporaneous. Taken together, the findings indicate that the green bond market exhibits a dependence structure against volatility shocks that varies across frequencies and market conditions, but remains limited overall.

Conclusion

This study examined the dependence structure between the green bond market and VIX, OVX, and MOVE by using the quantile coherence approach. The findings show that the relationship between green bond returns and these volatility indicators is generally weak, but varies across frequencies and market conditions. In particular, the results obtained under the same and cross quantiles reveal that the dependence structure is asymmetric and regime sensitive. The results further indicate that the dependencies with VIX and OVX remain limited in most cases (unlike Bouri et al. 2024 and Liu et al. 2025), whereas the relationship with MOVE is more pronounced and especially more persistent in the long run. This finding suggests that the green bond market is more sensitive to bond market volatility than to general market fear or oil market volatility. The fact that cross-quantile dependencies are stronger than those at the same quantile levels also shows that the green bond market responds more clearly under asymmetric market conditions. By contrast, the generally statistically insignificant imaginary components indicate that the relationship is largely contemporaneous rather than driven by a lagged transmission mechanism. The findings have important implications for investors and policymakers. For investors, the results show that green bonds are not fully insulated from volatility shocks, but that this sensitivity varies depending on the source of risk. While the relatively weak dependence on VIX and OVX suggests that green bonds may offer some diversification benefits, the more pronounced dependence on MOVE indicates that interest rate and bond market conditions should be monitored more closely. For policymakers, the findings suggest that the green bond market should be supported not only in line with environmental objectives, but also within a framework that strengthens bond market stability, liquidity conditions, and the long-term investor base. Among the limitations of this study is the analysis conducted within a single green bond index and a limited number of market-based volatility indicators. In addition, although the quantile coherence approach reveals the dependence structure across the quantile and frequency dimensions, it does not allow the time evolution of these relationships to be directly tracked. Future studies may use different indices representing green bond markets and may contribute to a more comprehensive assessment of how the green bond market responds to investor sentiment by incorporating news-based, text-based, or survey-based sentiment measures in addition to market-based indicators. In addition, adopting a dynamic framework to examine how the dependence structure changes over time may contribute to a more comprehensive evaluation of the responses of the green bond market to sentiment shocks.

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