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Research Article

New Frontiers in Sustainable Finance: Asymmetric Risk Connectedness of Green Bonds with Global Financial Markets

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Abstract

Purpose: This paper explores the asymmetric and state-dependent dependence relationship of the S&P Green Bond Index with six international markets and assesses whether such dependence patterns are correlated with the risk-reduction benefit associated with holding a green bond portfolio.

Design/Methodology: The analysis is based on 2,856 aligned daily log returns of the S&P Green Bond Index, S&P 500, DAX, Shanghai Composite, S&P GSCI, S&P Bitcoin Index, and S&P Global Clean Energy Index from 2 January 2014 to 30 April 2026. Quantile-on-Quantile Regression (QQR) is computed. An economic significance is measured using long-only two-asset minimum variance portfolios.

Findings: The findings show that there is significant asset and state-specific dependence. The minimum-variance portfolios invest relatively heavily in green bonds due to the significantly reduced unconditional volatility and yield significant in-sample variance reductions, but do not show universal hedging or safe-haven performance.

Practical Implications: Green bonds should be considered as a state contingent, low volatility diversifier and not a universally defensive or safe haven asset. Market-state stress testing, asset-specific dependence and currency exposure are to be taken into consideration by investors and portfolio managers as part of their allocation decision.

Originality: The present study is an incremental cross-market extension of the existing body of work, and then connecting asymmetric dependence estimates to formal portfolio evidence.

Introduction

Sustainable finance has grown rapidly, reshaping the global financial system and drawing investors' attention to environmentally responsible investment instruments. Among these instruments, green bonds stand out as one of the most powerful innovations in climate finance, enabling the financing of environmentally sustainable projects while providing institutional and individual investors with such investment opportunities (Hadhri et al., 2025; Nguyen et al., 2021). The global green bond market has grown significantly since the European Investment Bank issued the first green bond in 2007, reflecting growing awareness of climate change, carbon emissions, environmental degradation, and the transition to a sustainable economy. Green bonds are increasingly being used by governments, corporations and international financial institutions to fund renewable energy initiatives, energy efficiency programs, clean transportation and more (Monk & Perkins, 2020; World Bank, 2019). Consequently, green bonds are increasingly seen not only as investment products with ethical implications, but as a class of financial instruments with significant portfolio diversification, hedging, and risk-management attributes (Ben Ameur et al., 2024; Reboredo et al., 2020; Yadav et al., 2023).

As green finance has become more embedded in international capital markets, much discussion has focused on the degree of dependence of green bonds on conventional financial markets. Financial markets are very interdependent and a shock in one market can spread quickly to other markets, especially during economic and financial uncertainty (Pham & Nguyen, 2021; Reboredo & Ugolini, 2020; Rehan et al., 2024; Yadav et al., 2023). Thus, the connection between green bonds and key global financial markets is of paramount importance to investors and portfolio managers as well as policymakers in shaping resilient and sustainable investments. There are many ways in which green bonds have been reported to be linked, to more or less extent, to conventional bonds, stock markets, commodity markets, cryptocurrencies and clean energy assets (Aarif et al., 2022; Asiri et al., 2023; Nguyen et al., 2021; Reboredo & Ugolini, 2020). The relationships, however, are not fixed and frequently vary over market regimes, investment time frames, and market extremes. These asymmetric dynamics are often not well captured by the traditional econometric techniques which are based on mean-based estimations (Rizvi et al., 2022; Tiwari et al., 2025; Wu et al., 2025; Zhao & Park, 2024).

Moreover, the recent global financial environment, further emphasized the necessity of analyzing green bond dependence structures. Financial markets faced unprecedented uncertainty due to the pandemic, and the markets for equities, commodities, energy and cryptocurrencies experienced extreme volatility (Rehan et al., 2024; Yadav et al., 2023; Zhao & Park, 2024). In crisis times, there can be an increase in the correlation of financial assets, which can decrease the diversification opportunities available to investors. On the other hand, some research indicates that green bonds may exhibit characteristics of a relatively stable and resilient investment during crisis times due to their defensive and sustainability nature (Chai et al., 2025; Meo et al., 2026). Hence, it is worthwhile to empirically examine whether green bonds do provide diversification and hedging in times of market stress and whether its dependence with other international financial markets varies in bullish, bearish and normal markets.

In this context, the present study explores how green bonds are related to key international financial markets such as the S&P 500, DAX, Shanghai Composite Index, S&P GSCI Commodity Index, Bitcoin market and S&P Clean Energy Index. The paper adopts the Quantile-on-Quantile Regression (QQR) methodology to account for asymmetry of the dependence of green bonds on explanatory financial markets with respect to different quantiles (Shah et al., 2026; Yildirim & Mejri, 2026). The QQR methodology enables us to examine the relationship between different quantiles of green bond returns and other quantiles of financial markets, which is not possible with traditional regression methods. This pattern is especially helpful when it is used to spot a dependence pattern in the extreme bearish, regular and bullish markets (Baur, 2013; W. Jiang et al., 2025).

Thus, the study offers a more complete picture of market interdependence than do traditional mean-based methods.

The overarching research question in the present study is whether the asymmetric dependence between green bond returns and major international financial markets depends on market state and quantile and whether there is a measurable portfolio diversification, hedging, and risk-reduction effect. In order to answer this question, the study has three interrelated objectives. Firstly, it analyzes the asymmetric dependence between green bonds and the selected international financial markets, such as S&P 500 index, DAX index, Shanghai composite index, S&P GSCI index, bitcoin, and S&P global clean energy index, by applying a Quantile-on-Quantile Regression (QQR) framework (Sim & Zhou, 2015). Secondly, it examines the differences in these dependence relationships under bull market, bear market, and normal market conditions, which is measured by the upper quantile, the median quantile, and the lower quantile (Aarif et al., 2022). Third, the study quantifies the economic and portfolio consequences of the identified dependence structure by using the minimum-variance portfolio approach to analyze the in-sample risk reduction and diversification benefits of combining green bonds with the financial assets selected. The study also analyzes the empirical evidence on the diversification, hedging and safe haven attributes of green bonds, which is often touted as a fact but is essentially a theoretical stance in the green bond market, and whether these attributes are different across asset classes and market conditions.

This study has a number of significant theoretical contributions to the literature. First, it contributes to the increasing literature on sustainable finance by offering extensive evidence on the nonlinear and quantile-based dependence structure among green bonds, and between green bonds and a set of international financial markets (Nguyen et al., 2021; Reboredo & Ugolini, 2020; Shah et al., 2026; Sim & Zhou, 2015; Yadav et al., 2024). Second, the paper adds to a growing literature on the connectedness of markets by exploring the asymmetric dependence during extreme market conditions, thereby improving the understanding of the behavior of green bonds under different economic conditions. Third, the study contributes to the theoretical debate on Modern Portfolio Theory and considers the potential of green bonds as an asset class that can stand on their own to enhance the efficiency of portfolios and diversification benefits (BaŞci & Meo, 2024; Vihervuori, 2023; Zhang, 2025).

Practically, the study offers evidence for investors, portfolio managers and sustainable-finance institutions by highlighting the variation of green-bond dependence across counterpart markets and return states. The results can help investors find scenarios where green-bond inclusion can lead to lower in-sample portfolio variations, but the analysis does not yield an optimal allocation, a formal safe haven or a policy-induced stability effect. For policymakers the findings are relevant primarily as a way to better understand and monitor interdependencies between cross-market as they relate to green financial assets, but not necessarily to suggest policy interventions.

The rest of this paper is structured as follows. Section 2 provides a review of literature and theoretical interpretation. Section 3 presents the data, diagnostics, QQR estimator, inference procedure and portfolio calculations. Section 4 describes the empirical results, robustness checks, portfolio results, and implications. Section 5 concludes, states the limitations and identifies practically feasible directions for future research.

Literature Review

Evolution and Growth of the Green Bond Market

The focus on climate change, environmental degradation and sustainable economic development has increased the growth of sustainable finance. Green bonds have proven to be a vital funding tool for renewable energy, energy efficiency, clean transport, climate adaptation, and other sustainable environmental projects (Cortellini & Panetta, 2021). The modern green bond market emerged after the European Investment Bank's Climate

Awareness Bond issued in 2007 and World Bank's first green bond labelled issuance in 2008. The market was initially led by supranational institutions, and subsequently grew as governments, corporations and municipalities as well as financial institutions began to implement green financing mechanisms (Cortellini & Panetta, 2021; Ibrić et al., 2024).

In addition, investor demand for green financial instruments continued to grow since the Paris Climate Agreement was adopted in 2015 and the growing popularity of Environmental, Social and Governance (ESG) investing. Thus, green bonds have become more than just a niche instrument of financing, increasingly playing an integral role in the international capital markets and sustainable investment strategies (Driessen, 2024).

The growth of the green bond market has also spurred the academic interest in understanding its pricing efficiency, volatility behavior, connectedness with traditional financial markets, and portfolio diversification potential (Ferrer et al., 2021). At first, the literature mostly concentrated on the pricing features and yield spreads of green and conventional bonds. In recent studies, however, the dependence structure between green bonds and other asset classes (e.g., equities, commodities, energy markets, and cryptocurrencies) has become a focus of study (Kamal & Bouri, 2025; Nguyen et al., 2021; Vihervuori, 2023; Yadav et al., 2024). This increasing embedding of green bonds in global finance systems highlights the significance of the diversity and safe-haven properties of green bonds in times of economic and financial turmoil (Arif et al., 2022; Asiri et al., 2023; Tiwari et al., 2025). The financial markets were extremely volatile during the pandemic, and investors had to rethink their portfolio management strategies. In this context, green bonds secured significant attention for their relatively calm performance and strength in times of market turmoil. As a result, green bonds have emerged as a key theme in sustainable finance literature as a possible hedging and diversification instrument.

Theoretical Background: Modern Portfolio Theory and Diversification

This study's theoretical background is the Modern Portfolio Theory (MPT) introduced by Markowitz (1952). MPT argues that investors should consider the assets together since the risk of the portfolio is not only the variance of the individual assets' returns, but also the covariance between the assets' returns. Portfolio diversification, therefore, may lower the risk of the portfolio while not impacting the portfolio's expected return (Markowitz, 1952)

The expected return on an asset portfolio is given by:

$$\mathbf{E(R\_p) = \Sigma(w\_i\ E(R\_i))}$$

where:

- E(R_p) = expected portfolio return
- w_i = weight of asset iii in the portfolio
- E(R_i) = expected return of asset iii

Similarly, the risk of a two-asset portfolio is expressed as:

$$\boldsymbol{\sigma^2\_p = w^2_1\sigma^2_1 + w^2_2\sigma^2_2 + 2w_1w_2Cov(R_1, R_2)}$$

where:

- σ^2_p = portfolio variance
- $\sigma1,\sigma2$ = standard deviations of individual assets
- Cov (R_1, R_2) = correlation coefficient between two assets

This framework indicates that the portfolio risk can be significantly lowered if the relationship between the different asset classes is low or negative. The covariance is especially significant because the diversification gain is related to the lack of perfect correlation between asset prices. Assets that are negatively or not highly correlated can help to offset losses during periods of market decline, enhance portfolio stability and risk adjusted returns.

Modern Portfolio Theory is more relevant in green finance, as investors are always looking for financial assets that can offer diversification and hedging benefits during times of uncertainty. Given their sustainability focus, the investor base and the changing market dynamics of green bonds relative to traditional financial assets, green bonds offer the potential to be an interesting diversifying investment (Arif et al., 2022). Therefore, it is necessary to analyze the dependence structure between green bonds and international financial markets to see whether green bonds can indeed decrease the portfolio risk and boost the investment efficiency.
The diversification angle is even more significant in times of financial crisis and times of market volatility. During times of trouble, traditional assets like equities and commodities can become very highly correlated, which diminishes diversification possibilities. Green bonds, if they continue to be found to have weak or asymmetric dependence with these markets, could be used as effective hedging or safe haven assets (Chai et al., 2025; Mensi et al., 2023; Tiwari et al., 2025). Thus, the present study aims to empirically explore the diversification benefits of green bonds under various market conditions and quantiles, based on the above foundation, by extending Modern Portfolio Theory framework.

Green Bonds and International Financial Markets

Green Bonds and Equity Markets

Much attention has been paid to the link between green bonds and stock markets in the literature on connectedness. Equity markets define the overall economic landscape and investor sentiment and thus play an important role in determining the behavior of financial markets. Overall, research findings on green bond nexus with major stock exchanges like the S&P 500, DAX, and Shanghai Composite Index show that the nexus is time varying and asymmetric. During normal times, some studies find that green bonds are less connected to the stock markets, but more connected during crises when market uncertainty increases.

The S&P 500 index is an indicator of the U.S. equity market and is widely regarded as an indicator of worldwide financial performance. Because of the preeminence of the U.S. economy in international finance, shocks from the S&P 500 are likely to affect other markets. Some existing literature shows some degree of connectedness of green bonds with the U.S. equity market, with a tendency to increase this connectedness during times of financial stress like the COVID-19 pandemic (Mensi et al., 2023).

In the same way, the DAX index shows the performance of the big companies of Germany and Europe and is a vital indicator of the financial situation in Europe. Europe is regarded as one of the top regions in sustainable finance and green bond issuance. Therefore, the green bond–European equity market connection might be distinct from other markets because of the high level of ESG integration and climate-focused investment policies (Haranen, 2024; Nerlinger, 2020).

The Shanghai Composite Index is a symbol of the financial sector in China—the country that has rapidly emerged as one of the world's largest green finance markets (Guo et al., 2023). Growth of the green bond market has been driven by China's government's firm support for environmental financing and sustainable development. The existing research indicates that the dependence characteristics in China's markets on green bonds might be different, given regulatory frameworks, market segmentation and state-led financial policies.

Green Bonds and Commodity Markets

The commodity markets are an integral part of global economic activity and are very much linked to inflation, energy prices and industrial production. The broadest commodity market performance is typically measured by the S&P GSCI Commodity Index. Previous research shows that commodity markets are typically volatile and cyclical, particularly in periods of economic and geopolitical crises (Naeem, Nguyen, et al., 2021).

The linkage between green bonds and commodities in theory is significant as commodities are linked to carbon-intensive industries, while green bonds are intended to support environmentally sustainable projects. Several studies have indicated that green bonds can offer protection against commodity market risks as the fundamentals of these markets are different. But in times of economic turmoil and inflationary pressures, linkage to these markets may be stronger.

Green Bonds and Cryptocurrency Markets

The literature on financial market connectedness has been expanded by the booming development of cryptocurrencies, especially Bitcoin. Bitcoin is known for its volatility and speculation, with significant fluctuations in price and investor sentiment. The existing literature on the link between green bonds and Bitcoin markets is controversial. Although some researchers claim that Bitcoin is not correlated with traditional financial assets creating opportunities for diversification, others believe that cryptocurrencies are even more integrated with the wider financial markets during crises (Kamal & Bouri, 2025; Zhao & Park, 2024).

The connection between green bonds and Bitcoin is especially intriguing, given the stark contrast in risk profiles, investor types, and their respective sustainability implications. Bitcoin mining activities have frequently been criticized for their environmental impact due to high energy consumption, whereas green bonds are fundamentally linked with environmental sustainability. Thus, it is crucial to consider the asymmetric dependence of both these markets, in order to have a sustainable portfolio management.

Green Bonds and Clean Energy Markets

Clean energy markets and green finance go hand in hand considering that renewable energy and environment-friendly projects are often funded through the issuance of green bonds. The S&P Global Clean Energy Index is an index of companies that engage in renewable energy and clean technologies. Overall, existing literature indicates that the linkage of green bonds and clean energy markets is tighter than that of green bonds and traditional financial markets because they have a common sustainability focus.

But clean energy markets are also technologically uncertain, policy sensitive, and volatile. Thus, the impact of green bonds on clean energy markets can be large and different depending on the market conditions and quantiles. The two markets can do well in the same direction during the time of environmental policies incentive and green investment growth (Aloui et al., 2025). However, economic downturns and energy market disruption could have a negative impact on this relationship.

Comparative Empirical Literature on Connectedness and Quantile-Based Approaches

In this chapter, we will examine the empirical literature comparing the various approaches and methods of measuring quantiles and discuss some issues that need further consideration. There is significant variation across previous studies in terms of the markets they cover, the methodology used, the empirical approach and interpretation. This methodological diversity is helpful for understanding the value of the evidence, and it also limits the ability to make direct comparisons of the evidence across asset classes.

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Table 1. Comparative Empirical Literature on Connectedness and Quantile-Based Approaches

Study	Markets/Assets	Method	Period/Empirical Focus	Main Finding	Limitation/Relevance to Present Study
Reboredo & Ugolini (2020)	Green bonds and financial markets	Price connectedness	Pre-/early green-finance development period	Green bonds exhibit meaningful connectedness with conventional markets	Does not map dependence across joint quantile states
Nguyen et al. (2021)	Green bonds, stocks, commodities, clean energy and conventional bonds	Time-frequency/wavelet analysis	Multiple investment horizons	Connectedness varies across frequencies	Focuses on horizons rather than joint quantile combinations
Pham & Nguyen (2021)	Green bonds and multiple asset classes	Asymmetric tail dependence	Tail-market conditions	Dependence differs between normal and extreme states	Tail-focused rather than a common multi-market QQR design
Naeem, Nguyen, et al. (2021)	Green bonds and commodities	Extreme-quantile approach	Extreme market conditions	Commodity dependence is asymmetric	Concentrates mainly on one counterpart asset class
Jiang et al. (2022)	Green bonds and conventional financial markets	QQR and quantile coherence	Full-sample cross-market analysis	Dependence varies across quantiles and frequencies	Demonstrates that QQR is already established in green-bond research
Mensi et al. (2023)	Green bonds, global factors and stocks	Frequency spillovers	Before and during COVID-19	Connectedness varies under financial stress	Event/frequency focus rather than common QQR comparison
Zhao & Park (2024)	Green bonds, cryptocurrencies and conventional markets	Quantile time-frequency spillovers	Quantile and frequency states	Dependence differs across states and horizons	Different methodological framework and asset composition
Kamal & Bouri (2025)	Green bonds, stocks, cryptocurrencies and commodities	Multiscale and portfolio analysis	Multiple scales	Portfolio benefits differ by asset and investment scale	Does not provide the same common QQR comparison across the six markets considered here
Present study	Green bonds, S&P 500, DAX, Shanghai Composite, S&P GSCI, Bitcoin and Clean Energy	QQR and minimum-variance portfolio analysis	2014–2026; bearish, normal and bullish quantile states	Evaluates state-dependent dependence and corresponding portfolio risk-reduction evidence	Provides a consistent comparative framework across heterogeneous markets

Comparative evidence shows that the research on quantitative research and the use of QQR as a method are not new in the field of green bonds (Y. Jiang et al., 2022; Zhao & Park, 2024). Likewise, there are already a number of studies related to portfolio applications (Kamal & Bouri, 2025). Thus, novelty of the present study cannot be claimed to be the introduction of quantile analysis or portfolio analysis either alone or together. Rather, it is due to the specific implementation of a common state-dependent QQR framework in six markets that are very different internationally where there is formal minimum variance portfolio evidence.

Research Gap and Justification of the Study

Although much research has been done in the field, there are three related gaps in the literature. First, there is methodological and market heterogeneity that makes it difficult to compare the results of the various studies. In the literature, the various combinations of financial assets are used in previous studies to compute time-frequency connectedness (Nguyen et al., 2021; Pham & Nguyen, 2021), spillover indices (Y. Jiang et al., 2022), asymmetric tail dependence (Zhao & Park, 2024), extreme-quantile methods, and QQR. Thus, the evidence that is gathered for one asset or methodological setting is not necessarily directly comparable to evidence gathered for another asset or a different methodological setting. A common empirical specification, then, which is consistently employed in the various economically different markets could give clearer comparative evidence.

Secondly, past research often concentrates on one or more specific asset classes or more limited group of markets. While there has been some prior research on equities, commodities, cryptocurrencies and clean energy assets, there is comparatively little evidence from a single QQR framework that incorporates a comparison across green bonds, the U.S., European, Chinese, commodities, Bitcoin and clean energy equities. Such markets are associated with specific geographic, macroeconomic, speculative and sustainability risks, and it is especially relevant to compare such markets when implementing an international portfolio allocation.

Thirdly, statistically dependent data does not necessarily result in economically significant diversification. The portfolio outcome is also influenced by the variance of each asset and the covariance of each asset pair, which can be limited if the coefficient of the QQR is low. The dependence analysis should be supplemented by the portfolio optimization. The present study tackles this issue by combining QQR estimates with the minimum variance portfolio analysis method, to determine if state-dependent relationships are correlated with in-sample risk reduction of the portfolio.

Therefore, the present study is seen as an incremental and not a methodological first. Uses a uniform QQR specification for the S&P 500, the DAX, the Shanghai composite index, the S&P GSCI, Bitcoin, and the S&P Global Clean Energy index and combines these estimates with the evidence of minimum variance portfolios. The design also enables the study to examine whether the dependence on green bonds in different market regimes (bearish, normal, and bullish) have economically significant portfolio implications. The study, therefore, tests empirically if the diversification, hedging and safe-haven properties of green bonds as widely believed are substantiated or are dependent on the other asset and the state of the market.

Methodology

Data Description and Market Representation

The data set includes seven global market Indexes daily closing prices for each day spanning from up 1 January 2014 to 30 April 2026. In this analysis, five market indexes data are collected from S&P Global Indexes which are S&P 500, S&P GSCI, S&P Green Bond Index, S&P Bitcoin Index, and S&P Global Clean Energy Index all indexes are reported in USD. Data for the DAX and Shanghai Composite (SSE Composite) series was downloaded from Yahoo Finance and kept in their original currencies EUR and CNY/RMB, respectively. The

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common price sample has 2,857 observations from 2 January 2014 to 30 April 2026, where 2856 daily logarithmic differencing returns values are generated in this period. Complete case alignment: No interpolating, forward filling or substitutions are applied to weekends or holidays specific to the market. All the pairwise QQR estimates in this treatment are based on the same information dates by omitting the Bitcoin-only weekend observations.

Table 2. Description of Markets and Measurement Indices

Market	Exact index	Asset class	Provider / data source	Ticker / symbol	Currency	Return basis
Green bonds	S&P Green Bond Index	Sustainable fixed income	S&P Dow Jones Indices; Bloomberg ID	SPUSGRN Index	USD	Price return
U.S. equities	S&P 500 Index	Developed equity	S&P Dow Jones Indices; Bloomberg ID	SPX Index	USD	Price return
Bitcoin	S&P Bitcoin Index	Digital asset	S&P Dow Jones Indices; Bloomberg ID	SPBTC Index	USD	Price return
Clean energy	S&P Global Clean Energy Index	Transition equity	S&P Dow Jones Indices; Bloomberg ID	SPGTCLEN Index	USD	Price return
Commodities	S&P GSCI	Real asset	S&P Dow Jones Indices; Bloomberg ID	SPGCCI Index	USD	Spot index
Chinese equities	SSE Composite Index	Emerging-market equity	Yahoo Finance	SS; SHCOMP	CNY/RMB	Price return
German equities	DAX Performance Index	Developed equity	Yahoo Finance	GDAXI; DAX Index	EUR	Gross-return / performance

Notes: DATA-SOURCE AND CURRENCY NOTE: DAX and the SSE Composite are sourced from Yahoo Finance and are held in EUR and CNY/RMB, respectively. All other indexes are in U.S. dollars. S&P/Bloomberg Tickers are indicated for the indices provided on an index-details sheet. The official/Bloomberg Ticker for the former clean-energy index name is SPGTCLEN, while the current S&P Global Clean Energy Transition Index price-return ticker is SPGTCED. †SHCOMP/000001 and DAX Index are the supplied official/Bloomberg Tickers for the series corresponding to the Yahoo Finance index name.

The logarithmic return series was calculated using the following formula:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \times 100$$

where $R_{i,t}$ is the daily percentage return of market i and $P_{i,t}$ is the daily closing index level of market i. The currency does not get converted prior to the calculation of the return. The returns in the indices are therefore calculated in USD, whereas those in the DAX and SSE Composite stay in EUR and CNY/RMB, respectively. The corresponding dependence estimates from the QQRs between DAX and Shanghai are derived in the local-index-return space, not in the common-USD space for the investors. As such, realized returns on those exposures would also be sensitive to exchange rate changes, which are not included in the baseline model and which are considered a limitation in Section 5. This distinction is of special significance for the portfolio analysis. The DAX and Shanghai based portfolio calculations are comprised of observed returns reported in various currencies and are not meant to be actual allocations for a USD-based or other common-currency investor but rather local-currency illustrations of covariance and variance-reduction potential. If an investor wants to convert all the component returns into the same base currency, exchange-rate returns and its covariance with the underlying assets would also be part of the portfolio returns. Therefore, no investment suggestion is implied from the weights of the DAX and Shanghai portfolios presented herein in common-currency.

Descriptive Statistics and Stationarity

Volatility, asymmetry, fat tails and normality are assessed using descriptive statistics. The Jarque–Bera test is used to check normality and the augmented Dickey–Fuller (ADF) test is used to check the unit-root null with lag length determined by the Bayesian information criterion. All of the ADF tests fail the unit root test and all of the Jarque–Bera tests reject normality, indicating that stationary returns are appropriate and that a quantile based estimator should be used.

Table 3. Descriptive statistics and unit-root tests for daily returns

Market	Mean	SD	Min	Max	Skew.	Kurt.	Jarque–Bera	ADF	Obs.
S&P GB	-0.0006	0.4721	-4.4419	10.3928	4.462	105.243	1,249,047.5	-48.973	2856
S&P 500	0.0480	1.1149	-12.7652	9.0895	-0.664	19.347	31,891.5	-17.437	2856
S&P Bitcoin	0.1603	4.2714	-26.2716	22.8430	-0.039	7.391	2,285.2	-53.145	2856
Clean Energy	0.0229	1.6664	-12.4971	14.6326	-0.113	11.862	9,313.7	-48.472	2856
S&P GSCI	0.0075	1.4565	-12.5233	7.9820	-0.867	10.848	7,658.3	-53.980	2856
Shanghai Composite	0.0234	1.2940	-8.8729	7.7551	-0.875	11.340	8,608.3	-51.994	2856
DAX	0.0332	1.2456	-13.0549	10.4143	-0.608	13.448	13,115.1	-54.390	2856

Note. Returns are percentage daily log returns. All Jarque–Bera and ADF p-values are < .001.

Quantile-on-Quantile Regression

QQR allows for an estimation of how a quantile θ of the returns of the green bond is related to a quantile τ of the returns of a selected counterpart market. The logic of the unknown conditional relationship is followed locally with linear QQR, similar to Sim and Zhou (2015). For every pair, the loss function to be minimized is a linear combination of quantile losses:

$$\min_{a,\beta} \Sigma_t\, \varrho_\varphi[R^{GB}{}_t - a(\theta,\tau) - b(\theta,\tau)(R^M{}_t - q^M(\tau))]\; K((F^M(R^M{}_t) - \tau)/h)$$

The check-loss function is denoted as ϱ_φ, the return of the counterpart at time τ is denoted as $q^M(\tau)$ while the empirical distribution function of the return is denoted as F^M. K is the Gaussian kernel and h is the bandwidth. The quantile grid reported is {0.10, 0.25, 0.50, 0.75, 0.90} where 0.10 and 0.25 are bearish states, 0.50 is considered as normal, and 0.75 and 0.90 are bullish states. In the baseline QQR specification, the Gaussian-kernel bandwidth is set at h = 0.05 ex ante, consistent with the existing literature in the field (Sim & Zhou, 2015). The bandwidth controls the typical bias-variance dilemma of local estimation: a tighter bandwidth will put more weight on observations near the target quantile, but at the expense of greater variability in the estimation, while a wider bandwidth will give more smoothing but also may prevent capturing the local heterogeneity. A smoothing value of h = 0.05 is used for all six market pairs because the study is comparative and the smoothing value is the same across all of the market pairs. A data driven selector based on market-specific data, like cross-validation, was therefore not used for the baseline as it would select different smoothing levels for different markets, adding another layer of variability to the cross-market comparison. The choice of baseline value is not an approximation of the optimum, but rather a modelling choice and robustness is tested by re-estimating all of the QQR matrices for h = 0.03 and h = 0.07.

Estimation was performed with scikit-learn's QuantileRegressor and SciPy's HiGHS solver as well as stats models were used through Python 3 estimation. The paper reports the local slope b(θ,τ) along with an asymptotic standard error of this slope (based on a kernel-sandwich formula) and a two-sided p value and a 95% confidence interval for the slope in each cell. The variance estimator is based on a weighted design matrix and a weighted Gaussian estimate of the residual density at zero. In the baseline analysis, no bootstrap is used and inference is based on the kernel-sandwich approximation that is stated in the baseline analysis, with block-bootstrap confidence intervals for future research identified as a robustness extension. This procedure gives a statistical inference to the entire reported coefficient matrices, without interpreting the QQR as a causal model.

Portfolio Calculations

To measure economic significance, a long-only minimum variance portfolio is constructed for every counterpart market as well as for green bonds on a global level. The balance of a green bond that spreads its cost evenly across all the bonds is:

$$\mathbf{w^{*GB} = [\sigma^{2M} - Cov\ (R^{GB}, R^{M})]\ /\ [\sigma^{2GB} + \sigma^{2M} - 2Cov(R^{GB},R^{M})]}$$

All weights are bounded by 0 and 1. The analysis results are presented as green-bond weight, counterpart weight, annualized return, annualized volatility, a zero-risk-free-rate Sharpe ratio and variance reduction compared to the counterpart market holding only. These are calculations that are descriptive of the in-sample portfolio.

Results and Discussion

Distributional Evidence

Green bonds' daily standard deviation is the lowest (0.472%), while Bitcoin is the highest (4.271%). The returns of green-bond markets are strongly positively skewed, extremely leptokurtic and all of the seven markets fail normality tests. Evidence of distribution confirms that averages are not enough and supports a state dependent quantile analysis. The large green-bond weights found later in the minimum-variance portfolios must be interpreted primarily in view of the significantly lower sample volatility of the green bonds, rather than as evidence of their superior return performance.

QQR dependence across market states

The five-by-five QQR surfaces are displayed as heat maps in Figure 1. All panels share the same colour scale and asterisks indicate that $p < .05$ at the level of the kernel-sandwich standard errors. Matrices of numbers are presented in every QQR market segment. There are significant cross market differentials, and sign changes, in the estimates, therefore general conclusions of uniformly positive or uniformly defensive behavior are not warranted.

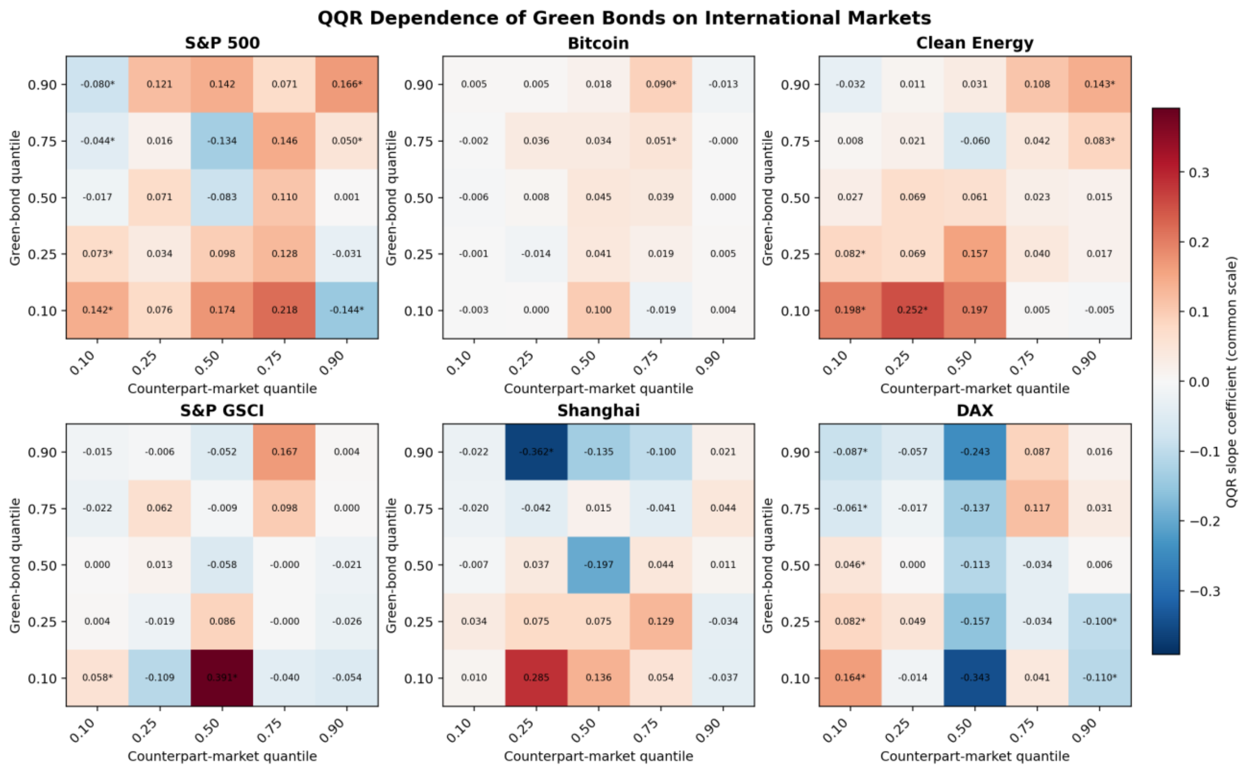

Figure 1. QQR coefficient heat maps with a common colour scale

*Note. The rows denote quantiles of green bonds; the columns denote quantiles of counterpart markets. * indicates p < .05. Coefficients quantify the conditional association, but not the causal transmission.*

Green Bonds and S&P 500

The QQR heat map and surface plot show that there is a generally positive relationship between the S&P Green Bond Index and the S&P 500 Index in most quantile combinations. The highest positive dependence occurs in the lower quantiles, especially if both markets are in bear phases.

The S&P 500 exhibits positive dependence when both markets are bearish (0.142, $p = .001$) and when both markets are bullish (0.166, $p < .001$). There are a few off-diagonal cells that are negative, such as bearish green bonds and bullish U.S. equities. The pattern reflects that there is association a function of the state, and not a fixed stable equity beta. The finding aligns with recent studies which have shown that the characteristics of green-bond relationships differ by market state and time horizon (Y. Jiang et al., 2022; Zhao & Park, 2024).

Table 4. Mean Quantile Values

Quantile Region	**Mean QQR Coefficient**
Lower Quantiles (0.05–0.30)	0.041–0.067
Middle Quantiles (0.35–0.65)	0.008–0.019
Upper Quantiles (0.70–0.95)	0.021–0.038

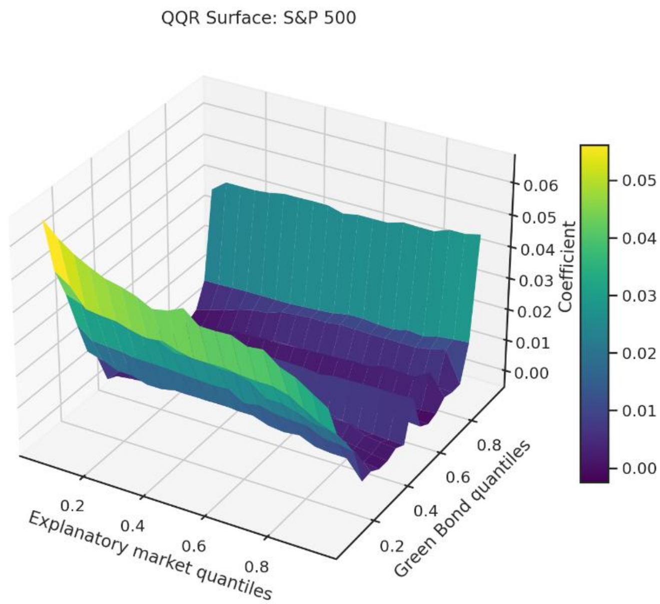

Figure 2. Three-Dimensional QQR Surface Plot: Green Bonds and S&P 500

Figure 2 includes the three-dimensional QQR surface plot illustrating the nonlinear dependence structure between Green Bonds and the S&P 500 market across all quantile combinations.

From the results it can be inferred that Green Bonds are partly linked with the developed equity markets. At times of severe declines in the market, diversification benefits are diminished as markets become more synchronized. But Green Bonds are relatively independent and provide a good diversification in normal circumstances (Nguyen et al., 2021).

In terms of portfolio, results are consistent with the principle of MPT that covariance is important for risk mitigation. From a practical perspective, the results indicate that state-dependent dependence should be taken into consideration when evaluating green-bond/equity diversification; but this in-sample study does not examine a dynamic trading and rebalancing strategy.

Green Bonds and Bitcoin Market

The weakest link among the markets analyzed is the one between Green Bonds and Bitcoin. The surface plot is relatively flat and the QQR heat map has very low coefficients for most quantiles.

Bitcoin has the lowest mean absolute QQR coefficient of the six counterpart markets. Most of the cells are not measurably different from 0 and a few upper state combinations exhibit some positive dependence. While it can offer diversification opportunities, weak dependence does not render Bitcoin appropriate for conservative investors due to its standalone volatility, which is more than nine times that of green bonds. The QQR evidence thus does not imply a specific 'best portfolio mix'.

Table 5. Mean Quantile Values

Quantile Region	**Mean QQR Coefficient**
Lower Quantiles (0.05–0.30)	0.001–0.006
Middle Quantiles (0.35–0.65)	0.000–0.004
Upper Quantiles (0.70–0.95)	0.005–0.021

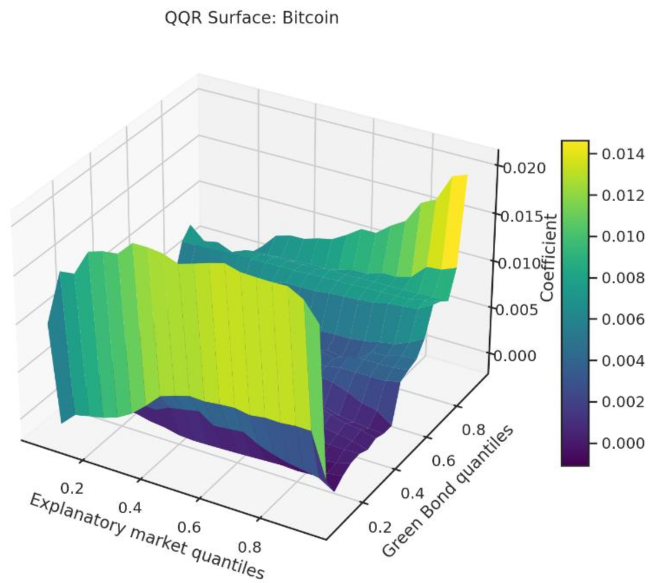

Figure 3. Three-Dimensional QQR Surface Plot: Green Bonds and Bitcoin

Figure 3 presents the QQR surface plot for Green Bonds and Bitcoin, showing weak dependence and relatively flat coefficient structures.

Based on the findings, it can be concluded that Green Bonds and Bitcoins have highly different risk profiles. Bitcoin has high volatility and is very speculative while Green Bonds are fixed-income instruments that are tied to sustainability goals. That QQR is not that strongly correlated with QQQ suggests diversification potential but it does not necessarily create a hedge or a safe haven relationship. The minimum-variance results illustrate, in-sample, the risk-reduction potential of using a low-volatility benchmark of green bonds to complement the far more volatile Bitcoin index.

The results on the theoretical side are in line with the diversification argument that the opportunity for risk reduction increases with lower dependence. In practice, this combination might require additional risk reduction tests but, in the current study, nothing more than the in-sample minimum variance calculation was warranted.

Green Bonds and Clean Energy Market

The most remarkable sustainability-related comovement is displayed by Clean Energy. Joint bearish dependence is 0.198 and joint bullish dependence is 0.143 with a statistically significant value. This decreases diversification when the two markets are in the same extreme condition and further reinforces the notion of locating the market in an environmentally aligned condition, leading to thematic concentration. Aloui et al. (2025) and Chai et al. (2025) both report on such 'green-bond–clean-energy integration'.

Table 6. Mean Quantile Values

Quantile Region	Mean QQR Coefficient
Lower Quantiles (0.05–0.30)	0.048–0.081
Middle Quantiles (0.35–0.65)	0.036–0.052
Upper Quantiles (0.70–0.95)	0.055–0.078

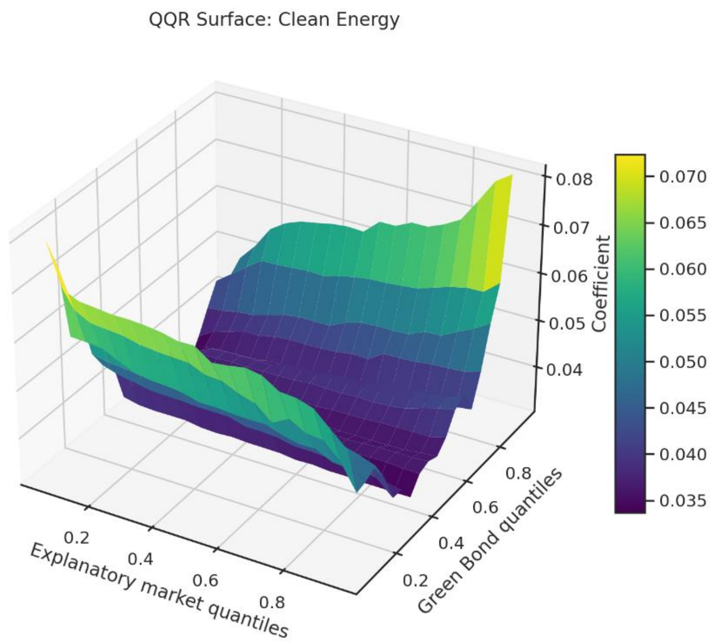

Figure 4. Three-Dimensional QQR Surface Plot: Green Bonds and Clean Energy Market

Figure 4 presents the QQR surface plot demonstrating the strongest dependence structure between Green Bonds and the Clean Energy market.

The results indicate that there is a sustainable finance ecosystem between Green Bonds and Clean Energy assets. Thus, diversification opportunities among these assets are relatively low compared to other markets. The higher correlation between Green Bonds and clean-energy stocks suggests that, for ESG investors, acquiring two assets with sustainability labels is not necessarily the best way to achieve greater diversification. Based on this, allocation decisions should therefore not be based on the common sustainability classification, but should take their measured covariance and standalone risk, as well.

Green Bonds and Commodity Market (S&P GSCI)

There is mixed dependence with commodities. Positive and negative off diagonal elements show up in the full matrix, and the joint bearish coefficient is positive and significant (0.058), while most normal or upper state diagonal elements are statistically insignificant. In the more positive states, diversification is lower in that state.

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Table 7. Mean Quantile Values

Quantile Region	Mean QQR Coefficient
Lower Quantiles (0.05–0.30)	0.028–0.069
Middle Quantiles (0.35–0.65)	0.005–0.017
Upper Quantiles (0.70–0.95)	0.012–0.031

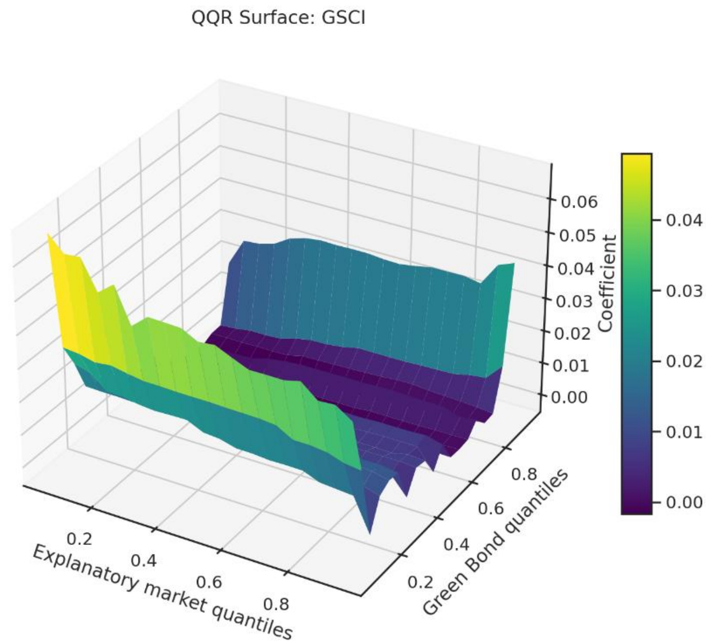

Figure 5. Three-Dimensional QQR Surface Plot: Green Bonds and S&P GSCI
Figure 5 presents the QQR surface plot for Green Bonds and the S&P GSCI commodity market, showing asymmetric dependence across extreme quantiles.

The findings reveal both state-dependent and heterogeneous association between green bonds and commodity. Selected lower return quantiles show possible decreases in diversification in these states, other quantile combinations are weak or mixed.

The primary implication for investors is to consider commodity-related diversification as a function of market state rather than on average. The QQR estimates do not reveal the macroeconomic, energy-price or crisis mechanism which is behind the observed association.

Green Bonds and Shanghai Composite Index

The Shanghai relationship is heterogeneous, and is estimated on the diagonal, but not very precisely. The isolated cell of a significant negative estimate when combined with weak equity conditions in China does not warrant a general hedge classification, although a negative estimate does happen in the context of bullish green bonds.

The dependence is stronger in some lower quantile combinations than the middle quantiles, which suggests that the relationship can vary in joint lower return states and does not necessarily reflect a dated crisis effect.

The mild positive estimates for the upper quantiles suggest state-dependent association in joint upper return combinations, but do not provide any clear evidence of an economic expansion effect.

Table 8. Mean Quantile Values

Quantile Region	Mean QQR Coefficient
Lower Quantiles (0.05–0.30)	0.014–0.038
Middle Quantiles (0.35–0.65)	0.006–0.015
Upper Quantiles (0.70–0.95)	0.010–0.026

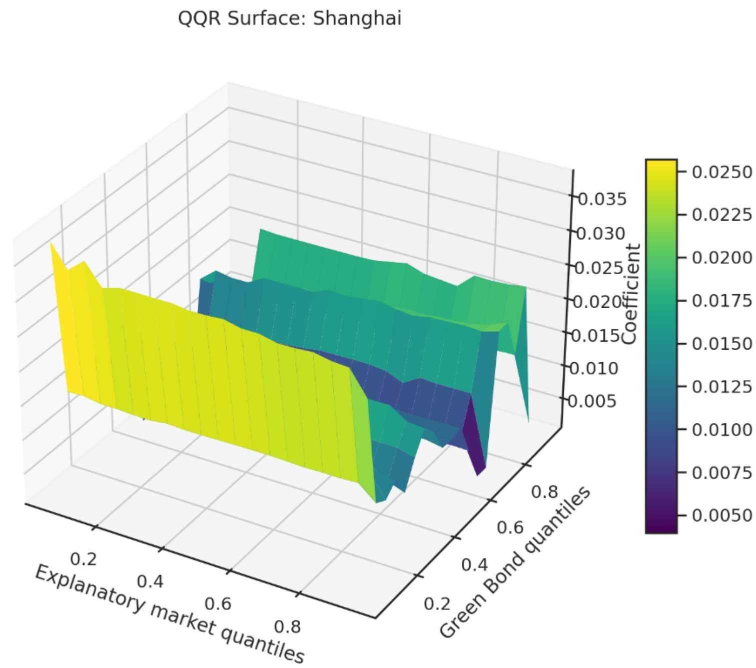

Figure 6. Three-Dimensional QQR Surface Plot: Green Bonds and Shanghai Composite Index

Figure 6 illustrates the QQR surface plot between Green Bonds and the Shanghai Composite Index, showing heterogeneous and mostly modest dependence across quantile combinations.

The results expressed that the Shanghai relationship is state-dependent rather than uniformly positive. No time trend is identified in the convergence of financial markets by the QQR results.

From a practical perspective, the results suggest diversification opportunities in some states, and that any cross-border allocations with Shanghai require an initial investment currency conversion of both the return series. This current local-currency outcome should be interpreted, therefore, as indicative of local-currency investment recommendations.

Green Bonds and DAX Index

The DAX relationship is state-dependent. Joint bearish dependence is positive and significant, several combinations of middle and top quantiles are weak and/or negative, and many of the quantile combinations are statistically equivalent to zero. Thus, the evidence suggests that DAX should not be considered a general diversifier or hedge, but rather a conditional diversifier in certain states. The lower quantile outcomes are not necessarily to be considered as crisis times, but as joint low-return states.

Table 9. Mean Quantile Values

Quantile Region	**Mean QQR Coefficient**
Lower Quantiles (0.05–0.30)	0.009–0.058
Middle Quantiles (0.35–0.65)	-0.004–0.011
Upper Quantiles (0.70–0.95)	-0.021–0.006

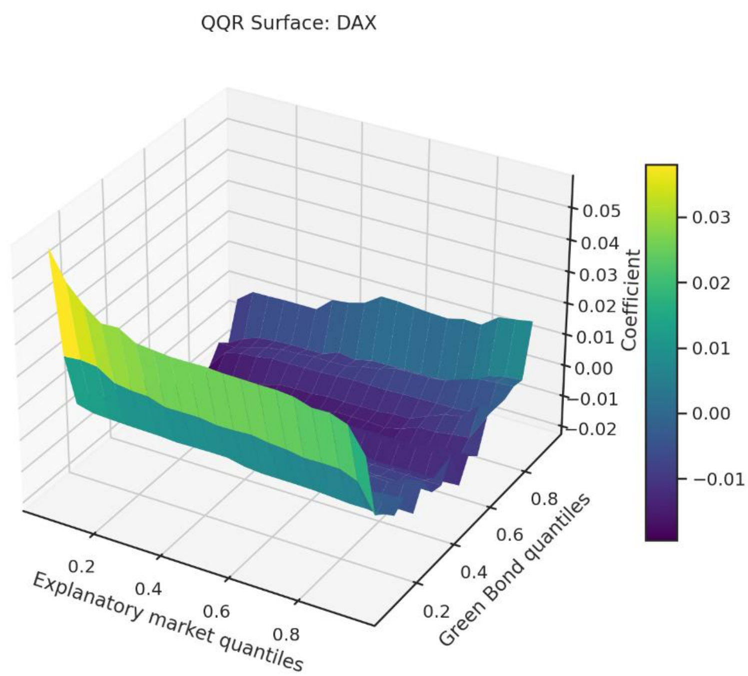

Figure 7. Three-Dimensional QQR Surface Plot: Green Bonds and DAX Index
Figure 7 presents the QQR surface plot for Green Bonds and the DAX Index, showing asymmetric and partially negative dependence structures.

The results show that the diversification contribution of the Green Bond-DAX pair is not necessarily stronger or weaker than the one of the other equity pairs, but dependent on the combination of quantiles.

From a portfolio perspective, the mixed DAX-dependency mix might help to reduce risk in some states, the current evidence suggests that a stabilizing effect cannot be generally assumed. Furthermore, the calculation of the DAX portfolio is still a local-currency example and the current dollars are not yet converted into the base-currency of the investor.

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Table 10. Representative diagonal QQR estimates and 95% confidence intervals

Counterpart market	State combination	Estimate	95% CI	p
S&P 500	Joint bearish (0.10, 0.10)	0.142	[0.057, 0.227]	0.001
S&P 500	Joint normal (0.50, 0.50)	-0.083	[-0.376, 0.210]	0.577
S&P 500	Joint bullish (0.90, 0.90)	0.166	[0.082, 0.250]	0.000
S&P Bitcoin	Joint bearish (0.10, 0.10)	-0.003	[-0.024, 0.019]	0.786
S&P Bitcoin	Joint normal (0.50, 0.50)	0.045	[-0.025, 0.115]	0.205
S&P Bitcoin	Joint bullish (0.90, 0.90)	-0.013	[-0.033, 0.006]	0.180
Clean Energy	Joint bearish (0.10, 0.10)	0.198	[0.133, 0.263]	0.000
Clean Energy	Joint normal (0.50, 0.50)	0.061	[-0.099, 0.222]	0.455
Clean Energy	Joint bullish (0.90, 0.90)	0.143	[0.084, 0.201]	0.000
S&P GSCI	Joint bearish (0.10, 0.10)	0.058	[0.007, 0.108]	0.026
S&P GSCI	Joint normal (0.50, 0.50)	-0.058	[-0.246, 0.131]	0.548
S&P GSCI	Joint bullish (0.90, 0.90)	0.004	[-0.070, 0.078]	0.923
Shanghai Composite	Joint bearish (0.10, 0.10)	0.010	[-0.046, 0.066]	0.720
Shanghai Composite	Joint normal (0.50, 0.50)	-0.197	[-0.429, 0.035]	0.096
Shanghai Composite	Joint bullish (0.90, 0.90)	0.021	[-0.047, 0.089]	0.541
DAX	Joint bearish (0.10, 0.10)	0.164	[0.074, 0.254]	0.000
DAX	Joint normal (0.50, 0.50)	-0.113	[-0.364, 0.138]	0.377
DAX	Joint bullish (0.90, 0.90)	0.016	[-0.072, 0.104]	0.725

Bandwidth Robustness

Estimates with $h = 0.03$ and $h = 0.07$ are compared to the baseline signs. Table 11 indicates that the 80% to 92% cell sign preservation characteristic of smoother $h = 0.07$ specification seems more stable compared to the narrower $h = 0.03$ specification, particularly in the case of DAX and commodities. The overall findings (low Bitcoin dependence, sluggish comovement of Clean Energy stocks and commodity stocks, and equity and commodity signs are state-specific) remain clear, but each cell is not necessarily structurally stable. However, $h = 0.05$ is kept as the base case as it offers some smoothing between the narrower and wider cases, and the sensitivity results demonstrate that the main bottom-line findings are not specific to this particular bandwidth.

Table 11. Bandwidth sensitivity of the QQR matrices

Market	Mean |Δ|, h=.03	Sign agreement, h=.03	Mean |Δ|, h=.07	Sign agreement, h=.07
S&P 500	0.111	76%	0.040	92%
S&P Bitcoin	0.038	72%	0.012	88%
Clean Energy	0.055	88%	0.018	92%
S&P GSCI	0.088	68%	0.023	88%
Shanghai Composite	0.128	88%	0.047	88%
DAX	0.081	56%	0.030	80%

Minimum-variance Portfolio Evidence

This section provides illustrative in-sample minimum-variance portfolio calculations and not specific portfolio recommendations. The long-only portfolios allocate between 86.8% and 99.3% to green bonds, mainly because green bonds are much less volatile than the counterpart markets in the sample. The resulting variance reductions can be seen as a mechanical risk-reduction effect of blending the less-volatile fixed-income asset with more volatile assets, but do not necessarily reflect a higher risk-adjusted return, given the low Sharpe ratios. Some series of equities have been reported in USD; the DAX and Shanghai rows are local-currency illustrations as their equity indexes are not reported in the same investor currency as the green-bond series. Calculations do not result in safe-haven behavior in an external crisis.

Table 12. Long-only two-asset minimum-variance portfolios

Pair with green bonds	Correlation	GB weight	Other weight	Ann. return	Ann. volatility	Sharpe	Variance reduction
S&P 500	0.077	86.8%	13.2%	1.47%	7.08%	0.207	84.0%
S&P Bitcoin	0.050	99.3%	0.7%	0.13%	7.48%	0.017	98.8%
Clean Energy	0.164	96.6%	3.4%	0.06%	7.44%	0.008	92.1%
S&P GSCI	0.008	90.7%	9.3%	0.05%	7.15%	0.007	90.5%
Shanghai Composite	0.012	88.6%	11.4%	0.55%	7.07%	0.077	88.2%
DAX	0.036	88.4%	11.6%	0.85%	7.09%	0.120	87.1%

Note. The risk free rate would be zero for the reported Sharpe ratio. Variance reduction is the reduction in variance compared to a counterpart market. Results do not include transaction costs and are in-sample. The DAX and Shanghai rows represent local-currency illustrations and are not directly usable common-currency portfolios. The USD- or other base-currency investor would have to translate all component returns back into the investor currency and include the currency risk prior to reweighting the portfolio and recalculating risk measures.

Investor, Managerial, and Policy Implications

The key investment implication is that low unconditional volatility does not necessarily mean state dependent protection. While green bonds have been paired with significant in-sample variance reduction with the chosen higher-volatility assets, the dependence of QQR is different depending on the market pair and return state. The results thus argue for a state-sensitive assessment of portfolios instead of a general description of defensive, hedge or safe-haven portfolios. Specifically, low dependence of Bitcoin should not be read in isolation from the high stand-alone volatility of bitcoin and high dependence of the Green Bond-clean energy market suggests that a shared sustainability orientation does not necessarily imply higher diversification.

For asset managers and institutional investors, the results support the use of market-state scenarios as an additional risk-monitoring input. The minimum-variance weights reported are in-sample allocations and are not necessarily appropriate for a particular investor's return, liquidity, duration or liability or transaction-cost preferences. DAX and Shanghai results should also be viewed as local currency index returns and thus cannot be foreseen as direct implementations for a common currency investor without explicit currency conversion.

The evidence is relevant most directly for policy makers and market institutions to monitor the integration and risk characteristics of green financial assets. There is no testing of regulatory, monetary, disclosure reform or green-bond issuance policy effects on financial stability. The policy implication is therefore only to promote transparent reporting of currency, return construction and other benchmark attributes that have an impact on the interpretation and comparability of sustainable-finance investments.

Conclusion, Limitations, and Future Research

This study employs a well-documented QQR framework with transparency to re-estimate the dependence of green bonds on six international markets and then incorporates in-sample minimum-variance portfolio calculations. The results do not provide a one-size-fits-all categorization of green-bond dependence of the markets. The joint bearish dependence is strongly positive for the S&P 500, Clean Energy and DAX while the joint bullish dependence is strongly positive for S&P 500, Clean Energy but not for DAX. Bitcoin shows the lowest overall dependence while the commodity, Shanghai and DAX relationship is different in various quantile combinations. The results are indicative of a conditional diversification interpretation which does not argue for a universal hedge or safe-haven classification.

The minimum-variance results also reveal that the relatively low unconditional volatility and covariance of green bonds can lead to significant in-sample variance reductions in conjunction with more volatile counterpart assets. However, the results should not be interpreted as investor-specific allocation recommendations as the analysis does not take into account return targets, transaction costs, liquidity constraints, out-of-sample rebalancing or for the DAX and the Shanghai a common investor currency.

There are six main limitations to the study. Firstly, DAX and the SSE Composite is analysed in their native currency (EUR and CNY/RMB), while the other indices are analysed in USD; the DAX and Shanghai portfolio rows are therefore not the common-USD investor returns. Second, the closing of common dates may not adequately account for non-synchronous closing effects from region to region and from data source to data source. Third, the QQR model models contemporaneous dependence, and fails to detect causal transmission. Finally, sensitivity checks are provided for $h = 0.03$ and $h = 0.07$ but the five-point quantile grid and fixed baseline bandwidth $h = 0.05$ are modelling choices, not data-driven optima. Fifth, baseline statistical inference is based on the kernel-sandwich approximation, instead of the block bootstrap. Sixth, the portfolio analysis is aggregate, long-only, two-asset and in-sample and the DAX/Shanghai portfolio rows are illustrative until the returns of the assets are expressed in a common investor currency.

Future research should be done in practical extensions. The first step is to translate all market returns into a common currency investor currency with a help of the market exchange rates at the time of the investment and then to compare the estimates with the baseline available in the local currency, especially for the DAX and Shanghai. Daily and weekly specifications can then be compared to eliminate the non-synchronous closing concerns. A rolling QQR design would allow for a clear definition of pre-COVID, COVID and post-COVID time periods, and not infer pandemic effects from the full sample coefficients. Additional inference strength would be gained by block-bootstrap confidence intervals, out-of-sample rebalancing with transaction costs and comparison to the traditional indexes of government bonds and corporate bonds. Finally, the bonds can be classified based on the bond's issuer, maturity, rating, currency, geographical region, and external bond certification to investigate whether the overall performance of the green bond index averages out the economically significant variations within the index.

Declaration

Funding:

This research received no external funding.

Conflicts of Interest:

The authors declare no conflict of interest.

Ethics Statement:

Ethics approval was not required for this study because it is based exclusively on secondary analysis of Financial Market Indexes, a publicly available and fully anonymized dataset collected by S&P Indexes and Yahoo Finance. The authors did not interact with human participants and had no access to personally identifiable information. Ethical review and informed consent procedures for the original data collection were the responsibility of Financial Index Provider, and the data were used in accordance with the provider's terms of use.

Data Availability Statement:

The data used in this study are based on publicly available financial market indices. The index series were obtained from recognized financial data providers and can be accessed by researchers through the relevant data platforms, subject to their respective licensing and access conditions. The authors can provide details on the index identifiers, sample period, and data construction procedure upon reasonable request.

Use of Generative AI:

No generative AI tools were used in the preparation of this manuscript.

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Appendix.

Complete QQR Coefficient Matrices

Each market pair matrix represents the local QQR slope. Rows represents the green-bond quantiles and columns are counterpart-market quantiles. ** p < .01; * p < .05 based on kernel-sandwich standard errors.

Table A1. Green bonds and S&P 500

GB q \ Market q	0.10	0.25	0.50	0.75	0.90
0.10	0.142**	0.076	0.174	0.218	-0.144**
0.25	0.073**	0.034	0.098	0.128	-0.031
0.50	-0.017	0.071	-0.083	0.110	0.001
0.75	-0.044*	0.016	-0.134	0.146	0.050*
0.90	-0.080**	0.121	0.142	0.071	0.166**

Table A2. Green bonds and Bitcoin

GB q \ Market q	0.10	0.25	0.50	0.75	0.90
0.10	-0.003	0.000	0.100	-0.019	0.004
0.25	-0.001	-0.014	0.041	0.019	0.005
0.50	-0.006	0.008	0.045	0.039	0.000
0.75	-0.002	0.036	0.034	0.051*	-0.000
0.90	0.005	0.005	0.018	0.090*	-0.013

Table A3. Green bonds and Clean Energy

GB q \ Market q	0.10	0.25	0.50	0.75	0.90
0.10	**0.198****	**0.252***	**0.197**	**0.005**	**-0.005**
0.25	**0.082****	**0.069**	**0.157**	**0.040**	**0.017**
0.50	**0.027**	**0.069**	**0.061**	**0.023**	**0.015**
0.75	**0.008**	**0.021**	**-0.060**	**0.042**	**0.083****
0.90	**-0.032**	**0.011**	**0.031**	**0.108**	**0.143****

Table A4. Green bonds and S&P GSCI

GB q \ Market q	0.10	0.25	0.50	0.75	0.90
0.10	**0.058***	**-0.109**	**0.391***	**-0.040**	**-0.054**
0.25	**0.004**	**-0.019**	**0.086**	**-0.000**	**-0.026**
0.50	**0.000**	**0.013**	**-0.058**	**-0.000**	**-0.021**
0.75	**-0.022**	**0.062**	**-0.009**	**0.098**	**0.000**
0.90	**-0.015**	**-0.006**	**-0.052**	**0.167**	**0.004**

Table A5. Green bonds and Shanghai Composite

GB q \ Market q	0.10	0.25	0.50	0.75	0.90
0.10	**0.010**	**0.285**	**0.136**	**0.054**	**-0.037**
0.25	**0.034**	**0.075**	**0.075**	**0.129**	**-0.034**
0.50	**-0.007**	**0.037**	**-0.197**	**0.044**	**0.011**
0.75	**-0.020**	**-0.042**	**0.015**	**-0.041**	**0.044**
0.90	**-0.022**	**-0.362****	**-0.135**	**-0.100**	**0.021**

Table A6. Green bonds and DAX

GB q \ Market q	0.10	0.25	0.50	0.75	0.90
0.10	0.164**	-0.014	-0.343	0.041	-0.110**
0.25	0.082**	0.049	-0.157	-0.034	-0.100**
0.50	0.046*	0.000	-0.113	-0.034	0.006
0.75	-0.061**	-0.017	-0.137	0.117	0.031
0.90	-0.087**	-0.057	-0.243	0.087	0.016