

Asymmetric Risk Sensitivity of Low-Carbon Assets: Dynamic Wavelet Quantile Correlation and Beta Analysis

Halilibrahim GÖKGÖZ¹

Abstract

This study examines the sensitivity of low-carbon equity indices in developed and emerging markets to global market uncertainty, oil price volatility, and inflation expectations. In the analysis, we employ the wavelet quantile correlation approach, which decomposes the dependence structure across investment horizons and market conditions, and we dynamically extend both the wavelet quantile correlation framework and the quantile beta measures derived from wavelet quantile correlation through a rolling-window methodology to move beyond static correlation analysis. The empirical findings reveal that developed market low-carbon indices exhibit stronger negative dependence on global market uncertainty, particularly in the VIX channel, whereas the DM-EM distinction in the OVX channel is less systematic over time. The dynamic results further show that dependence and exposure vary across quantiles and over time, while the T5YIE channel exhibits a more heterogeneous dynamic pattern. Overall, the results show that the diversification benefits of low-carbon assets vary depending on market conditions, investment horizon, and the level of market development.

Keywords: Low Carbon Indices, Global risk factors, Dynamic Wavelet Quantile Correlation (DWQC), Dynamic Wavelet Quantile Beta (DWQB).

JEL Codes: C58, G11, G15, Q54

Düşük Karbonlu Varlıkların Asimetrik Risk Duyarlılığı: Dinamik Dalgacık Kantil Korelasyon ve Beta Analizi

Öz

Bu çalışma, gelişmiş ve gelişmekte olan piyasalardaki düşük karbonlu hisse senedi endekslerinin küresel piyasa belirsizliği, petrol fiyat oynaklığı ve enflasyon beklentilerine duyarlılığını incelemektedir. Analizde, yatırım ufukları ve piyasa koşulları boyunca bağımlılık yapısını aydınlatan dalgacık kantil korelasyon yaklaşımını kullanıyoruz ve statik korelasyon analizinin ötesine geçmek için hem dalgacık kantil korelasyon çerçevesini hem de dalgacık kantil korelasyondan türetilen kantil beta ölçümlerini kayan pencere metodolojisiyle dinamik olarak genişletiyoruz. Ampirik bulgular, gelişmiş piyasalardaki düşük karbonlu endekslerin küresel piyasa belirsizliğine, özellikle VIX kanalında, daha güçlü negatif bağımlılık sergilediğini; buna karşılık OVX kanalında DM-EM ayrımının zaman içinde daha az sistematik olduğunu göstermektedir. Dinamik sonuçlar ayrıca bağımlılık ve maruziyetin kantiller ve zaman boyunca değiştiğini, T5YIE kanalının ise daha heterojen bir dinamik yapı sergilediğini ortaya koymaktadır. Genel olarak sonuçlar düşük karbonlu varlıkların çeşitlendirme faydalarının piyasa koşullarına, yatırım ufkuna ve piyasaların gelişmişlik düzeyine göre değiştiğini göstermektedir.

Anahtar Sözcükler: Düşük Karbon Endeksleri, Küresel risk faktörleri, Dinamik Dalgacık Kantil Korelasyon (DWQC), Dinamik Dalgacık Kantil Beta (DWQB).

JEL Kodları: C58, G11, G15, Q54

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1. Introduction

Global financial markets have brought about a paradigmatic shift in the thinking processes of both policymakers and investors towards financial innovations and the greening of the financial system, together with the pricing of climate risks, concerns over the irreversibility of climate change, and the acceleration of the low-carbon transition (Henriques & Sadorsky, 2018; Gökgöz et al., 2025). In the transition to a low-carbon economy, investors seek to diversify their portfolios with green assets (Arif et al., 2022) while questioning their resilience to traditional risk factors (Dutta et al., 2020). However, because financial asset returns often deviate from normality and investors' risk perceptions vary across investment horizons, mean-centred linear frameworks may be limited in specific regimes. Indeed, the descriptive statistics for our dataset (see Table 1) show that the series exhibit pronounced skewness and high kurtosis; that the Jarque–Bera test rejects normality; and that this further underscores the need for a methodology that accounts for tail behaviour. A distinct source of heterogeneity arises from differences in investors' investment horizons. The Fractal Market Hypothesis (FMH), proposed by Peters (1994) and arguing that markets are not homogeneous, offers a more realistic theoretical framework for analysing investor behaviour across short-, medium-, and long-term time scales and emphasises that heterogeneity in investment horizons can shape market dynamics (Kristoufek, 2013; Konak & Türkoğlu, 2024). Thus, while non-normality and tail behaviour motivate the consideration of different market conditions, investment-horizon heterogeneity motivates the examination of dependence across different time scales.

In the literature, alongside studies that examine the performance of low-carbon assets mainly through mean and volatility focused dynamic models (Tan et al., 2021; Wang et al., 2025), there are also studies showing that risk spillovers display an asymmetric structure depending on market conditions and investment horizons (Hasan et al., 2024; Doğan et al., 2025). In this context, our study is based on the WQC approach, which decomposes the dependence structure along both the frequency (investment horizon) and quantile (market condition) dimensions (Kumar & Padakandla, 2022). The main advantage of WQC is that it makes visible how dependence varies not only in the mean case but also across different quantiles and different time scales.

To better understand the pricing dynamics of low-carbon assets, it is necessary to extend the analytical framework to incorporate global risk sentiment and energy market uncertainties. In the literature, Bajra et al. (2025) emphasise the decisive role of the global market uncertainty (VIX) index, which represents global risk appetite, on green assets and energy markets, while Gökgöz et al. (2025) document the strong connectedness of this index with sustainable (blue and green) ETFs. With respect to energy market risks, Dutta et al. (2020) note that the oil volatility index (OVX) may serve as a diversification instrument for clean energy stocks, whereas Wang et al. (2026) show that carbon price fluctuations are sensitive to developments in the crude oil market and to shocks

originating from the crude oil market.

The emphasis on frequency heterogeneity in the carbon price inflation nexus has become increasingly prominent in recent empirical studies. For instance, strong spillover effects between carbon returns and inflation, which differ across time scales, have been documented, with short-term components often driving overall connectedness (Xu & Lien, 2024). Moreover, evidence indicating that carbon prices can raise inflation expectations suggests that climate policies may be transmitted to investment decisions through the macro-financial risk channel (Hensel et al., 2024). From the perspective of the green energy system, some findings emphasise that the effects of shocks may vary across regimes and with the role of markets (Hanif et al., 2025).

In this study, we analyse the dependence of the MSCI World Low Carbon Target (DM) and MSCI Emerging Markets Low Carbon Target (EM) indices on the VIX, the OVX, and the 5-year breakeven inflation rate (T5YIE) across different quantiles and frequencies using the WQC framework. In the first stage, WQC heat maps are employed to illustrate how dependence varies along the quantile and frequency dimensions; in the second stage, we use dynamic WQC (DWQC) and dynamic quantile beta (DWQB) to capture the time-varying dimension of this framework. The static WQC results indicate that correlations between VIX and OVX and the low-carbon indices are generally negative across different quantiles and frequencies; in contrast, the relationship with T5YIE diverges from volatility indicators, exhibiting a positive structure at the median quantile while weakening markedly at the lower and upper quantiles. In the DM–EM comparison, the finding that the absolute correlations of DM are higher than those of EM across most regions in the VIX and OVX channels suggests that the developed-market low-carbon index responds more strongly to short-term risk conditions.

The dynamic analysis (reported in this study for the 2–4 day band) shows that correlations with VIX and OVX generally remain negative; however, their magnitudes strengthen and weaken over time and vary across quantiles. The DWQB profiles further indicate that the DM–EM distinction is particularly pronounced in the VIX channel, whereas the OVX profiles are more time-varying and display a less systematic distinction between the two markets. The T5YIE channel exhibits a different dynamic structure, with both the sign and magnitude of dependence and exposure varying over time and across quantiles. Moreover, several pronounced movements in DWQB broadly coincide with changes observed in DWQC, suggesting that changes in exposure are accompanied by changes in the underlying dependence structure.

The contribution of our study to the literature is positioned along three dimensions. First, the WQC approach is extended into a dynamic rolling-window framework, and DWQB is derived from this structure, allowing not only dependence but also quantile-specific exposure between low-carbon indices and VIX, OVX, and T5YIE to be traced across different quantile levels. Second, by showing that negative dependence in the VIX and OVX channels varies across quantiles and investment horizons, and that the DM and

EM distinction becomes more pronounced particularly in the VIX channel, especially at short horizons, it is demonstrated that low-carbon indices possess a condition-dependent risk profile that cannot be summarised by a single average relationship. Third, the fact that there are only a limited number of studies in the examined literature that consider T5YIE when analysing the relationship between low-carbon indices and inflation expectations constitutes a distinct contribution, and the finding of positive dependence at the median quantile and weakening at the lower and upper quantiles in the static WQC results, together with the heterogeneous dynamic behaviour of the T5YIE channel, indicates that the role of low-carbon indices vis-à-vis inflation expectations should be addressed in a quantile- and time-sensitive manner.

In the remainder of the article, the related literature, the data, and the proposed dynamic WQC–QBETA framework are described in detail; subsequently, the empirical quantile- and frequency-based responses of the DM and EM low-carbon indices to the VIX, OVX, and T5YIE risk factors are presented.

2. Literature Review

This study is closely related to the strand of the literature that examines the risk sensitivity of low-carbon and ESG-compliant indices and investments, and that addresses the diversification and safe-haven properties of low-carbon investment strategies. Low-carbon indices and climate-sensitive investment strategies allow investors to take positions close to the market portfolio with the objective of reducing carbon risk, and the relationship of these strategies with risk factors, particularly during periods of stress, renders diversification strategies more important (Andersson et al., 2016). Related studies also provide evidence on the portfolio implications of environmentally oriented investment strategies. Trinks et al. (2018) find that fossil-fuel divestment does not appear to impair portfolio performance, while Reboredo (2018) shows that green bonds weakly co-move with stock and energy commodity markets and provide sizeable diversification benefits for investors in these markets. The mechanism through which financial markets price climate change risks goes beyond the homogeneous and rational market assumptions implied by traditional asset pricing theories and becomes a distinct risk component (Bolton & Kacperczyk, 2021).

The behaviour of low-carbon and green assets during periods of global uncertainty is heterogeneous and may vary across market regimes. Vergili and Çelik (2023) identify a negative long-run relationship between the VIX and the Dow Jones Sustainability Emerging Markets Index, while Demirez and Kandır (2024), focusing on the BIST Sustainability Index, find a negative long-run effect of the VIX and unidirectional causality from VIX, OVX, and GVZ to the sustainability index. Gökgöz et al. (2025), who dynamically examine the connectedness between blue and green ETFs and volatility indices, demonstrate the need to reassess volatility spillover channels and diversification dynamics, particularly during periods of heightened uncertainty. Similarly, Doğan et al. (2025) analyse the relationships between green financial assets and the G7 and Chinese

stock markets and find that volatility spillovers vary across different time frequencies. Rehan et al. (2024) show that connectedness among green assets increases markedly during global uncertainty episodes such as the Covid-19 pandemic and the Russia-Ukraine conflict, and that these assets exhibit tail dependence. Hasan et al. (2024) further demonstrate that the relationship between green bonds and green equities differs across tail quantiles and that their diversification properties vary depending on market regimes. In addition, Rahman and Hasan (2025) use the Quantile-VAR Connectedness approach to examine relationships among green and sustainable assets and show that connectedness patterns differ across market regimes.

The interaction between energy markets and low-carbon assets is examined along the axes of the substitution effect and the financialization hypotheses. Henriques and Sadorsky (2008) document a Granger-causal relationship between oil prices and the stock prices of alternative energy companies, while Kumar et al. (2012) find that oil prices and technology stock prices affect clean-energy stock prices. Managi and Okimoto (2013), accounting for structural changes, further document a positive relationship between oil prices and clean-energy stock prices. Özçim (2022) finds that Brent oil prices do not affect the volatility of the BIST Sustainability Index, while Kaya (2023) shows that the BIST Sustainability Index exhibits relatively low sensitivity to fossil-fuel prices and that petroleum-based fuel prices have a greater influence than natural gas and coal. Hanif et al. (2025) investigate the asymmetric structure of the linkages among regional green economies, carbon markets, and oil shocks, showing that the impact of energy-driven shocks on green assets is not uniform and may change in direction and magnitude depending on conditions. Similarly, Leone et al. (2025) report that geopolitical risks and market conditions are decisive in the dynamic connectedness between energy and carbon markets, and that the hedging capacity of green assets against energy risk is not unconditional.

One of the most prominent gaps in the literature concerns the behaviour of low-carbon assets in relation to inflation expectations, particularly T5YIE. Hung (2025) shows that the relationship between carbon emission futures and inflation is positive and that inflation reduces equity returns. Similarly, Hensel et al. (2024) demonstrate that carbon pricing increases inflation expectations and that the relationship is positive. Xu and Lien (2024), focusing on the macroeconomic effects of carbon pricing, reveal that spillovers from carbon costs to inflation exhibit a multiscale structure and differ across market regimes and investment horizons. The literature reviewed indicates that research examining the relationship between low-carbon assets and inflation is limited in explicitly considering T5YIE in the context of inflation expectations. In this respect, the use of T5YIE as a proxy for inflation expectations can be expressed as a potential additional contribution to the literature.

The literature reviewed indicates that, as the field of low-carbon and green finance has increasingly emphasised tail behaviour, regime asymmetry, and horizon

heterogeneity, approaches beyond mean-centred linear frameworks have become more widespread. This methodological development is also reflected in studies that jointly consider market conditions and investment horizons. Pham (2021) combines frequency connectedness and cross-quantile dependence to examine the relationship between green bonds and green equity markets. Chatziantoniou et al. (2022) extend this line of research by examining quantile time-frequency connectedness among green bonds, green equities, sustainable investments, and clean-energy markets. Gao et al. (2024) employ quantile-based approaches to investigate interdependence and network connectedness between green financial and energy markets. More directly related to low-carbon equities, Wang and Qiao (2025) examine static and dynamic volatility connectedness among crude oil, green bonds, and low-carbon equities across time, frequency, and quantile dimensions, with particular attention to extreme events. Similarly, Nawaz and Su (2026) examine the impact of sustainability uncertainty on green finance using the Quantile-on-Quantile Regression model and argue that the structure of risks in the tails can be captured only through such hybrid methods. The WQC approach developed by Kumar and Padakandla (2022), which combines wavelet-based multiscale decompositions with a quantile framework, provides a toolkit for tracing the dependence structure across both investment horizons and market conditions. This study aims to address this methodological and empirical gap in the literature by extending WQC into a time-varying framework through a rolling-window approach, by computing quantile betas to move beyond correlation and quantify exposure, and by dynamically revealing the effects under different market conditions.

3. Data and Methodology

3.1. Data

The study uses a daily dataset spanning 30 November 2010² to 29 December 2025 to analyse the sensitivity of low-carbon equities across developed and emerging economies to risk factors. To represent low-carbon-sensitive equities in developed and emerging markets, we use the DM and EM indices, which reflect the performance of companies with low emission intensity. These indices are selected because they belong to the same MSCI Global Low Carbon Target framework while representing developed and emerging markets, respectively, thereby allowing the DM-EM comparison to be conducted under a consistent index-construction methodology. The Low Carbon Target methodology is designed to reduce exposure to carbon emissions and fossil fuel reserves relative to the corresponding parent index while controlling tracking error and limiting country and sector deviations (MSCI, 2024). Accordingly, the use of DM and EM enables the sensitivity of low-carbon equities to be compared across different levels of market development without introducing differences arising from alternative low-carbon index methodologies. As risk factors, we employ the VIX, the OVX, which measures oil price

² Since the DM and EM variables have a starting date of 30 November 2010, this date determines the beginning of the sample period.

volatility, and the T5YIE as a proxy for long-term inflation expectations. In the study, DM and EM are obtained from msci.com, while the other variables are sourced from fred.stlouisfed.org. For the analysis, daily logarithmic returns of DM and EM are used, whereas the risk factors are employed in their raw (level) form since they are rate and volatility indicators and are stationary in levels (see Table 1). Table 1 illustrates the descriptive statistics of the series.

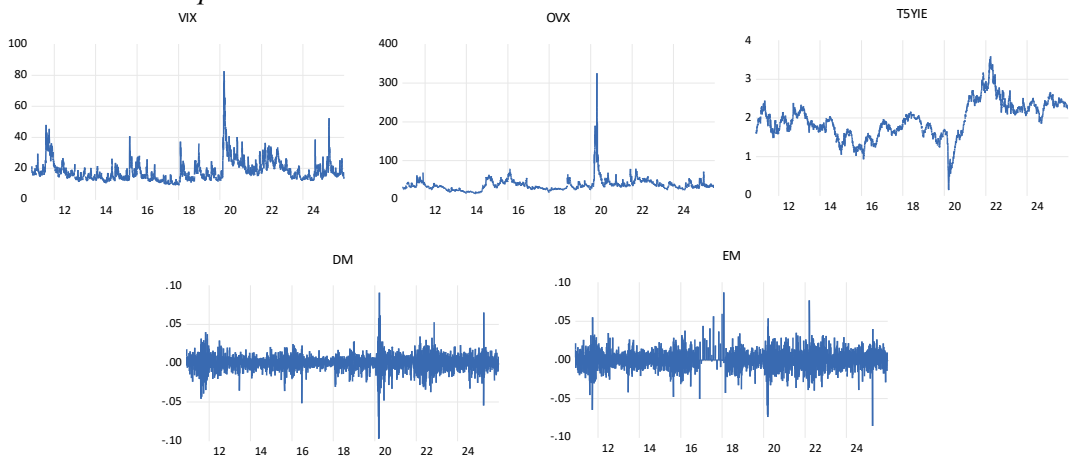
Table 1
Descriptive Statistics

	VIX	OVX	T5YIE	DM	EM
Mean	18.13078	37.15295	1.946467	0.000461	0.000222
Median	16.37	34.36	1.92	0.000791	0
Maximum	82.69	325.15	3.59	0.090912	0.087194
Minimum	9.14	14.5	0.14	-0.097606	-0.085308
Std. Dev.	6.868055	17.04058	0.471097	0.009525	0.0109
Skewness	2.557019	5.451	0.136414	-0.595144	-0.125269
Kurtosis	15.13955	56.481	3.529637	15.35822	9.09385
Jarque-Bera	27221.27*	467349*	55.68*	24181.08*	5835.4*
ADF	-7.2022*	-5.9908*	-3.4612*	-20.1423*	-58.8147*

Note: * indicates statistical significance at the 5% level.

The descriptive statistics indicate that OVX is the series with the highest standard deviation and that all series are stationary. In addition, according to the Jarque–Bera test statistics, none of the series follows a normal distribution, all exhibit leptokurtosis (kurtosis > 3), and therefore highlight the importance of employing a methodology that accounts for tail behaviour in the distributions. Figure 1 presents the time-path plots of the series.

Figure 1
Time Series Graphs



The time series graphs show that all series vary over time, and that fluctuations become more pronounced during periods associated with major global economic events, particularly in recent years, such as the Covid-19 episode in March 2020. In addition, the onset of the Russia–Ukraine war in February 2022 coincides with the period when T5YIE reaches its highest level, while significant deviations are observed, especially in the DM and EM series, during April and May 2025, when sharp changes in tariff policies under the Trump administration were implemented. These findings indicate that the evolution of the series is sensitive to global events. This, in turn, highlights the importance of examining the sensitivity of low-carbon indices to risk factors not only by focusing on tail quantiles but also within a dynamic framework.

3.2. WQC, DWQC, and DWQB

The WQC approach developed by Kumar and Padakandla (2022) combines the Maximal Overlap Discrete Wavelet Transform (MODWT) proposed by Percival and Walden (2000) to decompose time series into different investment horizons (frequencies) with the quantile-based dependence framework developed by Li et al. (2015). In this way, it allows quantile-based dependence to be examined across different time horizons.

$$WQC_{\tau}(d_j[LC], d_j[RF]) = \frac{qcov_{\tau}(d_j[RF], d_j[LC])}{\sqrt{\text{var}\left(\phi_{\tau}\left(d_j[RF] - Q_{\tau, d_j[RF]}\right)\right) \text{var}(d_j[LC])}} \quad (1)$$

Where, LC denotes low carbon indices (DM or EM), RF denotes risk factors (VIX, OVX, or T5YIE), d_j represents the time frequency, and τ denotes the quantile level of the risk factor variable. While qcov refer to quantile covariance, $\text{var}(d_j[LC])$ denotes the variance of the low-carbon index, and $\text{var}\left(\phi_{\tau}\left(d_j[RF] - Q_{\tau, d_j[RF]}\right)\right)$ denotes the indicator variance of the risk factor, since the calculation is performed conditional on a specific quantile level of the risk factor. WQC reveals the correlation levels between low-carbon indices and risk factors across different quantile levels of the risk factors, ranging from 0.01 to 0.99, and across different frequencies, from 2 to 4 day band to the 128-256 day band. Accordingly, WQC captures the sensitivity of low-carbon indices to risk factors across different time horizons under conditions in which risk factors lie at different quantile levels.

WQC provides static evidence across different time horizons and quantile levels. One of the methodological contributions of our study is that we compute dynamic WQC (DWQC) measures by applying a rolling-window procedure to the static WQC results. In this way, we dynamically reveal the correlations between low-carbon indices and risk factors at different quantile levels of the risk factors. DWQC employs a window width of

128 days, and a step size of 5 days. The 128-day window, corresponding approximately to a six-month trading period, is selected to balance the need for a sufficiently informative local sample with the ability to capture relatively short-lived changes in the dependence structure. The use of relatively short rolling windows is also consistent with the time-frequency and quantile-based literature. Nguyen et al. (2021) and Naeem et al. (2024) employ 120-day rolling windows, while Guesmi et al. (2026) employ a 100-day baseline rolling window together with a 200-day alternative specification. The 5-day step is used as a weekly update interval to reduce redundancy from highly overlapping consecutive windows while retaining the time-varying structure of the estimates. When reporting DWQC results, we focus on the 0.10, 0.50, and 0.90 quantiles and the short-term (2-4 days frequency band) investment horizon. The DWQC and DWQB results across alternative frequency bands at the same quantile levels, using the 128-day rolling window, are reported in Appendix 1. To assess the sensitivity of the dynamic estimates to the selected rolling-window length, the DWQC and DWQB analyses are also estimated using a 256-day rolling window while keeping the quantile levels, the 2-4 days frequency band, and the 5-day step unchanged. These results are reported in Appendix 2.

Another methodological extension of the study is the computation of quantile beta (QBETA) as an exposure measure derived from WQC. The construction of QBETA follows the covariance-to-variance scaling logic underlying dynamic hedge ratios (Kroner & Sultan, 1993), while adapting this structure to the quantile-based dependence framework of WQC. Specifically, conventional covariance is replaced by quantile covariance, while the variance term is represented by the quantile-state indicator variance of the risk factor. QBETA is calculated as the ratio of the quantile covariance between the risk factors and the low-carbon indices to the indicator variance of the risk factor:

$$QBETA(d_j[LC], d_j[RF]) = \frac{qcov_{\tau}(d_j[RF], d_j[LC])}{\text{var}\left(\phi_{\tau}\left(d_j[RF] - Q_{\tau, d_j[RF]}\right)\right)} \quad (2)$$

QBETA goes beyond correlation and measures the exposure of low-carbon indices under conditions in which risk factors lie at different quantile levels. However, QBETA should not be interpreted as a conventional hedge ratio or market beta and does not represent a marginal effect. Instead, it captures regime-sensitive exposure within the WQC framework. In this study, we report the dynamic version of QBETA in a manner consistent with DWQC. Accordingly, we dynamically present both the correlations and the exposures of low-carbon indices to VIX, OVX, and T5YIE across different quantile levels.

4. Results and Analysis

In this study, we examine the sensitivity of low-carbon indices in developed and emerging markets to risk factors using the WQC approach, as well as its dynamic version that incorporates time-varying behaviour. In the first stage, we report the standard WQC

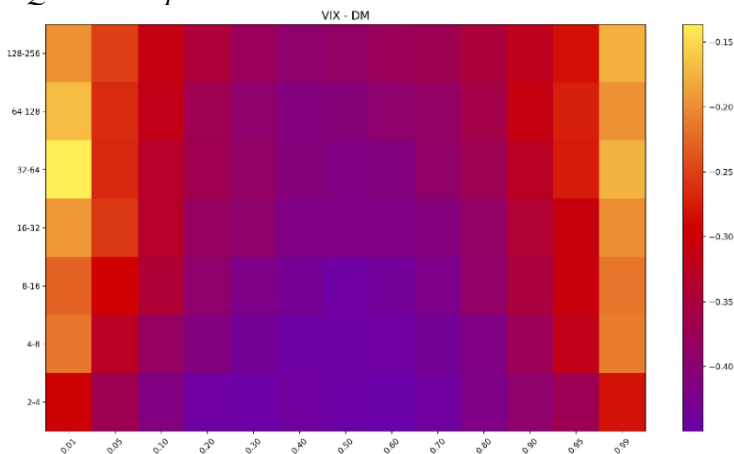
results; in the second stage, we present the DWQC and DWQB results.

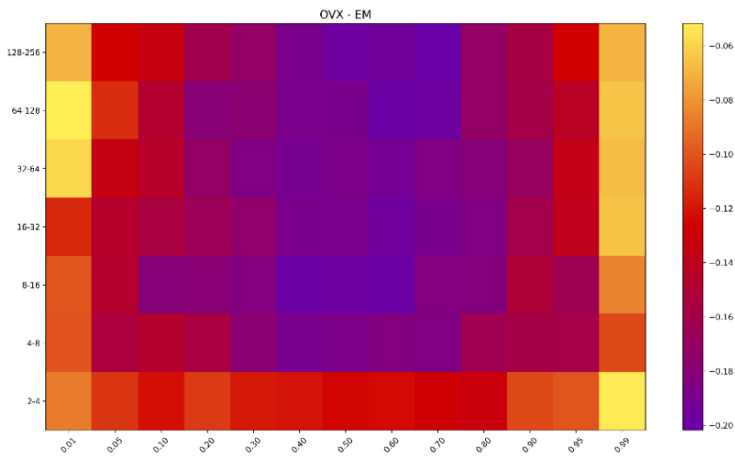
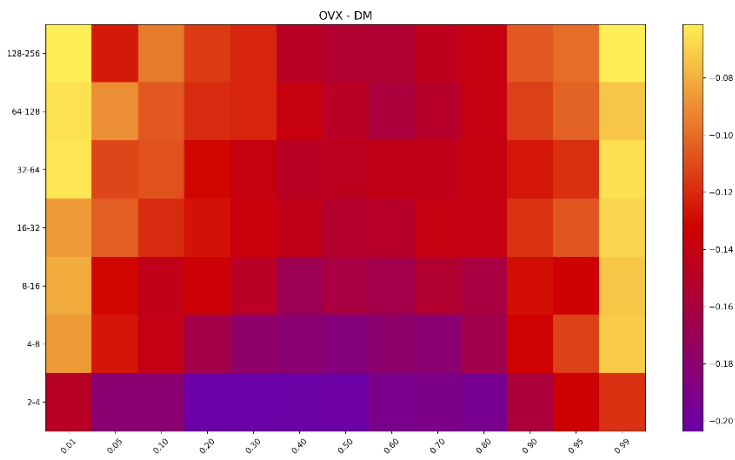
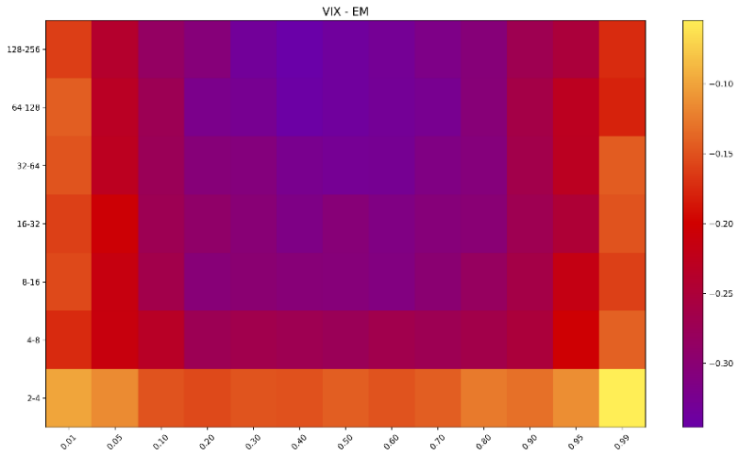
4.1. WQC

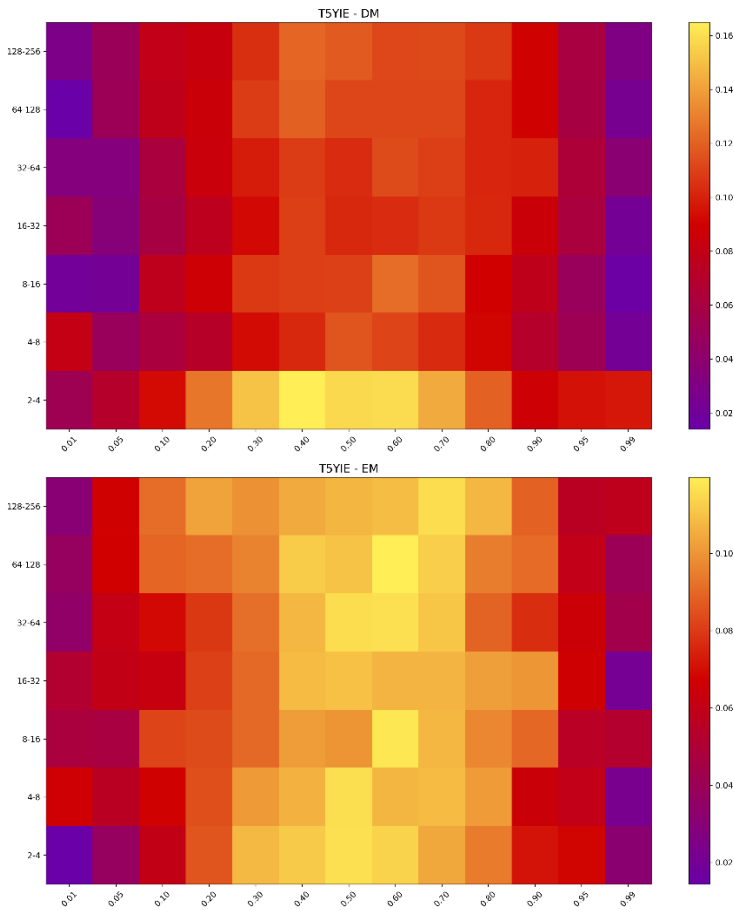
The WQC results display the correlations between low-carbon-sensitive indices and risk factors across different frequencies and quantiles. WQC reveals the degree of co-movement between low-carbon indices under varying market conditions in which risk factors change.

Figure 2 presents, through heat maps, the degree of co-movement between low-carbon indices and risk factors across different frequencies under conditions in which risk factors are at different quantile levels. In the heat maps, the horizontal axis (x) shows the quantile thresholds for the risk factors (0.01, 0.05, 0.10, 0.20, 0.30, 0.40, 0.50, 0.60, 0.70, 0.80, 0.90, 0.95, 0.99). Accordingly, the estimated coefficients, shown by the colour scale, reflect the quantile-specific dependence between the low-carbon index and the corresponding risk factor. Thus, the quantile levels refer to the quantiles of VIX, OVX, and T5YIE rather than those of the low-carbon indices. The vertical axis (y) displays frequency domains ranging from high to low, from 2–4 days to 128–256 days. The colour bars on the right side of the maps indicate the correlation values.

Figure 2
WQC Heatmaps







The WQC results show that the correlations between VIX and low-carbon indices are negative across different quantiles and frequencies. The absolute values of the correlation coefficients for DM are higher than those for EM. This finding indicates that the negative dependence of the developed-market low-carbon index on VIX is stronger. This outcome is consistent with Su and Luo (2026), who emphasise that, due to higher financialisation and greater global investor diversity in developed markets (the EU case), carbon prices are more sensitive to international risk factors, such as the VIX, than in emerging markets (the China case). From an economic perspective, this higher sensitivity suggests that stronger financial integration in developed markets accelerates contagion effects during periods of panic. At the median quantile threshold ($\tau = 0.50$), correlations reach their maximum, while at the tail quantile thresholds ($\tau = 0.01/0.05$ and $\tau = 0.95/0.99$), the coefficients decline. In addition, the results indicate that correlations with DM are more strongly negative at high frequencies, whereas correlations with EM are more strongly negative at low frequencies. This suggests that responses to market uncertainty materialise over longer horizons in emerging markets and that, at tail

quantiles, the diversification property is stronger in the short run for EM relative to DM. The variation in dependence across frequency bands is consistent with the investment-horizon heterogeneity emphasised by the Fractal Market Hypothesis, suggesting that the response of low-carbon indices to global risk conditions cannot be characterised independently of the time horizon considered (Peters, 1994; Kristoufek, 2013).

The correlations with OVX are also generally negative and display patterns similar to those observed for VIX, although they are weaker than the VIX correlations. Moreover, correlation values approach zero particularly at tail quantiles, and, as in the case of VIX, the values are lower for EM. This finding indicates that sensitivity to energy market uncertainty is lower than sensitivity to VIX and that EM is more resilient to oil price volatility. The results of Hanif et al. (2025), who document that the relationship between the green economy, carbon indices, and oil prices exhibits regional heterogeneity, support this outcome.

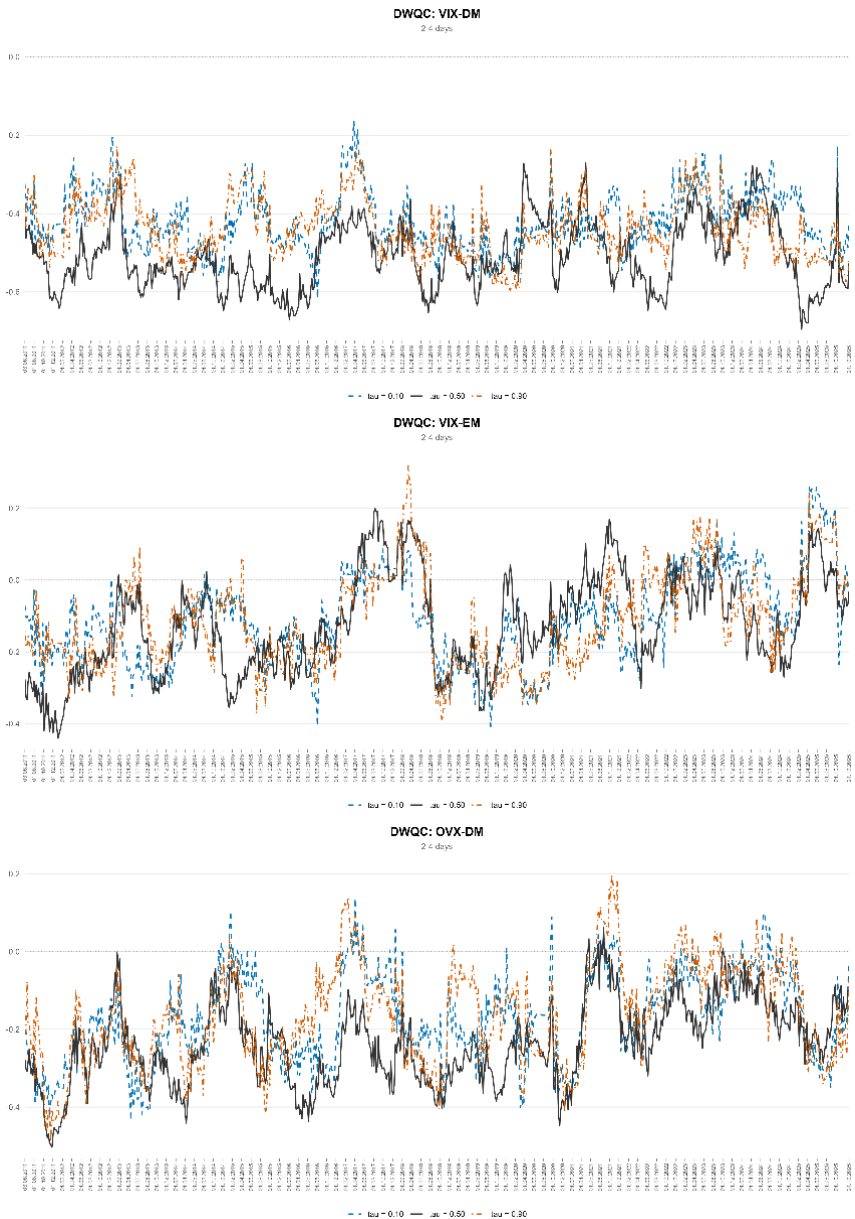
The relationship between T5YIE, which represents inflation expectations, and low-carbon indices exhibits a structure that differs from volatility indicators. While a positive dependence is observed at the median quantile, the relationship weakens markedly at the tail quantiles. This finding suggests that low-carbon indices possess with respect to inflation expectations. The positive relationship in the median regime supports the view discussed by Xu and Lien (2024) and Hensel et al. (2024) that carbon pricing co-moves with the general price level through the cost channel. However, the weakening observed in lower and upper quantiles is consistent with Hung (2025), who shows that carbon-driven high inflation increases investor concerns, suppresses equity returns, and renders the hedging function asymmetric. Overall, the WQC results indicate that quantile-based correlations vary across different quantile conditions of the risk factors and that DM is more sensitive to risk indicators than EM.

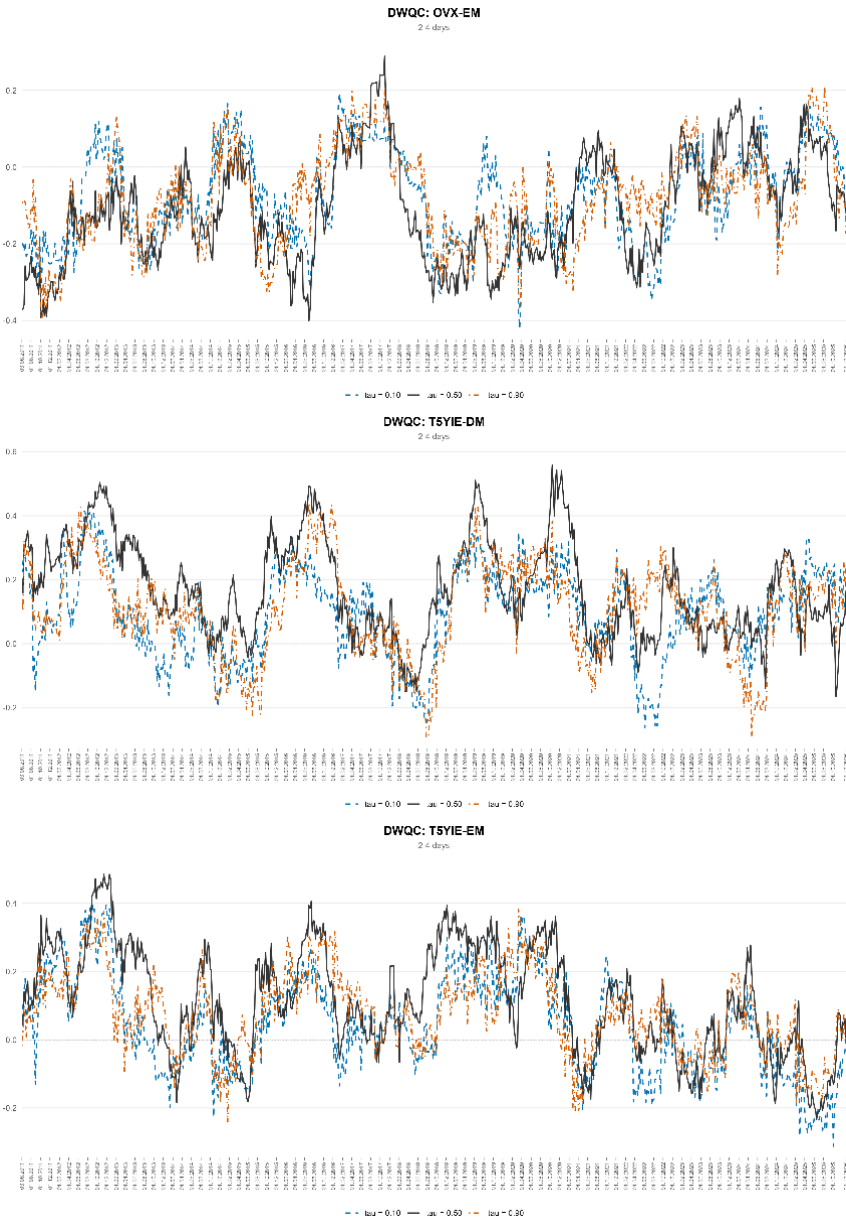
Given that the sample period includes events with global economic impacts, correlations are expected to be influenced by global shocks. In this respect, examining the time-varying effects of quantile-based correlations is important for both identifying the impact of such events and conducting a dynamic analysis.

4.2. DWQC and DWQB

While the WQC results reveal correlations across quantile and frequency dimensions, DWQC captures the evolution of these correlations over time across quantiles and frequencies. Figure 3 presents the DWQC results at the 0.10, 0.50, and 0.90 quantile threshold levels of the corresponding risk factors and at the 2–4 days time frequency.

Figure 3
DWQC Graphs





The DWQC results indicate that correlations between VIX and OVX and the low-carbon indices generally remain negative, while the magnitudes of the correlation coefficients strengthen and weaken over time. In particular, the more volatile behaviour of correlations at the lower and upper quantile thresholds of the risk factors suggests that the relationships between low-carbon indices and risk indicators vary more markedly over time across different risk-factor conditions. This dynamic and asymmetric structure is

consistent with the findings of Tan et al. (2021), who note that downside risk responses intensify during extreme periods relative to normal times. Moreover, our results are consistent with the evidence emphasised by Rehan et al. (2024) that tail dependence and market connectedness increase at extreme levels during crisis periods such as the Russia-Ukraine war and the COVID-19 episode. The T5YIE channel differs from the volatility indicators: dependence frequently remains positive but varies over time, becoming negative in some periods.

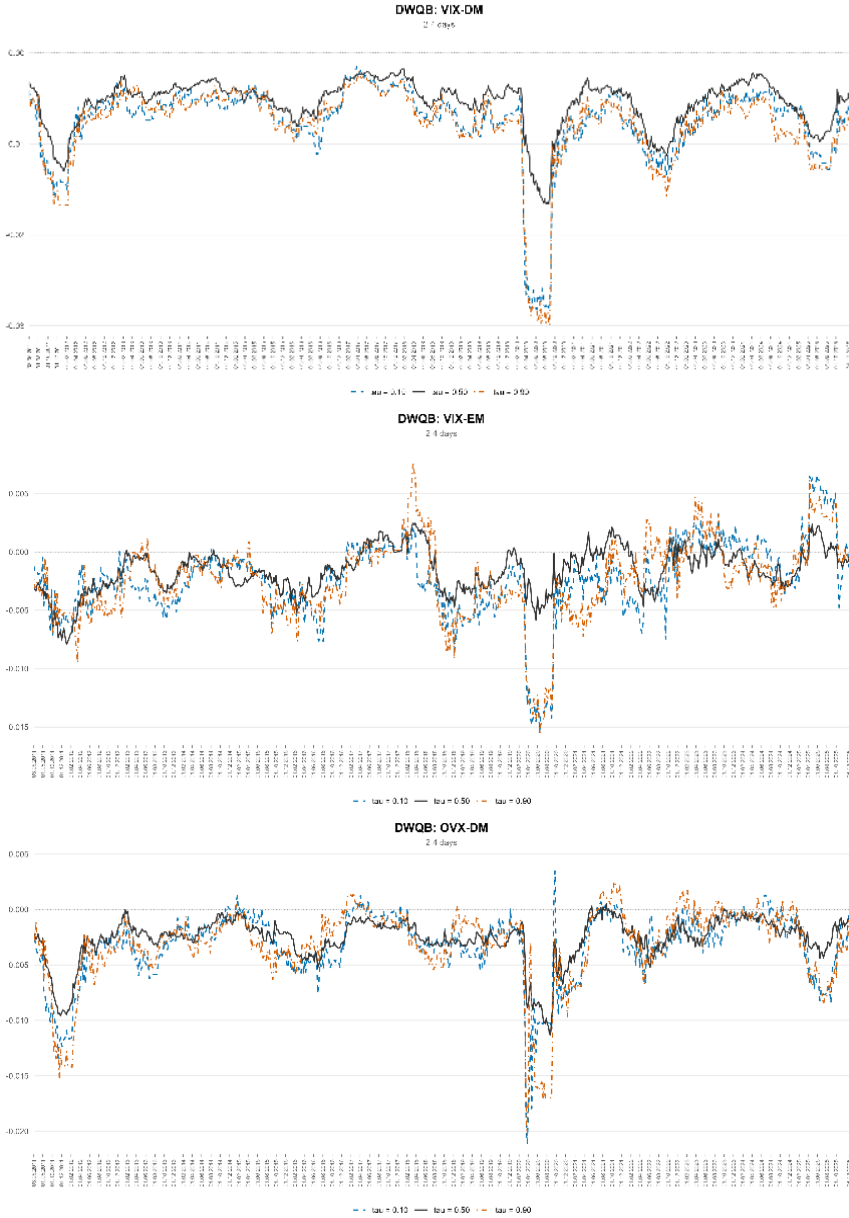
The dynamic results are consistent with the static findings, and the comparison between low-carbon indices is also preserved within the dynamic framework. The absolute value of the correlations for DM is higher than that for EM in most periods, particularly in the VIX channel, indicating that developed-market low-carbon indices exhibit stronger short-term responses to global risk conditions. Nevertheless, this difference is not constant over time and narrows in specific periods.

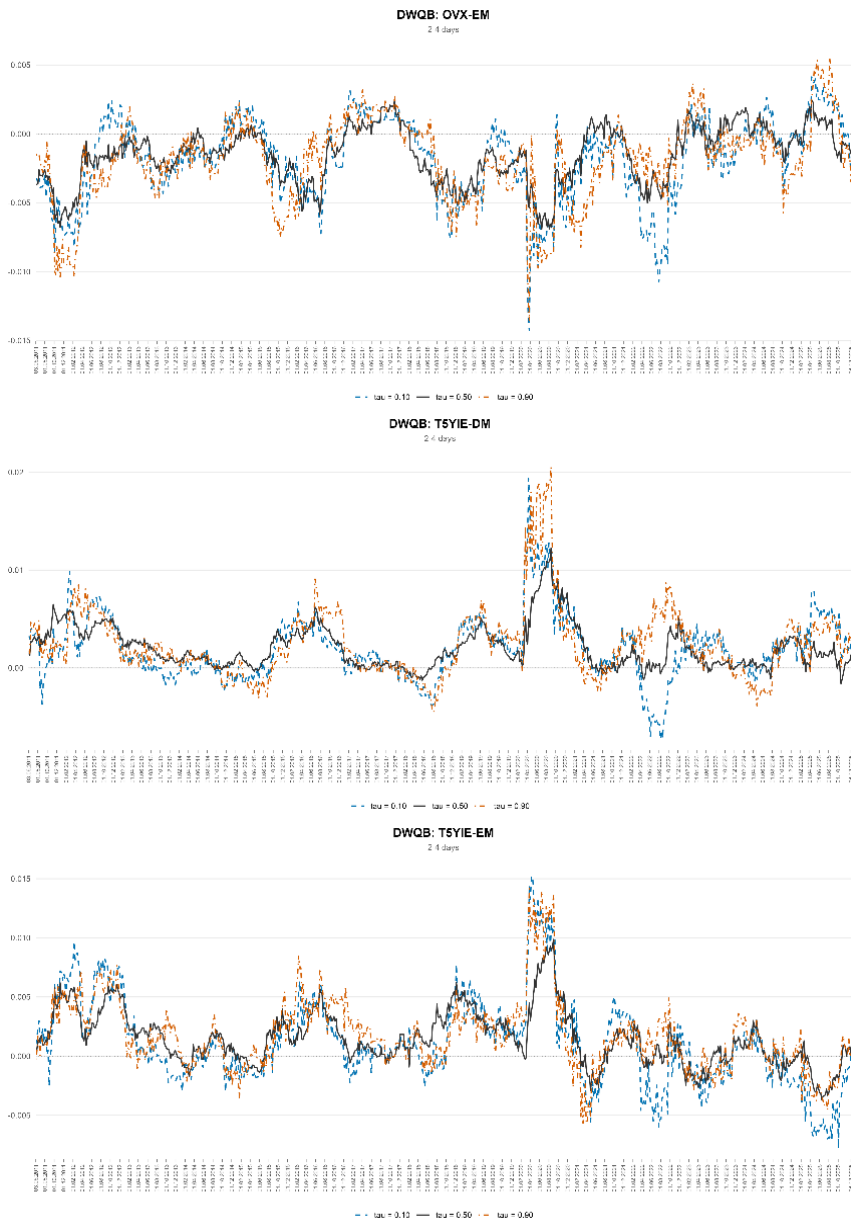
The concentration patterns observed in the dynamic correlation plots generally coincide with periods of heightened uncertainty and volatility in global markets, indicating that the relationship between low-carbon indices and risk indicators is sensitive to the global uncertainty environment. The onset of the COVID-19 episode in March 2020, during which correlations across several variable pairs exhibit sharp increases and decreases, serves as a clear example. These abrupt changes are consistent with the findings of Gökgöz et al. (2025), who document that diversification benefits erode and integration across assets increases during periods of market stress.

While the DWQC analysis reveals how the dependence structure between low-carbon indices and risk indicators evolves over time and across quantile regimes, the study further examines the economic magnitude of this dependence and risk sensitivity from a different perspective by computing DWQB coefficients using the quantile covariance and variance components derived from DWQC.

The DWQB coefficients provide a regime-sensitive beta measure that captures the magnitude of low-carbon indices' sensitivity to risk indicators across different market regimes and time–frequency horizons. In this way, going beyond the correlation structure, the quantile-based exposure of low-carbon indices to risk factors can be evaluated within a dynamic framework. Figure 4 presents the DWQB results dynamically across different quantiles.

Figure 4
DWQB Graphs





The DWQB coefficients presented in Figure 4 show that the sensitivity of low-carbon indices to risk indicators varies across the quantiles of the corresponding risk factors and over time. The DWQB employed in this study is not a conventional market beta; instead, it should be interpreted as a regime-sensitive exposure measure based on quantile-based covariance and variance components derived from the DWQC framework. The DWQB results indicate a distinction between DM and EM that is particularly

pronounced in the VIX channel, where DM generally exhibits stronger exposure than EM. This pattern, in line with the static WQC findings, indicates that the developed-market low-carbon index responds more strongly to global market uncertainty. This result is consistent with Doğan et al. (2025), who document that developed markets, such as the United States and Europe, exhibit higher integration and a stronger transmitter structure in response to global shocks. In contrast, emerging markets, such as China, tend to behave in a more insulated manner.

With respect to risk indicators, the DWQB profiles indicate particularly pronounced exposure in the VIX-DM channel, while the OVX profiles are more time-varying and do not display an equally systematic DM-EM distinction. This suggests that the stronger exposure to general market uncertainty is most evident for DM, whereas exposure to oil price volatility is less systematically differentiated between developed and emerging markets. The DWQB pattern obtained for T5YIE diverges from volatility indicators, with the 0.10, 0.50, and 0.90 quantile profiles frequently intersecting and both the sign and magnitude of exposure varying over time. Thus, the T5YIE channel does not exhibit a stable median-versus-tail pattern, but rather a heterogeneous exposure structure across quantiles and time. A particularly pronounced change is observed around the onset of the COVID-19 pandemic in 2020, when DWQB exposure to VIX and OVX becomes sharply more negative, while exposure to T5YIE increases markedly in the positive direction, although the magnitude of these movements differs between DM and EM. Moreover, several pronounced movements observed in DWQB broadly coincide with changes observed in DWQC, supporting the view that changes in exposure are accompanied by changes in the underlying dependence structure.

5. Conclusion

This study examines the dependence structure between low-carbon indices and VIX, OVX, and T5YIE using WQC, DWQC, and DWQB. The findings indicate that the dependence of low-carbon indices on risk factors exhibits pronounced asymmetry depending on the level of market development, frequency, quantile conditions, and events with global economic impact. The static WQC results show stronger negative dependence for DM than for EM in the VIX and OVX channels, whereas the dynamic results indicate that the DM-EM distinction is particularly pronounced in the VIX channel and is less systematic over time for OVX. In the static WQC results, negative dependence with VIX and OVX is generally stronger around the median quantiles but weakens at the lower and upper quantiles. Dependence with T5YIE is distinctly positive under at the median quantile, while it becomes weaker at tail quantiles. The DWQC and DWQB results further show that both dependence and exposure vary substantially over time and across quantiles, with the T5YIE channel displaying a particularly heterogeneous dynamic pattern in both sign and magnitude.

The findings offer important implications for both investors and policymakers. The diversification functions of low-carbon assets vary depending on quantile conditions,

investment horizons, and the level of market development. For investors holding low-carbon assets in their portfolios, the comparatively weaker short-term dependence of EM on global market uncertainty, particularly in the VIX channel, suggests potential diversification benefits; however, these benefits vary across quantile conditions and over time. In addition, the time variation documented by DWQC and DWQB suggests that diversification decisions based solely on static dependence measures may overlook important changes in risk-factor dependence and exposure.

For the stability of low-carbon financial assets and the green financial system, it is necessary to closely monitor not only energy policies but also global financial conditions and inflation expectations. Therefore, policymakers should consider the sensitivity of low-carbon financial assets to macro-financial risk conditions when designing policies related to green-transition financing and decarbonisation. Future studies may enrich the findings by analysing low-carbon assets at different regional or firm levels and by incorporating additional macro-financial risk indicators such as geopolitical risk (GPR) and trade policy uncertainty (TPU).

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Artificial Intelligence Statement: The author declares that generative artificial intelligence was used solely for grammatical and linguistic corrections in this study and that they complied with international rules as well as the Council of Higher Education (YÖK) “Ethical Guideline on the Use of Generative Artificial Intelligence in Scientific Research and Publication Activities of Higher Education Institutions.”

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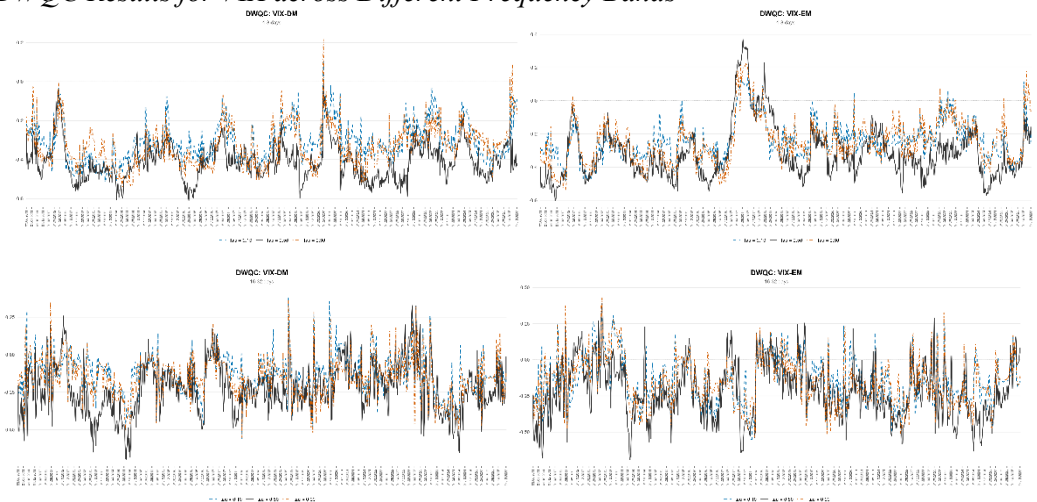
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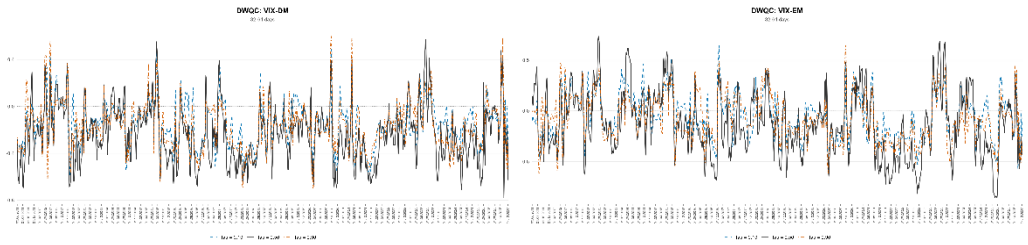
Appendix 1. DWQC and DWQB Results across Alternative Frequency Bands

This appendix presents the DWQC and DWQB results across different frequency bands at the 0.10, 0.50, and 0.90 quantile levels using a 128-day rolling window.

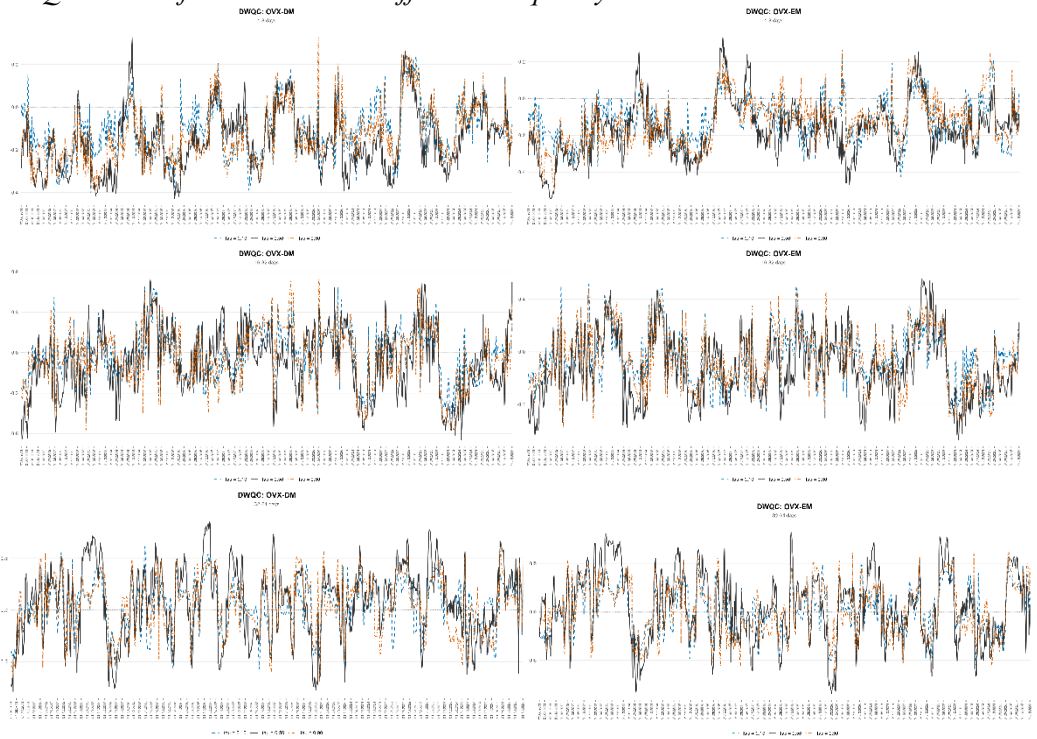
Figure A1.

DWQC Results for VIX across Different Frequency Bands

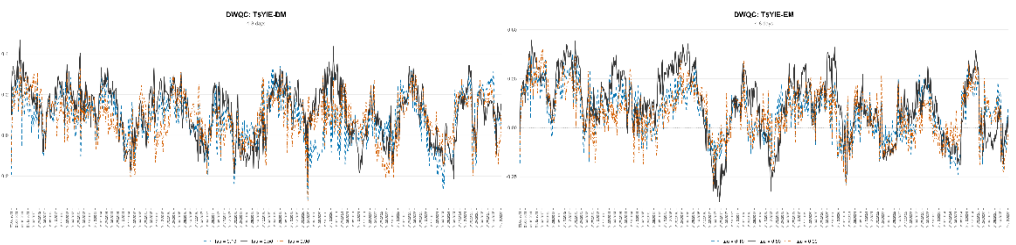


**Figure A2.**

DWQC Results for OVX across Different Frequency Bands

**Figure A3.**

DWQC Results for T5YIE across Different Frequency Bands



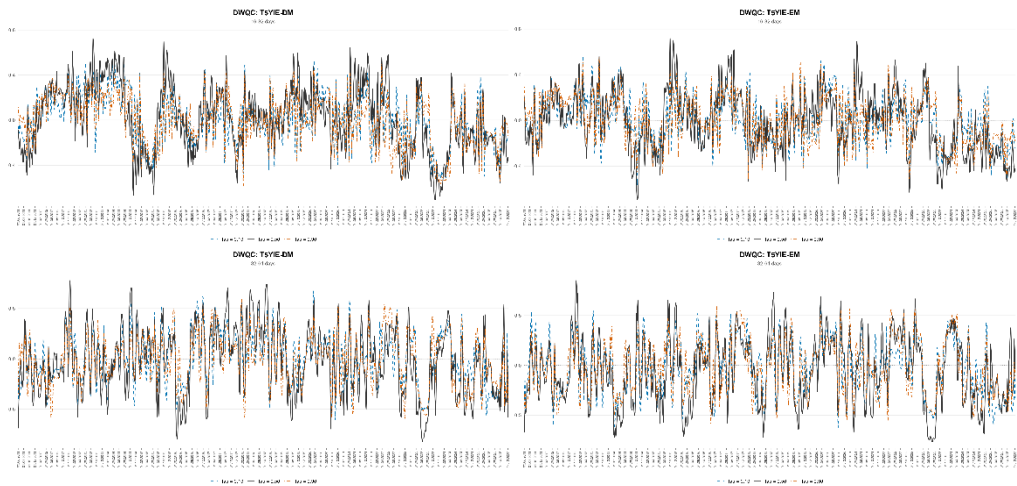


Figure A4.
DWQB Results for VIX across Different Frequency Bands

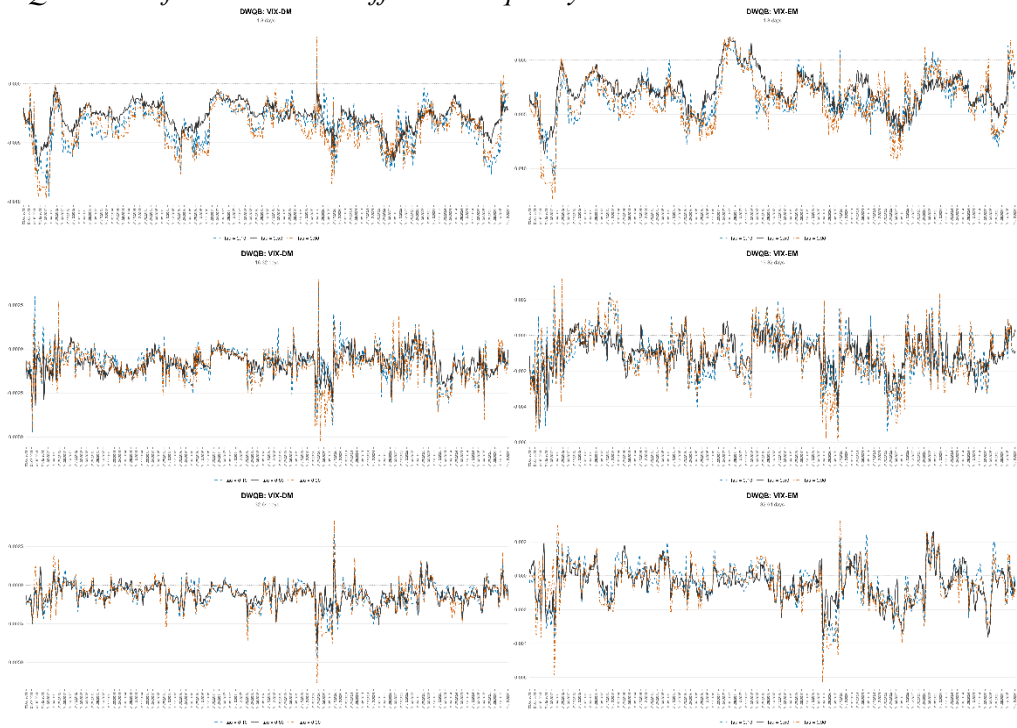


Figure A5.

DWQB Results for OVX across Different Frequency Bands

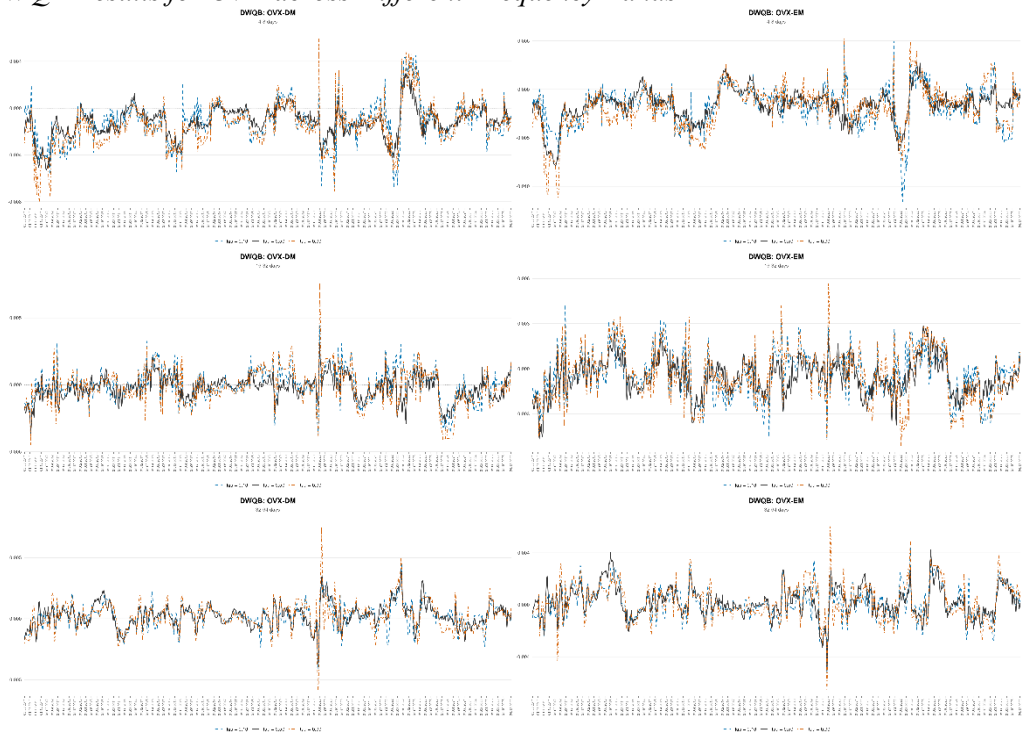
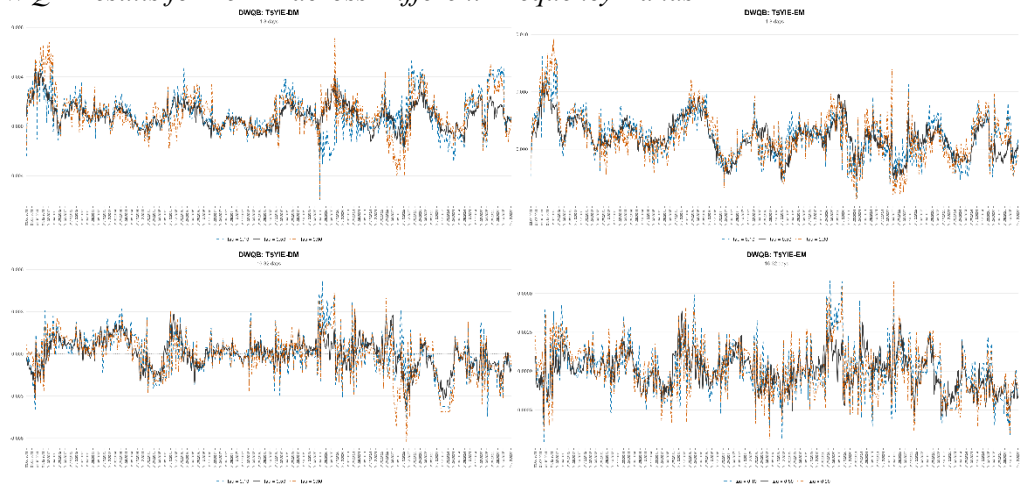
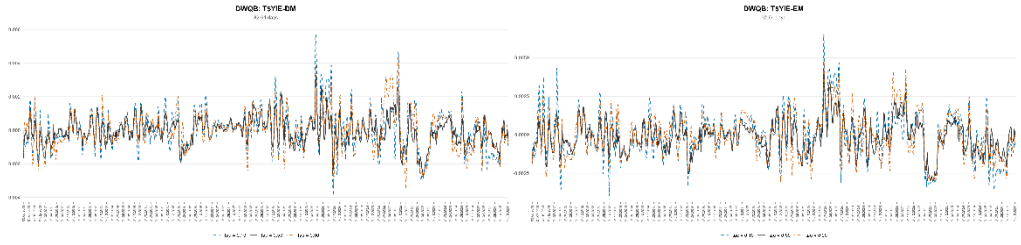


Figure A6.

DWQB Results for T5YIE across Different Frequency Bands





Appendix 2. Sensitivity Analysis Using a 256-Day Rolling Window

This appendix illustrates the DWQC and DWQB results at the 0.10, 0.50, and 0.90 quantile levels using a 256-day rolling window and the 2-4 days frequency band. Compared with the baseline 128-day specification, the 256-day window broadly preserves the direction of the main DWQC and DWQB patterns, although the magnitude and timing of some movements differ across specification.

Figure A7.

DWQC Results Using a 256-Day Rolling Window



Figure A8.

DWQB Results Using a 256-Day Rolling Window

