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The Evolving Landscape of Stock Market Diversification: A Comprehensive Study of Green and Conventional Indices

(Landskap Pemelbagaian Pasaran Saham yang Berkembang: Satu Kajian Komprehensif Mengenai Indeks Hijau dan Konvensional)

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ABSTRACT

This study examined the diversification dynamics between green and conventional stock indices from January 2015 to December 2023, utilising MGARCH-DCC and the Continuous Wavelet Transform (CWT). The current study analysed five green indices (BIST, CSI, DJSI, S&P ESG, STOXX) and five conventional indices (DJIA, S&P 500, FTSE 100, China, KOSPI) to explore their time-varying volatility and correlation. The results reveal that BIST exhibits the highest volatility, suggesting exposure to speculative movements, while DJSI demonstrates greater stability, reflecting the resilience of sustainability leaders in developed markets. Despite its relatively high volatility, the China index remains a viable instrument for diversification. The KOSPI index emerged as a balanced option, offering moderate volatility and correlation, while the S&P ESG index was positioned as a comparatively safer investment due to its stable performance and moderate comovement with conventional indices. The pairing of CSI and the China index was identified as optimal for risk-averse investors, driven by their consistently low correlation throughout the study period, as identified by the CWT analysis.

Keywords: Stock market diversification; green indices; conventional stock indices; multivariate GARCH-DCC; continuous wavelet transform

ABSTRAK

Kajian ini meneliti dinamika pemelbagaian antara indeks saham hijau dan konvensional dari Januari 2015 hingga Disember 2023 dengan menggunakan MGARCH-DCC dan Transformasi Gelombang Berterusan (CWT). Kajian ini menganalisis lima indeks hijau (BIST, CSI, DJSI, S&P ESG, STOXX) dan lima indeks konvensional (DJIA, S&P 500, FTSE 100, China, KOSPI) bagi meneroka turun naik dan korelasi yang berubah mengikut masa. Hasil kajian menunjukkan bahawa BIST mencatatkan turun naik tertinggi, mencadangkan pendedahan kepada pergerakan spekulatif, manakala DJSI menunjukkan kestabilan yang lebih tinggi, mencerminkan ketahanan pemimpin kelestarian di pasaran maju. Walaupun indeks China mempunyai turun naik yang agak tinggi, ia kekal sebagai instrumen yang sesuai untuk pemelbagaian. Indeks KOSPI muncul sebagai pilihan seimbang dengan tahap turun naik dan korelasi yang sederhana, manakala indeks S&P ESG didapati sebagai pelaburan yang lebih selamat disebabkan prestasinya yang stabil dan pergerakan bersama yang sederhana dengan indeks konvensional. Gabungan indeks CSI dan indeks China dikenal pasti sebagai pilihan terbaik untuk pelabur yang mengelakkan risiko, dipacu oleh korelasi rendah yang konsisten sepanjang tempoh kajian seperti yang dikenal pasti melalui analisis CWT.

Kata kunci: Pemelbagaian pasaran saham; indeks hijau; indeks saham konvensional; GARCH-DCC multivariat; transformasi gelombang berterusan

INTRODUCTION

Green finance has recently emerged as a crucial component of sustainable development strategies, driven by growing awareness among investors and policymakers about the environmental implications of financial decisions (Busch et al. 2016). It encompasses investments in environmentally sustainable projects, the development of green financial instruments, and the establishment of green indices to track the performance of companies with strong environmental, social, and governance (ESG) practices. As global capital shifts towards ESG-aligned assets, understanding how green finance interacts with conventional financial markets becomes increasingly vital for sustainability advocates and investors seeking portfolio stability in uncertain times (Pedersen et al. 2021).

Despite growing attention to ESG investing, much of the existing literature has primarily focused on the returns of green assets and screening strategies (Friede et al. 2015). Hence, less is known about the volatility and correlation dynamics between green and conventional indices, particularly over time and across different market conditions. Moreover, relatively few studies have explored these dynamics using both time-domain and frequency-domain methodologies to reflect how investor behaviour and index relationships evolve over multiple time horizons.

This study addressed that gap by investigating whether green indices differ significantly from conventional indices in terms of volatility and dynamic correlation, especially during periods of systemic market stress. Specifically, we examined:

1. Whether green indices exhibit distinct volatility and correlation behaviours compared to conventional indices,
2. How these behaviours evolve over time across short-, medium-, and long-term investment horizons,
3. Whether green indices offer practical diversification benefits during major global disruptions, such as the COVID-19 pandemic and geopolitical shocks.

We employed a dual-method analytical framework that combines Multivariate Generalised Autoregressive Conditional Heteroskedasticity – Dynamic Conditional Correlation (MGARCH-DCC) and Continuous Wavelet Transform (CWT) to achieve these objectives. These models offer distinct advantages over standard correlation and regression techniques. MGARCH-DCC captures time-varying comovements and conditional heteroskedasticity among multiple indices, reflecting the dynamic and clustered nature of market volatility. Meanwhile, CWT decomposes correlations across both time and frequency dimensions, providing granular insights into how market relationships behave differently across short-term reactions and long-term structural trends.

Our empirical analysis covered the period from January 2015 to December 2023, encompassing diverse market phases, including economic growth, the COVID-19 pandemic, and the Russia-Ukraine conflict. The dataset includes green indices as well as conventional benchmarks. The study drew on global financial data from the United States (US), the United Kingdom (UK), China, and other key economies to facilitate regional comparisons in green finance integration.

Key findings indicate that green indices, such as DJSI and STOXX, offer lower volatility and substantial diversification benefits, particularly in the short to medium term. The FTSE China 50 Index has the lowest average correlation with others, but its high volatility limits its appeal. BIST and CSI also exhibit low correlations, but they are too volatile for risk-averse investors. In contrast, the S&P ESG index provides a balanced option with moderate volatility and lower correlations. The tendency of green indices to decouple from conventional markets during global disruptions highlights their hedging potential and value in ESG-based portfolio strategies.

The remainder of the paper is organised as follows: Section 2 reviews the relevant literature and outlines the theoretical basis of the study. Section 3 explains the research design and methodology. Section 4 presents the empirical findings and discussion. Section 5 concludes by summarising the insights and discussing their implications for investment and policy.

LITERATURE REVIEW

Green finance has grown rapidly, leading to extensive research on its impact on financial performance and market behaviour. Despite numerous studies, a need remains for further comparative analyses on the impact of green finance on various stock market indices. Key studies by Eccles et al. (2014) and Friede et al. (2015) have demonstrated a positive correlation between ESG factors and corporate financial performance, indicating that sustainability can have a positive impact on financial outcomes. Jain et al. (2019) examined whether ESG indices outperform MSCI indices, and they found that both sustainable and traditional indices perform similarly, suggesting that integrating both can help investors manage risk and maximise returns. This reveals an opportunity for financial managers to adopt a more balanced investment strategy.

Despite the varied global performance, Cunha et al. (2020) analysed various Dow Jones Sustainability World Indices and found opportunities for superior risk-adjusted returns in certain regions from 2013 to 2018. Gupta and Jham (2021) observed that historically underperforming green investments rebounded and excelled post-crisis, indicating a trend toward green bonds, funds, and indices. Chiappini et al. (2021) investigated the performance of sustainable indices during pandemic lockdowns and found that, despite the challenges, these indices matched traditional indices in terms of returns, confirming the viability of sustainable investments in adverse market conditions.

The prominence of ESG-focused investment strategies is growing as shown by Meira et al. (2023), who assessed ESG strategies globally and identified significant regional differences in how governance factors affect investment performance. Specifically, governance-related factors are associated with higher risk-adjusted returns in regions like emerging markets and the US, suggesting that stronger governance frameworks may enhance financial outcomes. Despite these insights, research on green stock indices remains sparse and methodologically inconsistent, indicating a gap in the literature. To address this, the present study employed advanced econometric tools, namely MGARCH-DCC and CWT, to examine the dynamic relationships and comovement patterns between green and conventional indices. While these methods are effective in capturing correlation and volatility over time and across frequencies, it is important to note that they do not establish causality. The findings should thus be interpreted as indicative of associations rather than definitive causal links.

Muhmad and Zainul Abidin (2025) examined the link between corporate sustainability initiatives and firm value in Malaysia, highlighting the importance of institutional ownership and governance mechanisms. Their findings support the argument that sustainable practices can enhance firm valuation, especially in emerging markets, making sustainability a relevant factor in investment decisions and financial modelling.

To underpin the analytical framework of this study, relevant financial theories are employed to contextualise the relationship between sustainability and investment performance. Modern Portfolio Theory (MPT), introduced by Markowitz (1952), emphasises the importance of diversification and risk optimisation. This study applies MPT to compare green and conventional indices by examining their diversification potential. The Sustainable Finance Theory used by Busch et al. (2016) highlights the role of finance in sustainable development, in which the study examined whether sustainability leads to superior financial returns. This study builds on research by Clark et al. (2015), who found a generally positive correlation between ESG practices and financial performance, and Busch et al. (2016), who reviewed a broader body of literature, concluded that while the results are mixed—ranging from outperformance to underperformance—there is no strong evidence of a negative relationship between sustainability performance and financial returns (Mercer 2009).

In conclusion, a detailed comparative analysis of green and traditional stock indices is lacking despite extensive research on green finance. This study addressed this gap by applying the Modern Portfolio Theory and Sustainable Finance Theory to examine the in-depth impact of green finance on stock market returns. It assessed whether green indices outperform conventional ones under various market conditions and their diversification potential. The study employed the MGARCH-DCC and CWT techniques to provide a nuanced understanding of the effects of green finance, thereby enhancing investment strategies and integrating sustainability into financial decision-making.

METHODOLOGY

DATA

The data for this study comprise daily closing prices of 10 stock market indices from January 4, 2015, to December 29, 2023, selected to reflect geographical diversification across North America, Europe, and Asia, encompassing both developed and emerging markets. The five green indices include the BIST Sustainability Index (BIST), representing sustainability-aligned companies in Turkey; the Dow Jones Sustainability World Index (DJSI World), selected from the DJSI family for its broad global ESG coverage with data sourced from S&P Global; the S&P 500 ESG Index, reflecting ESG-screened large-cap US stocks; and the STOXX Global ESG Environmental Leaders Index, representing global environmental leaders across developed markets. The Corporate Sustainability Index (CSI) was included to measure and track companies' performance on various sustainability issues, including ESG factors. The five conventional indices comprise the Dow Jones Industrial Average (DJIA), the S&P 500 Index, the FTSE 100 Index, the FTSE China 50 Index, and the Korea SE KOSPI 100 Index. Although the DJIA and S&P 500 both represent the US markets, they differ in their weighting methodologies, being price-weighted versus market-cap-weighted, and are retained for comparative insights. The data were primarily sourced from Refinitiv Eikon, except for DJSI World and S&P 500 ESG Index, which were obtained from the S&P Global platform.[1]

The data were transformed into returns using the equation rt = ln(Pt/Pt-1), where rt represents the series return derived from the natural logarithm, and Pt represents the index value at time t. This study employed a multifaceted methodological approach to scrutinise the impact of green finance on stock market returns. Specifically, we utilised two key techniques: The MGARCH - DCC model and the CWT.

MGARCH-DCC MODEL

The MGARCH-DCC model, developed by Engle (2002), was applied in this study to examine the dynamic volatility and correlation between green and conventional stock indices. Extending the traditional univariate GARCH model, MGARCH-DCC allows for the estimation of time-varying correlations and conditional variances across multiple financial assets—key elements for assessing diversification potential and market risk.

In this framework, the mean reflects the average return over time, typically estimated using models, such as AR or MA. The variance, representing volatility, is modelled dynamically to capture changing market behaviour. MGARCH-DCC effectively tracks both variances and correlations over time, offering a comprehensive view of inter-index relationships.

To address our first research objective, we applied the MGARCH-DCC model using both normal and t-distributions to evaluate conditional cross-asset correlations and improve model robustness. To compute these correlations, the MGARCH model incorporates the MGARCH-DCC methodology, as illustrated by the following formula:

$$\tilde{\rho}_{ij,t-1}(\phi) = \frac{q_{ij,t-1}}{\sqrt{q_{ii,t-1}q_{jj,t-1}}}$$

Where $q_{ij,t-1}$ is represented as

$$q_{ij,t-1} = \bar{\rho}_{ij}(1 - \phi_1 - \phi_2) + \phi_1 q_{ij,t-2} + \phi_2 \tilde{r}_{i,t-1}\tilde{r}_{j,t-1}$$

The unconditional correlation between assets i and j is denoted as $\bar{\rho}_{ij}$. The parameters $\phi 1$ and $\phi 2$, representing estimated values, are constrained such that their sum remains below one, i.e., $\phi 1 + \phi 2 < 1$. This condition is vital to ensure model stability. The standardised changes in the assets are represented by $\tilde{r}_{i,t-1}$. Additionally, the parameters (1 – λi1 – λi2) are crucial in defining the mean reversion process within the model, indicating how quickly the series revert to their mean value. To ascertain the reliability and accuracy of our estimates, we undertook several robustness checks, following the methodologies suggested by Pesaran and Pesaran (2010). These procedures are essential to validate the model's effectiveness and the integrity of our findings.

While MGARCH-DCC is effective in capturing time-varying volatility and correlation (Engle 2002), it assumes conditional linearity and may not fully capture non-linear or extreme dependencies. Alternatives, such as Copula models (Patton 2006; Jondeau & Rockinger 2006), address these issues but require subjective choices of distributions, thereby increasing complexity. VAR models (Sims 1980) capture linear interdependencies but are not suitable for modelling high-frequency volatility.

MGARCH-DCC remains a practical and efficient choice for modelling comovement and volatility spillovers (Silvennoinen & Teräsvirta 2009). Its integration with CWT further enhances analysis across time and frequency domains, addressing MGARCH's limitations and aligning with the goal of this study which was to assess diversification across green and conventional indices (Torrence & Compo 1998; Rua & Nunes 2009).

CONTINUOUS WAVELET TRANSFORM (CWT)

The CWT complements the MGARCH-DCC model by capturing dynamic relationships across time and frequency (Torrence & Compo 1998). CWT is particularly effective in distinguishing short- and long-term comovements among indices. Its growing use in financial analysis (e.g., Abdullah et al. 2023) reflects its ability to clarify complex data patterns. Unlike discrete methods like DWT or MODWT, CWT requires no pre-set wavelet numbers and provides intuitive two-dimensional visualisations, making it a more flexible and user-friendly tool for detecting hidden correlations.

The equation for the CWT, denoted as $WX(u,s)$, is formulated by aligning a fundamental wavelet, symbolised by ψ, with the intended time series $x(t)$ that falls within the $I2(R)$ space. This alignment is encapsulated in the following mathematical expression:

$$W_X(u,s) = \infty_{-\infty} x(t) \frac{1}{\sqrt{s}} \psi\left(\frac{t-u}{s}\right) dt$$

In the specified equation, 'u' represents the time domain, while 's' denotes the frequency domain. The wavelet coherence methodology, originating from the research by Torrence and Webster in 1999, was employed to analyse two separate time series:

$$R\frac{2}{n}(s) = \frac{IS\ (s^{-1}W\frac{xy}{n}(s))I^2}{S(S^{-1}IW\frac{x}{n}(S))I^2 S(S^{-1}IW\frac{y}{n}\ (S))I^2}$$

In this framework, 'S' acts as a bifunctional smoothing parameter, exerting its influence across both the temporal and scale dimensions. The metric $R\frac{2}{n}(s)$, which is confined to a range from 0 to 1 as highlighted by Rua and Nunes (2009), serves as a key indicator. Values approaching 1 signal a robust comovement between the series, whereas values closer to 0 indicate a more tenuous correlation. By analysing the contour plot of this metric, one can pinpoint regions in the time-frequency space where the two series move in unison. This method provides a detailed examination of comovement, taking fluctuations and variations that occur at different times and frequencies into account (Rua 2010).

In our study, we employed the wavelet phase difference approach, first introduced by Bloomfield et al. (2004), to delve into the interplay and directional impact among the variables. This method defines the phase difference between m(t) and n(t) as follows:

$$\emptyset_{mn} = tan^1 (\frac{\Im\{S(s^{-1}W_{mn}(u,s))\}}{\Re\{S(s^{-1}W_{mn}(u,s))}$$
$$(xi) with\ \emptyset_{mn} \in [-\pi, \pi]$$

In the analyses of this study, we employed the least asymmetric wavelet filter with a length of 8, referred to as LA(8), initially proposed by Daubechies (1992). This specific wavelet filter yields eight coefficients, making it adequately suitable for time series data analysis, as underscored in the works of Gençay e al. (2001) and In and Kim (2013). Compared to alternative wavelet filters, such as the Haar filter, the LA(8) filter can generate more refined wavelet coefficients, thereby improving the precision of our analysis.

RESULTS

DESCRIPTIVE STATISTICS

Figure 1 illustrates the dynamic movements of selected indices from 2015 to 2023. BIST and CSI exhibit high volatility, characterised by sharp declines and rebounds, particularly around 2020, due to the impact of COVID-19. DJSI and S&P ESG experienced early 2020 drops but recovered steadily, with S&P ESG showing a consistent upward trend, reflecting growing ESG interest. STOXX rose until 2018, then moved sideways, while the China index showed repeated sharp declines, notably in 2015 and 2020.

The S&P 500 and DJIA maintained upward trends with a COVID-19 dip and subsequent recovery, indicating investor resilience and bullish sentiment. KOSPI fluctuated with less consistent growth, and the FTSE 100 showed modest gains. Overall, market movements reflect responses to economic, political, and pandemic-related shocks.

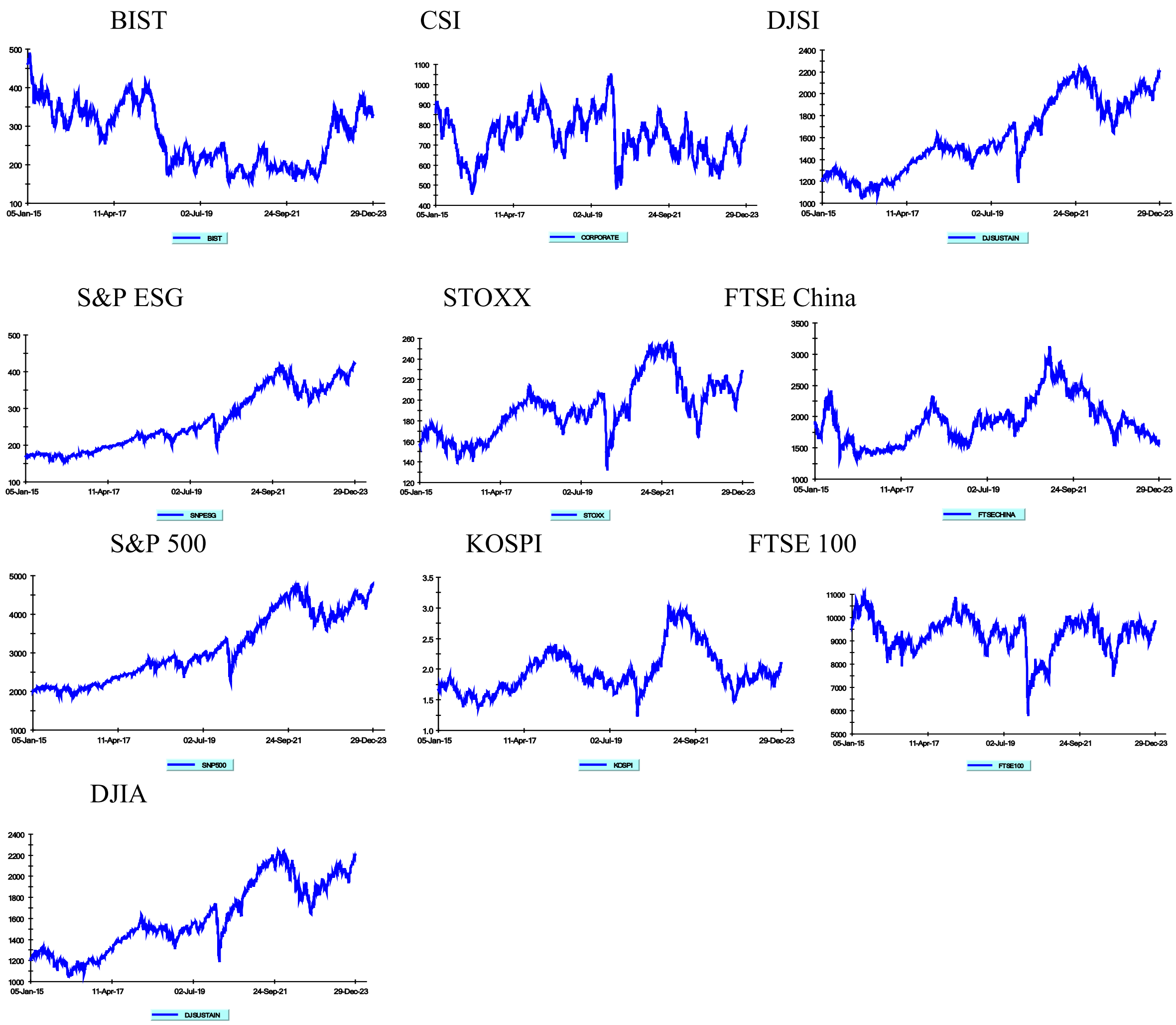


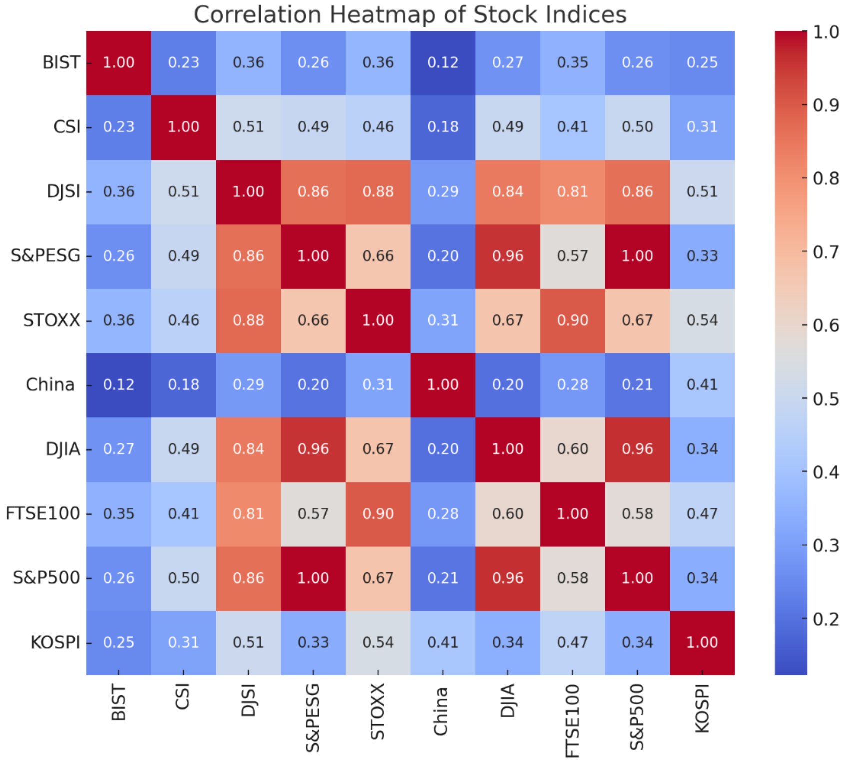
FIGURE 1. Dynamics of original data series

TABLE 1. Descriptive statistics

Index	No. of observation	Mean	Std. Deviation	Min	Max	Skewness	Kurtosis
BIST	2127	-0.00016	0.02267	-0.18048	0.18841	-0.32329	8.22719
CSI	2127	-0.00005	0.02270	-0.18706	0.15154	-0.52404	7.09245
DJSI	2127	0.00028	0.00974	-0.10605	0.07694	-0.97698	16.55691
S&P ESG	2127	0.00043	0.01182	-0.12769	0.09146	-0.68370	15.58169
STOXX	2127	0.00018	0.01103	-0.11314	0.08448	-0.68655	11.74034
China	2127	-0.00008	0.01533	-0.10044	0.09076	-0.45466	5.15581
DJIA	2127	0.00036	0.01168	-0.13842	0.10764	-0.88612	21.83502
FTSE 100	2127	0.00000	0.01266	-0.13474	0.10460	-0.95371	15.26965
S&P 500	2127	0.00040	0.01176	-0.12765	0.08968	-0.71538	15.85674
KOSPI	2127	0.00011	0.01391	-0.07875	0.11951	0.08827	6.00129

Table 1 summarises the descriptive statistics of ten indices over 2127 days. The mean returns are modest, with S&P ESG and DJIA slightly outperforming, while BIST and China show small declines. BIST and CSI are the most volatile, indicating higher risk, whereas DJSI and STOXX are more stable. Skewness is mostly negative, implying more frequent extreme losses, except for KOSPI, which is slightly right-skewed. Several indices, including the DJIA and DJSI, exhibit high kurtosis, indicating a higher likelihood of extreme returns. These findings highlight diverse risk-return profiles essential for aligning with investor strategies.

TABLE 2. Correlation matrix



Note: Each cell in the heatmap shows the correlation coefficient between the stock indices, with values closer to 1 indicating a strong positive correlation and values closer to -1 indicating a strong negative correlation. A value close to 0 suggests little to no linear correlation.

In Table 2, the correlation heatmap highlights key relationships among indices. The S&P 500 and S&P ESG exhibit the strongest correlation (~0.998), followed by the S&P 500–DJIA and DJIA–S&P ESG correlations, indicating similar market behaviour. Strong correlations are observed between the FTSE 100–STOXX and STOXX–DJSI indices. In contrast, China and BIST show the weakest correlation (~0.122), with other low correlations involving China suggesting strong diversification potential. These insights help investors balance portfolios between highly and weakly correlated markets.

MGARCH-DCC FINDINGS

This research employed the MGARCH-DCC methodology to explore the diversification potential within the selected sample variables. The MGARCH-DCC model helps us track how the risk (volatility) and connection (correlation) between different stock indices change over time. In simple terms, it shows when two markets move closely together or differently, like when green investments move independently from traditional markets, or not, which is important for deciding how to spread investments to reduce risk. The dynamic conditional correlation (DCC) values help investors understand how the relationships between indices evolve over time. A rising correlation indicates fewer diversification benefits, while lower or fluctuating correlations suggest better hedging opportunities. This is crucial for portfolio managers seeking to allocate assets effectively in response to changing market conditions. For example, a high and stable correlation between the S&P 500 and the S&P ESG means that investors cannot expect significant risk reduction when combining them. Conversely, low or unstable correlations, such as between BIST and China, suggest those combinations might offer better diversification. Presented in Table 3 are the maximum likelihood estimates for λ_{i1} and λ_{i2} across various indices, providing a basis for comparison between multivariate normal and Student-t distributions, with reference to δ_1 and δ_2 parameters.

For δ parameters, δ_1 estimate hovers around one, accompanied by robust T-ratios in both models, signalling a significant effect and statistical validity. Although δ_2 estimates are minimal, its T-ratios nevertheless point to statistical importance. The Multivariate t Distribution registers a superior maximised log-likelihood value (77724 versus 76880), suggesting enhanced model fit, likely attributable to its proficiency in accommodating outlier data or distributions with heavier tails—as indicated by the degrees of freedom (df) at 9.2699.

Although both models demonstrate statistical significance, one should consider the underlying data distribution characteristics when selecting the most appropriate one. This implies that during turbulent market periods, the choice of indices and distribution assumptions can significantly influence perceived volatility, informing investors' risk assessment and mitigation strategies. In light of the findings, subsequent analyses will proceed within the multivariate t-distribution framework, grounded in its marginally superior fit, as evidenced by the log-likelihood metric. The robust T-ratios across both models reinforce the conclusion that these results are not merely fortuitous.

TABLE 3. Estimates of λ_{i1} and λ_{i2}, and δ_1 and δ_2, for the Ten Indices

		Multivariate Normal Distribution		Multivariate *t* Distribution	
		Estimate	T-Ratio	Estimate	T-Ratio
Lambda 1 ($\lambda 1$)	BIST	0.8757	52.197	0.8323	27.524
	CSI	0.8940	51.575	0.9260	69.471
	DJSI	0.9045	105.908	0.9209	115.811
	S&P ESG	0.8970	97.820	0.9229	122.406
	STOXX	0.9082	118.220	0.9207	118.052
	CHINA	0.9104	81.139	0.9271	90.652
	DJIA	0.9024	101.366	0.9279	126.013
	FTSE 100	0.9051	72.629	0.9225	87.998
	S&P 500	0.8987	102.720	0.9235	125.970
	KOSPI	0.8771	39.520	0.8866	37.122
Lambda 2 ($\lambda 2$)	BIST	0.0605	8.677	0.0782	6.458
	CSI	0.0583	6.809	0.0462	6.081
	DJSI	0.0635	13.156	0.0535	11.024
	S&P ESG	0.0576	13.270	0.0448	11.431
	STOXX	0.0606	13.369	0.0514	10.934
	CHINA	0.0824	8.513	0.0677	7.528
	DJIA	0.0574	12.687	0.0448	10.924
	FTSE 100	0.0620	9.541	0.0537	8.630
	S&P 500	0.0572	13.570	0.0450	11.632
	KOSPI	0.0564	7.036	0.0517	5.914
Delta 1 ($\delta 1$)		0.9190	109.016	0.9014	121.575
Delta 2 ($\delta 2$)		0.0239	16.634	0.0255	17.706
Maximised log-likelihood		76880		77724	
Degree of freedom (df)		-		9.2699	

Note: λ_1 and λ_2 are decay factors for variance and covariance, respectively.

Table 4 presents the estimated unconditional volatilities and correlations among ten key global stock indices, providing insights into market dynamics and investment strategies. BIST is identified as the most volatile, possibly prone to speculative trading, while the DJSI World Index shows minimal volatility, reflecting the overall stability of large-cap sustainability leaders included in the index, which is primarily based in developed economies. A notable finding is a strong correlation (0.96) between DJIA and S&P 500, indicating synchronous movements and limited diversification benefits for investors focusing on these indices. In contrast, the low correlation (0.122) between the FTSE China 50 and BIST suggests opportunities for strategic diversification. This variation in correlations, influenced by regional economic factors, policies, and investor behaviours, is crucial for understanding the balance between risk and potential return. High volatility indices may not only offer greater returns but also carry higher risks whereas strategic diversification using the correlation data can help construct resilient portfolios. These insights are vital for investors seeking to optimise their portfolios by considering both volatility and correlation, providing a detailed understanding of the diverse risk profiles and complex interconnections within global financial markets. This comprehensive analysis is essential for making informed investment decisions, emphasising the need to assess individual market characteristics against the backdrop of an interconnected global financial landscape.

TABLE 4. Estimated unconditional volatility matrix for stock indices return

	BIST	CSI	DJSI	S&PESG	STOXX	CHINA	DJIA	FTSE100	S&P500	KOSPI
BIST	0.02274 (1)	0.22791	0.35491	0.25956	0.36105	0.12586	0.26886	0.35098	0.26238	0.25112
CSI	0.22791	0.02273 (2)	0.51094	0.49059	0.46144	0.17269	0.49400	0.40806	0.49479	0.31125
DJSI	0.35491	0.51094	0.00975 (10)	0.86014	0.87559	0.29278	0.84347	0.81371	0.86209	0.50674
S&PESG	0.25956	0.49059	0.86014	0.01184 (6)	0.66461	0.20923	0.95614	0.56910	0.99795	0.33482
STOXX	0.36105	0.46144	0.87559	0.66461	0.01105 (9)	0.31738	0.67278	0.89711	0.67364	0.53858
CHINA	0.12586	0.17269	0.29278	0.20923	0.31738	0.01513 (3)	0.20016	0.28650	0.21068	0.42176
DJIA	0.26886	0.49400	0.84347	0.95614	0.67278	0.20016	0.01169 (8)	0.59592	0.96163	0.34211
FTSE100	0.35098	0.40806	0.81371	0.56910	0.89711	0.28650	0.59592	0.01268 (5)	0.57796	0.46972
S&P500	0.26238	0.49479	0.86209	0.99795	0.67364	0.21068	0.96163	0.57796	0.01178 (7)	0.33934
KOSPI	0.25112	0.31125	0.50674	0.33482	0.53858	0.42176	0.34211	0.46972	0.33934	0.01393 (4)

Table 5 presents an insightful analysis of unconditional correlations among various global stock indices, providing valuable guidance for investors on diversification strategies. The table is particularly intuitive in highlighting the distinct position of the FTSE China 50 index, which consistently shows weaker correlations ('a' in Table 5) with other indices. This characteristic earmarks it as a potential diversification tool. However, its higher volatility demands careful consideration, which could introduce greater unpredictability into portfolio returns.

Interestingly, the analysis suggests that the KOSPI index, a conventional choice, is a more balanced diversification option. It is less volatile and maintains the third-lowest correlation with most other indices, striking a favourable balance between risk and diversification potential. For ‘green’ indices, BIST is identified as the least correlated, yet its high volatility, as indicated in Table 4, marks it as a high-risk option. Similarly, despite being the second least correlated, the CSI index also carries substantial volatility. In light of these findings, the S&P ESG index emerged as a more attractive option for investors seeking to diversify their portfolios. It offers the dual benefit of lower volatility (ranked sixth) and moderate correlation with other indices, presenting a safer yet effective diversification path. Understanding the correlation and volatilities helps investors build a stronger, more balanced portfolio, especially when navigating today’s fast-changing and unpredictable global markets.

TABLE 5. Ranking of unconditional correlations among the stock indices return and other variables

BIST (BIST)		CSI (CSI)		DJSI (DJSI)		S&P ESG (S&PESG)		STOXX (STOXX)		CHINA (CHINA)		DJIA (DJIA)		FTSE 100 (FTSE100)		S&P 500 (S&P500)		KOSPI (KOSPI)	
STOXX		DJSI		STOXX		S&P500		FTSE100		KOSPI		S&P500		STOXX		S&PESG		STOXX	
DJSI		S&P500		S&P500		DJIA		DJSI		STOXX		S&PESG		DJSI		DJIA		DJSI	
FTSE100		DJIA		S&PESG		DJSI		S&P500		DJSI		DJSI		DJIA		DJSI		FTSE100	
DJIA		S&PESG		DJIA		STOXX		DJIA		FTSE100		STOXX		S&P500		STOXX		CHINA	
S&P500		STOXX		FTSE100		FTSE100		S&PESG		S&P500		FTSE100		S&PESG		FTSE100		DJIA	
S&PESG		FTSE100		CSI	d	CSI	d	KOSPI	c	S&PESG		CSI	d	KOSPI	c	CSI	d	S&P500	
KOSPI	c	KOSPI	c	KOSPI	c	KOSPI	c	CSI	d	DJIA		KOSPI	c	CSI	d	KOSPI	c	S&PESG	
CSI	d	BIST	b	BIST	b	BIST	b	BIST	b	CSI	d	BIST	b	BIST	b	BIST	b	CSI	d
CHINA	a	CHINA	a	CHINA	a	CHINA	a	CHINA	a	BIST	b	CHINA	a	CHINA	a	CHINA	a	BIST	b

Note: Superscripts a, b, c, and d indicate the relative suitability of each index for diversification pairing based on low correlation values: a = Most suitable for diversification (lowest correlation), b = Suitable, c = Less suitable, d = Least suitable (high correlation). These classifications help identify the best index pairings for portfolio diversification based on the correlation strength between indices.

This study adopted a broad, unconditional method to scrutinise volatilities and correlations over a nine-year span, a technique that might not fully capture the fluctuating nature of these metrics. To better account for the dynamic shifts in volatility and correlation, we utilised the Dynamic Correlation Coefficient (DCC) model. Figure 2 graphically depicts the conditional volatilities for the indices in question. Notably, the BIST index stands out for its marked volatility, surpassing other indices throughout the period, signalling a degree of unpredictability that brings potential risks alongside its advantages, possibly affecting its efficacy in portfolio diversification strategies. Following BIST, the CSI index emerges as the second most volatile, echoing the findings in Table 4. Moreover, Figure 2 does not reveal a distinct volatility pattern that separates the green and conventional indices, with both categories exhibiting comparable fluctuations throughout the timeline. Market events, particularly those around mid-2019 and late 2021, which were likely linked to the COVID-19 pandemic, have led to noticeable spikes in volatility, affecting numerous indices simultaneously. Contrary to initial observations, the BIST and CSI indices are not the most volatile; indices like China and KOSPI have experienced more significant volatility spikes. This visualisation implies that sustainable indices do not inherently possess lower or higher volatility than conventional indices, suggesting that sustainability considerations might not dominate market volatility.

Figure 3 focuses exclusively on green indices, visually representing their volatility trends without indicating any single index as being consistently more volatile across the observed period. Volatility peaks are interspersed throughout the timeline for all indices, hinting at their collective sensitivity to macroeconomic events or shifts within the market. The STOXX and CSI indices spikes are noteworthy, possibly reflecting acute market reactions or news impacting specific sustainability sectors. Despite these fluctuations, the graph reveals no unique volatility pattern that distinguishes any green index from the others in the long term. This homogeneity suggests that green indices have a volatility risk profile similar to that of the broader market, implying that investors in these indices may anticipate a volatility trajectory comparable to that experienced by the market as a whole.

Figure 4 presents the conditional volatilities of five conventional stock market indices over a nine-year period, highlighting that while the China and KOSPI indices often reach higher volatility peaks, suggesting more pronounced market reactions, the DJIA and FTSE 100 indices appear comparatively more stable, with fewer and lower spikes. The aligned volatility spikes across indices, especially noticeable around mid-2019 and late 2021, suggest that global events have a significant influence on market volatility. No single index consistently exhibits the highest or lowest volatility, indicating that both market-specific factors and international economic events contribute to the observed fluctuations in the market.

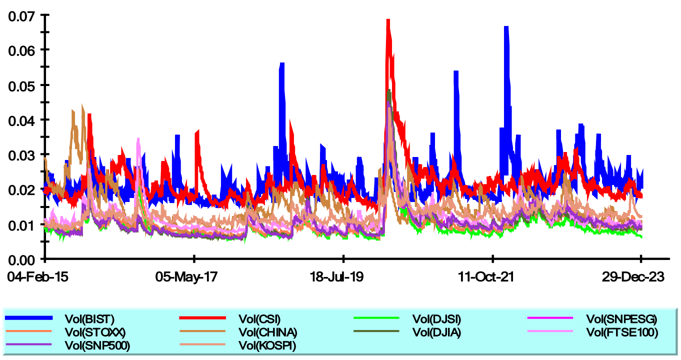


FIGURE 2. Conditional volatilities of green and conventional stock indices return

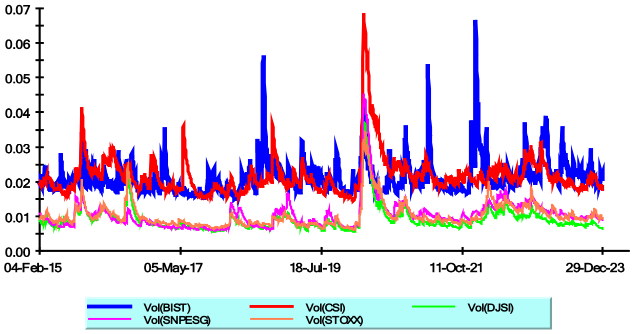


FIGURE 3. Conditional volatilities of green indices

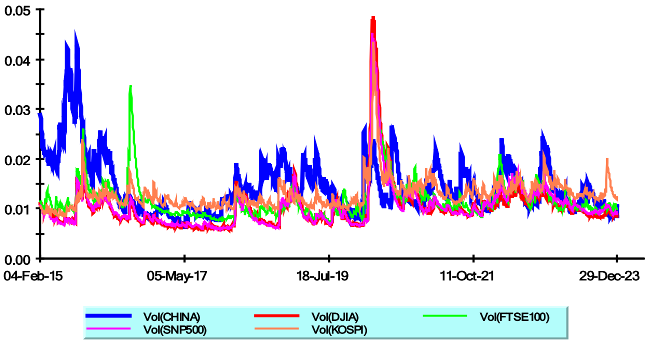


FIGURE 4. Conditional volatilities of conventional stock indices return

Our analysis delved deeper into the correlation dynamics of the DJSI, STOXX, DJIA and S&P 500 indices, as these four indices exhibit the lowest levels of volatility. This characteristic volatility profile positions them as prime candidates for diversification strategies. By examining their interrelationships with other indices, we aimed to understand their potential to enhance portfolio robustness through diversification benefits. Figure 5 displays the dynamic conditional correlations between the DJSI and a selection of conventional indices: DJIA, S&P 500 (labelled SNP5), FTSE 100, FTSE China 50 (labelled CHIN), and KOSPI, over nearly nine years. The correlations range between -0.2 and 1.0, where values close to 1 indicate a strong positive relationship, meaning the indices move in tandem, and values near 0 suggest no linear relationship. The minimal negative correlations show that DJSI rarely moves inversely to the conventional indices. Throughout the period, the correlations remain predominantly positive, with the DJSI maintaining a consistently high correlation with these conventional indices, suggesting that sustainability factors, while distinct in investment philosophy, often share common market movement with traditional indices. Notable shifts in correlation strength may reflect market reactions to global economic events, where investor behaviour tends to converge across different types of indices during times of economic stress or recovery. The DJSI and DJIA exhibit a relatively stable, moderate correlation, whereas the correlation between the DJSI and the S&P 500 is moderate, albeit more variable. A strong and often stable correlation is evident between the DJSI and FTSE 100, consistently trending towards the higher end. In contrast, the DJSI and FTSE China 50 exhibit the most significant fluctuation in correlation, indicating a highly variable relationship, but are the least correlated among the conventional indices. The DJSI and KOSPI display the second-lowest correlation range, suggesting less synchrony in their market movements. These patterns reveal the varying degrees to which sustainability-focused market movements are related to conventional market indices.

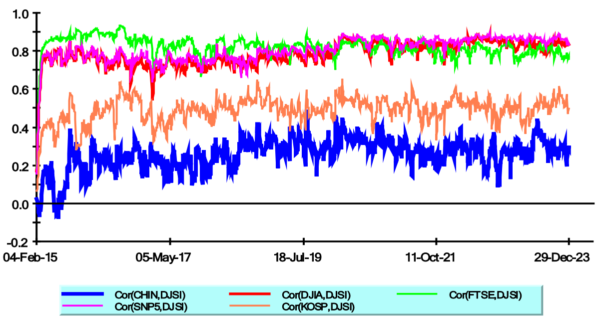


FIGURE 5. Conditional correlation of DJSI with conventional indices

Figure 6 illustrates the dynamic conditional correlations between the STOXX and various conventional indices, including the DJIA, S&P 500 (SNP5), FTSE 100, FTSE China 50 (CHIN), and Korea SE KOSPI 100 (KOSPI). The correlation with the FTSE 100 (green line) remains the highest and most stable over time, indicating a strong and consistent relationship with STOXX. The correlations with the S&P 500 (pink line) and KOSPI (orange line) are moderately high but more variable, indicating some degree of synchronicity with STOXX, albeit with fluctuating intensity. The correlation with China (blue line) is the most variable and generally lower, highlighting a less consistent relationship. Lastly, the correlation with the DJIA (red line) appears moderately variable, occupying a middle ground between the stable S&P 5000 and the more volatile KOSPI. Overall, the graph suggests that the STOXX's movements are more in line with the FTSE 100 and, to a lesser extent, with the DJIA and S&P 500, while the correlation with Asian markets (CHIN and KOSPI) is less consistent, possibly reflecting regional market dynamics or different responses to global sustainability trends.

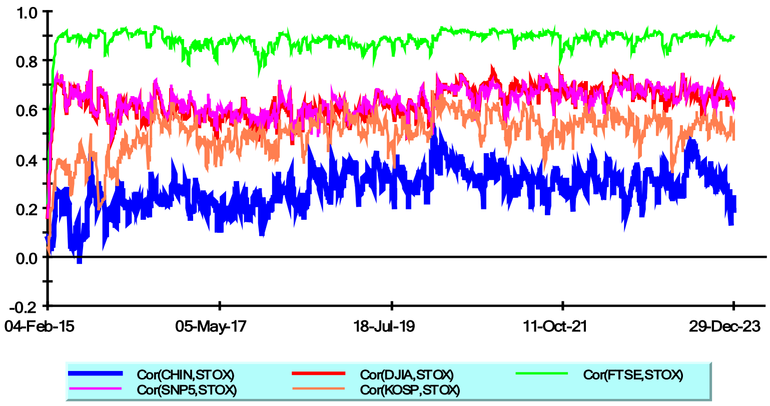


FIGURE 6. Conditional correlation of STOXX with conventional indices

Figure 7 shows the dynamic conditional correlations between the DJIA and various green indices over approximately nine years. The correlations with the DJSI and the S&P 500 ESG Index (SNPE) remain high and relatively stable over time, suggesting that these sustainability indices tend to move in concert with the DJIA. The correlation with the CSI is moderately high but displays more variability, indicating a less consistent but still notable relationship with the DJIA. The STOXX shows the most fluctuation in correlation with the DJIA, suggesting a more variable relationship. Finally, the BIST correlation is the lowest, indicating the least synchrony in movement with the DJIA. These varying degrees of correlation suggest that while some green indices closely follow the trends of conventional market indicators, such as the DJIA, others demonstrate more independence and could offer diversification benefits in a sustainability-focused investment portfolio.

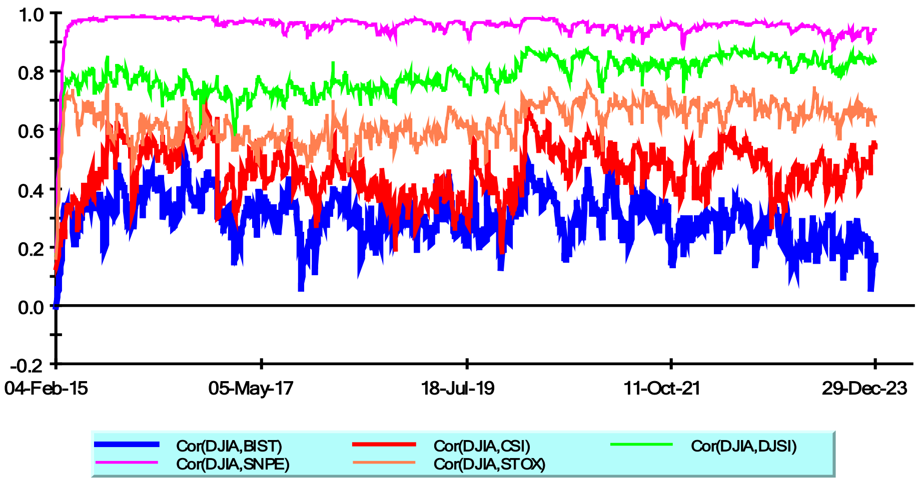


FIGURE 7. Conditional correlation of DJIA with green indices

The correlation graph between the S&P 500 index (SNP5) and various green indices in Figure 8 demonstrates that the S&P 500 maintains a high and stable correlation with the ESG indices, the S&P 500 ESG Index (SNPE), indicating similar market behaviours. The correlations with the DJSI and the STOX are moderately high but more variable, suggesting that while ESG factors influence these indices, other factors contribute to their movements. The S&P 500 exhibits the most variability in correlation with the CSI, indicating differing market influences, and the least correlation with the BIST, suggesting that the BIST may offer distinct diversification advantages in an investment portfolio that includes conventional indices, such as the S&P 500.

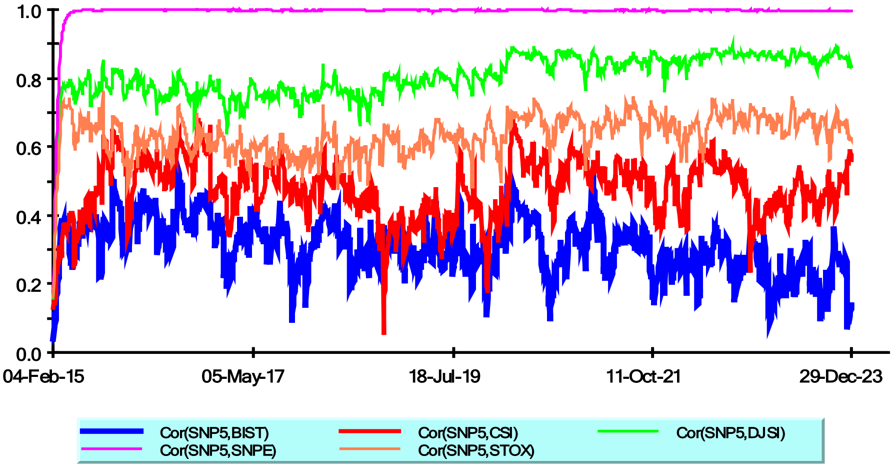


FIGURE 8. Conditional correlation of S&P 500 with green indices

CORRELATION OF GREEN WITH CONVENTIONAL STOCK INDICES AT DIFFERENT TIME AND INVESTMENT HORIZONS BASED ON THE CONTINUOUS WAVELET TRANSFORM

This study employed the CWT methodology to investigate the phase differences between selected market indices across various time scales, ranging from short bursts of 1-4 days to broader windows spanning approximately 512 trading days. The horizontal axis of the resultant graphical representations is designated for trading days, whereas the vertical axis correlates with the length of the investment horizon under consideration. A carefully chosen colour palette aids in visual interpretation: Red hues indicate high correlation, while shades of blue denote lower levels of correlation between indices. A significant feature of these graphs is the delineation of the 5 % significance threshold, established via Monte Carlo simulations, which appears as a curve along the lower edge of the plots. Figures 9 to 16 present the CWT analysis for each pair of variables, encapsulating the dynamic interplay of their correlations over time.

Wavelet coherence is like a zoom lens that lets us see how closely two markets move together at different timeframes, short-term, medium-term, and long-term. It shows if the connection between green and conventional indices is strong or weak during events like financial crises or policy changes, helping investors make smarter timing decisions.

The directionality and character of the interdependencies and potential lead-lag relationships between the FTSE China 50 Index (China) and the other indices are inferred using arrow symbols, following methodologies established by Torrence and Webster (1999), Tiwari (2013), Yang et al. (2017), and Pal and Mitra (2019). China was selected for this analysis due to its notably low correlation with other indices, as well as its strategic role as a major emerging market, making it a valuable reference point for examining diversification potential and market influence. Arrows pointing right (→) are indicative of a positive correlation with the China index, while those pointing left (←) signify a negative correlation. Diagonally upward (↗) and downward (↙) arrows suggest that other indices are predictive of movements in the China index, while arrows pointing downward-right (↘) and upward-left (↖) imply the China index is predictive of future movements in the other indices. Vertical arrows indicate immediacy in influence, with downward (↓) arrows denoting the China index as a leading indicator and upward (↑) arrows indicating it as a lagging one.

Figure 9, derived from wavelet analysis, suggests that diversification between the China index and BIST may yield advantages in the short to medium term. Remarkably, this diversification potential appears robust, showing resilience to major disruptive events, such as the COVID-19 pandemic and the Russia-Ukraine conflict. Despite this, as highlighted in Table 4, the notable volatility of BIST and China indices must be considered, as it may reduce the diversification benefits. Notably, a high degree of correlation is observed at longer-term scales (approximately a 512-day investment horizon), indicating that diversification merits are primarily confined to shorter and intermediate investment periods. Thus, while short and medium-term investment strategies between these indices can enhance portfolio diversity, caution is warranted for long-term allocations due to the increased correlation observed over extended timeframes. In the long-term investment horizon, right-pointing (→) and diagonally upward (↗) arrows signify that the BIST index exhibits a positive correlation with the China index and tends to be a leading indicator. This suggests that movements in the BIST index precede those in the China index over extended periods and may forecast corresponding trends.

Figure 10 indicates that a combined investment portfolio featuring the CSI and the China index exhibits the lowest volatility over the entire investment duration, positioning it as the most stable option among all the indices analysed in this study. This stability suggests that the CSI and China index pairing could be prudent for investors seeking risk-averse strategies, given their persistently low correlation across various time frames. Nonetheless, caution is advised due to the inherent volatility levels of the individual indices, where the CSI is the second most volatile and the China index is the third, as delineated in Table 4. Investors are thus encouraged to consider these volatility rankings to balance potential risks with the safety implied by the low correlation in crafting their investment portfolios.

Figure 11, illustrating the relationship between the STOXX and the China index, indicates that the ideal holding period for achieving optimal diversification benefits is less than six months, corresponding to 1 to 128 trading days. Beyond this range, particularly past a 256-day threshold, the correlation between these indices tends to rise, potentially diminishing the diversification advantage. Since STOXX is the second least volatile index in the study, it can be considered a strong candidate for portfolio investment due to its relative stability over short to medium terms. Thus, investors should target the identified holding duration to maximise diversification and effectively manage correlation-related risks.

In Figure 12, the analysis of the correlation dynamics between the S&P 500 and the China index reveals that, for the period between 2015 and 2020, an optimal diversification strategy would involve holding periods of less than 32 days. Beyond this window, the diversification potential decreases as the correlation between the indices increases. Interestingly, from 2020 to 2023, a persistent low correlation across a longer time frame suggests that these indices offer solid diversification and hedging opportunities, even in the face of global economic turmoil. While pairing the S&P 500 and the China index offers a viable diversification route, the length of the investment horizon remains crucial. Historically, a shorter duration of under 32 days has been ideal for maximising diversification benefits, yet recent trends point to broader windows of opportunity in the current market environment.

Figure 13 presents the correlation landscape between the DJSI and the China index, highlighting a distinct phase of low correlation within investment periods shorter than 64 days. Extending the investment horizon beyond this threshold introduces a higher correlation risk, potentially undermining the diversification strategy between these two indices. Significantly, as detailed in Table 4, the DJSI ranks as the least volatile among all indices examined in the study, underscoring its potential as a robust investment choice when paired with the China index for durations within the 64-day window. Therefore, for investors aiming to capitalise on low volatility and enhance portfolio stability, the DJSI, in tandem with the China index, emerges as an attractive investment conduit for short-term strategies.

Figure 14 delineates the correlation pattern between the S&P ESG and the China index, revealing distinct variations across different investment durations. Specifically, the analysis reveals a phase of low correlation for holding periods of less than 32 days, followed by a higher correlation phase for durations ranging from 32 to 128 days. Interestingly, the correlation dips again for investment periods extending beyond 128 days. This fluctuating correlation pattern underscores the importance of selecting the appropriate investment duration to harness the potential diversification benefits. Notably, major global events, such as the COVID-19 pandemic in 2020 and the Russia-Ukraine conflict, appear to have had a minimal impact on the correlation between these indices, as evidenced by the consistently low correlation during these periods across all investment durations. This observation suggests that the S&P ESG and the China index maintain their distinctive market behaviours irrespective of these significant events, presenting investors with steady diversification opportunities through varying market conditions.

Figure 15 provides insights into the correlation dynamics between the Dow Jones Industrial Average (DJIA) and the China index, highlighting a nuanced approach to portfolio diversification. The analysis suggests that the most effective holding period for leveraging diversification benefits is short-term, specifically within a window of 1 to 32 trading days. In this interval, the correlation remains low, enhancing diversification potential. However, between 32 and 128 days, a noticeable increase in correlation is observed, which may diminish the diversification effect. Intriguingly, the correlation drops again for holding periods extending beyond the 128-day mark, potentially reinvigorating the diversification benefits. The DJIA is identified as the third least volatile index in the study; so it emerges as a viable option for investors seeking portfolio stability in short- and long-term investments. Therefore, investors are advised to focus on these specific holding durations—under 32 days and beyond 128 days—to optimise diversification and effectively manage the inherent correlation risks. This strategic approach could maximise an investment portfolio's stability and potential returns by incorporating these indices.

Figure 16 illustrates the correlation between the FTSE 100 and the China Index, revealing distinct patterns across various investment durations. The initial phase, encompassing holding periods of less than 64 days, is characterised by a low correlation between the indices, suggesting effective diversification potential during these shorter intervals. However, this trend shifts to a higher correlation in investment periods extending beyond 64 days, indicating a reduced diversification benefit. Notably, the analysis also indicates that the COVID-19 pandemic has a significant influence on the correlation dynamics for investment holdings longer than 128 days, where an increased correlation is observed. This observation contrasts with the majority of other indices examined in this study, which generally did not exhibit heightened correlation during the COVID-19 period (2020) or the Russia-Ukraine conflict (post-February 2022), particularly across longer investment horizons of more than 128 trading days. This finding highlights the distinct responses of the FTSE 100 and the China index to global events, underscoring the importance of considering external factors when evaluating investment strategies based on these indices.

TABLE 6. Date for horizontal axis

Horizontal Axis	Date	Event
0	January 2015	
500	February 2017	
1000	March 2019	the start of COVID-19
1500	April 2021	the Russia-Ukraine war started in February 2022
2000	June 2023	

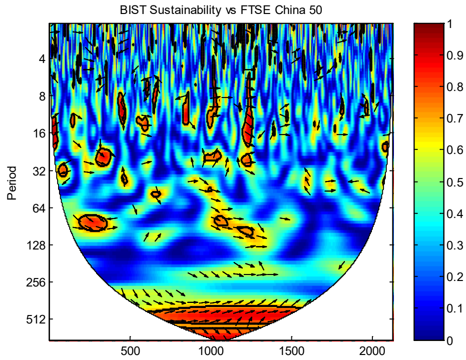


FIGURE 9. CWT – BIST vs China 50 index

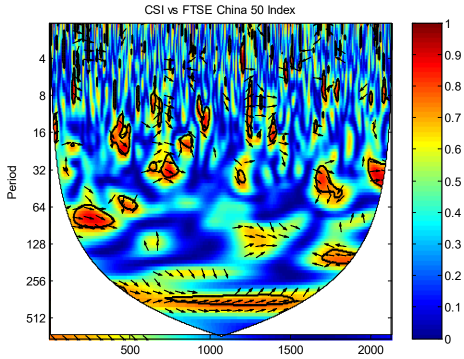


FIGURE 10. CWT – CSI vs China 50 index

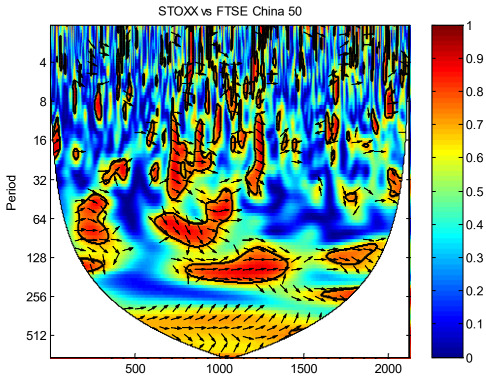


FIGURE 11. CWT – STOXX vs China 50 index

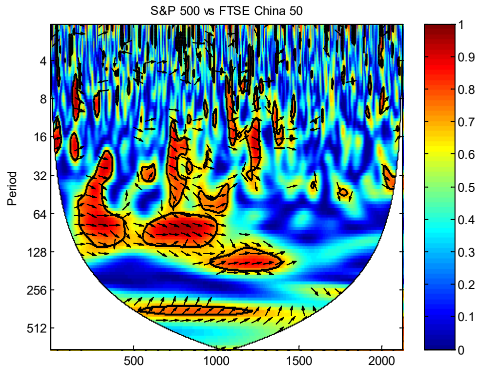


FIGURE 12. CWT – S&P 500 vs China 50 index

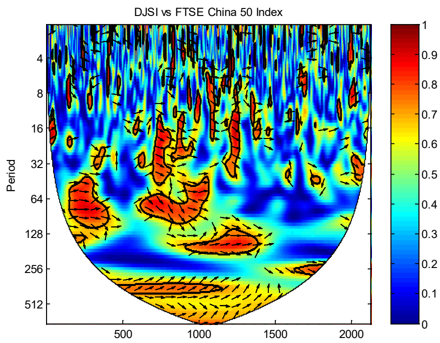


FIGURE 13. CWT – DJSI vs China 50 index

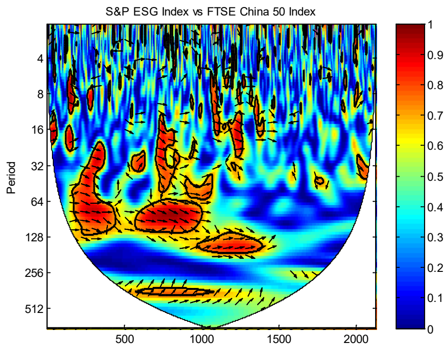


FIGURE 14. CWT – S&P ESG vs China 50 index

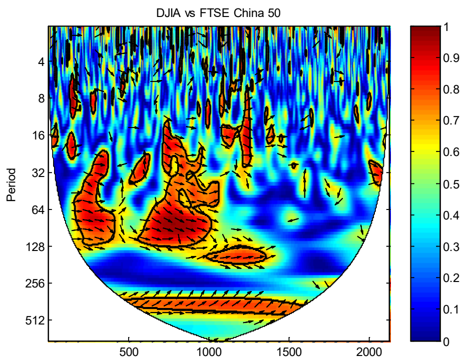


FIGURE 15. CWT – DJIA vs FTSE China 50

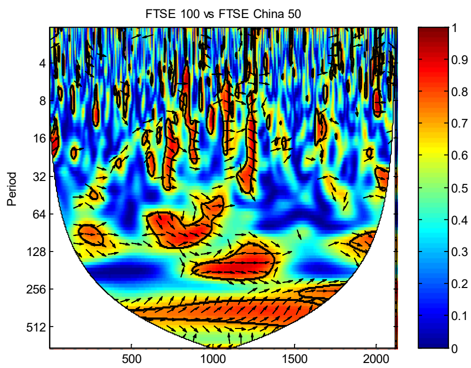


FIGURE 16. CWT – FTSE 100 vs China 50 index

CONCLUSION

This study examined the dynamic relationship between green and conventional stock indices from January 2015 to December 2023, utilising MGARCH-DCC and the CWT. It assessed the volatility and correlation patterns of ten indices to evaluate the diversification potential of green investments. Key findings show that indices like the DJSI and STOXX demonstrate relatively low volatility and stable performance, aligning with prior literature by Friede et al. (2015), which suggests that ESG-aligned assets can deliver favourable risk-adjusted returns. In contrast, indices such as the BIST and CSI displayed higher volatility, which limits their suitability for risk-averse investors.

These results underscore that green indices are not homogeneous. Diversification benefits depend on index composition, market maturity, and regional financial structures. For instance, the low correlation between CSI and the China index offers strategic diversification opportunities, while KOSPI and S&P ESG represent balanced choices. These findings reinforce the notion that ESG assets can serve as functional components in portfolio construction, extending beyond ethical considerations, especially during times of market stress. This aligns with the findings of Chiappini et al. (2021), who observed that sustainable indices maintained stable performance during pandemic-induced market disruptions, thereby reinforcing their role as potential hedging tools. The dynamic relationships between indices are not uniform across all time horizons. Our wavelet-based analysis reveals that the stability and strength of comovement between green and conventional indices vary significantly between short-, medium-, and long-term investment periods.

Overall, the study underscores the relevance of green indices in contemporary portfolio construction and signals the need for more refined strategies and regulations to support sustainable finance.

IMPLICATION

THEORETICAL

This study contributes to the theoretical discourse on sustainable finance in several ways. By applying the Modern Portfolio Theory (Markowitz 1952), our findings support the notion that effective diversification can be achieved through the inclusion of green indices, particularly those with low correlation and stable volatility, such as the S&P ESG and DJSI. Furthermore, the results extend the application of MPT by demonstrating that not all green indices offer equal diversification benefits. While MPT emphasises portfolio risk reduction through low-correlation assets, our analysis reveals that only specific ESG indices consistently exhibit such characteristics, reinforcing the importance of evaluating ESG instruments individually rather than treating them as a homogeneous asset class.

The results also reinforce the Sustainable Finance Theory (Busch et al. 2016), which posits that financial markets are economic mechanisms and vehicles for achieving long-term societal goals. The ability of certain green indices to maintain stability during periods of systemic stress provides empirical backing to the argument that ESG-oriented assets contribute to market resilience. Additionally, the findings reinforce and nuance the theory by demonstrating that sustainability-oriented assets are ethically aligned and economically resilient during crises, such as the COVID-19 pandemic. This supports the theory's core claim that financial markets can promote long-term societal value. However, the observed variability in correlation and volatility across different green indices indicates that the sustainability, financial performance link is conditional, shaped by factors such as index construction, market maturity, and regional policy frameworks. As such, this study supports the existing theory and calls for its refinement to incorporate asset-specific characteristics and temporal dynamics into the sustainability–performance relationship. Future research could build upon the findings of this study by investigating how the integration of green and conventional indices might influence the evolution of modern investment theories.

From a global perspective, the study reflects broader trends in sustainable investing. Although green finance is becoming mainstream, the varying correlation patterns indicate it is not yet fully decoupled from conventional markets. This evolving interdependence raises key questions for the future: Will ESG markets become more resilient and independent, or will they become more integrated into traditional financial systems? Such considerations are vital for shaping long-term strategies in green finance.

PRACTICAL IMPLICATIONS

For policymakers, the indices of specific green demonstrate stability and diversification benefits, indicating a need to further embed ESG principles within financial policy and market regulation. Economic policy could be refined by strengthening ESG disclosure standards, expanding the accessibility and credibility of regional green indices, and integrating sustainable finance objectives into broader capital market development agendas. These recommendations align with evolving international frameworks, such as the European Union (2021) and the People's Bank of China & China Securities Regulatory Commission. (2021), which aims to promote transparency and resilience in financial systems through sustainability-focused regulation. Policymakers can leverage the findings of this study to support capital market stability while advancing environmental and social objectives. For emerging markets and BRICS economies, policymakers could focus on improving ESG data transparency and regulatory consistency to attract institutional investors. Initiatives such as introducing local ESG rating agencies, tax incentives for green investments, and mandating climate risk disclosures can promote decoupling green assets from conventional market cycles.

For investors and asset managers, the study offers timely insights into how green indices can be strategically integrated into portfolios to manage volatility and improve resilience during market disruptions. Rather than viewing ESG assets solely through an ethical lens, the empirical results validate their role as functional diversification tools—particularly in short- to medium-term horizons—when aligned with appropriate risk tolerance and timeframes. The ability of certain green indices to deliver relatively stable returns during periods, such as the COVID-19 pandemic or geopolitical conflicts, further strengthens their appeal as part of a risk-managed investment approach.

In terms of academics, this study contributes to the growing body of literature on sustainable finance by applying a dual-method framework that integrates both time- and frequency-domain analysis to capture the evolving nature of financial comovements. This methodological approach enables a more comprehensive understanding of how green and conventional indices interact, particularly under volatile conditions, and adds empirical clarity to the performance dynamics of ESG-aligned investments.

LIMITATIONS

This study is not without limitations. The reliance on historical data may compromise its predictive value amidst rapidly evolving ESG standards and regulatory shifts. The sample, though global, does not fully capture emerging or frontier markets. Methodologically, MGARCH-DCC assumes linearity and may not detect structural breaks, while CWT is sensitive to edge effects, particularly at short time scales. Future studies could integrate non-linear models or machine learning to increase robustness and explore multi-asset ESG portfolios, including green bonds and carbon markets.

In conclusion, this research provides timely insights into the diversification role of green indices, contributing to a deeper understanding of their strategic value in sustainable investment and financial risk management.

ACKNOWLEDGEMENTS

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NOTES

1. The indices analysed in this study are grouped into two categories — green (sustainability/ESG) and conventional (market benchmark) indices — to reflect their environmental and financial orientations:

a. BIST Sustainability Index (BIST) – Turkey. Tracks companies listed on Borsa İstanbul that demonstrate strong sustainability practices. (Green / ESG-focused)

b. Corporate Sustainability Index (CSI) – Brazil. Measures and monitors firms' environmental, social, and governance (ESG) performance. (Green / ESG-focused)

c. Dow Jones Sustainability World Index (DJSI World) – Global. Developed by S&P Global to evaluate the stock performance of the world's leading sustainability-driven companies. (Green / ESG-focused)

d. S&P 500 ESG Index (S&P ESG) – United States. Comprises large-cap U.S. companies that meet specific ESG criteria, mirroring the risk and return profile of the S&P 500. (Green / ESG-focused)

e. STOXX Global ESG Environmental Leaders Index (STOXX) – Europe / Global. Represents companies recognised for superior environmental and sustainability management across developed markets. (Green / ESG-focused)

f. Dow Jones Industrial Average (DJIA) – United States. A price-weighted index of 30 major U.S. industrial firms, widely used as a gauge of overall market performance. (Conventional)

g. S&P 500 Index (S&P 500) – United States. Tracks 500 of the largest publicly traded U.S. companies, representing the broad U.S. equity market. (Conventional)

h. FTSE 100 Index (FTSE 100) – United Kingdom. Represents the 100 largest companies listed on the London Stock Exchange by market capitalisation. (Conventional)

i. FTSE China 50 Index (China) – China. Includes 50 of the largest and most liquid Chinese stocks listed on the Hong Kong Stock Exchange. (Conventional)

j. Korea Composite Stock Price Index 100 (KOSPI 100) – South Korea. Tracks the top 100 firms listed on the Korea Exchange, serving as a key benchmark for the Korean stock market. (Conventional)

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