# الصكوك الخضراء أو السندات الخضراء:

# دراسة مقارنة لآفاق التنويع والتحوط

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## الملخص:

اعتمد الباحث على منهجي (Waveletو Spillover Index) للمقارنة بين فاعلية الصكوك الخضراء والسندات الخضراء في التحوط من المخاطر الناشئة من S&P500 وFTSE100 و KBW NASDAQ Financial Technology Index والبتكوين، خلال الفترة من أكتوبر 2019 إلى ديسمبر 2022. تبينت النتائج بأن النمط السائد للترابط بين الصكوك الخضراء أوالسندات الخضراء مع الأصول الأخرى كانت ضعيفة، كما أشارت نتائج (wavelet) إلى فشل الصكوك الخضراء والسندات الخضراء في توفير ملاذ آمن للمستثمرين خلال جائحة الكوفيد. وبشكل عام وجلي، تفوقت الصكوك الخضراء كأداة للتنويع والتحوط على نظيره السندات الخضراء. وكشفت نتائج (Spillover Index) عن مدى تأثير السوق الهابط على ترابط الأسواق بأنه تسبّب انتقالا مؤقتا للمخاطر بين الأسواق لمدة أقصاها ثمانية أيام من حين حصول الهزة.

وبالخلاصة، تفوقت الصكوك الخضراء بشكل طفيف على السندات الخضراء في قدرتها على تنويع المحفظة وسط انخفاض (Total Spillover) في السوق، وانخفاض (Net Spillover)، وانخفاض (Net Pairwise Spillover) كما كشفت نتائج (Spillover Index). فمن المرجح أن يوفر دمج الصكوك الخضراء أو السندات الخضراء مع S&P500 و FTSE100 و Index KBW NASDAQ Financial Technology والبتكوين تحت نفس المحفظة الاستثمارية فرصا طويلة الأجل للتنويع والتحوط للمستثمرين.

**الكلمات المفتاحية:** الصكوك الخضراء، السندات الخضراء، الحركة المصطحبة، (wavelet)، (Spillover Index)، إدارة المخاطر.

# Green Sukuk or Green Bonds: A Comparative Study of Diversification and Hedging Prospects

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## Abstract

This study employs the wavelet coherence and the spillover index methodologies to compare time-varying relationship between green sukuk (GSI) and green bonds (SPGB) with S&P 500, FTSE 100, KBW NASDAQ Financial Technology Index and Bitcoin between October 2019, and December 2022. While the predominant tonality of the coherence of GSI and SPGB was weak, GSI and SPGB failed to offset spillover during the covid-19 pandemic. Overall, GSI exhibited superior diversification and hedging performance. The spillover index results unveiled the influence of bearish market conditions on the intensity of market connectedness, prompting temporal transmission of risks between markets which can last up to eight days following the emergence of a shock. GSI slightly outperformed SPGB in portfolio diversification amid low total market connectedness, less net spillover, and less net-pairwise spillover as revealed by the findings of the spillover index. A combination of GSI or SPGB with S&P 500, FTSE 100, KBW NASDAQ Financial Technology Index, and Bitcoin under the same investment portfolio is likely to offer long-term investors diversification and hedging opportunities.

***Keywords:*** Green Sukuk, Green Bond, Co-Movement, Spillover, Wavelet, Risk Management.

## 1. Introduction

The complex battle against climate change impairs the effectiveness of the traditional strategies that do not account for environmental risks, paving the path for the emergence of new environmental-oriented and sustainable assets as alternatives to traditional assets. Climate change is a serious threat to the stability of portfolios exposed to carbon intensive investments. Climate related risks, in the form of physical risks and transition risks, are likely to translate into multiple sources of risks intimidating the financial stability, disrupting economic activities, and resulting in market volatilities, systematic risks and formidable losses for individuals and institutions. A case in point is the damage from physical risks which is estimated to amount 5% of the global GDP by 2050 with a potential rise to 15% by 2100.(1)

The perceived climate risks have significant implications for investment decisions and the cost of capital which emphasizes the need for investors, businesses, and policymakers to alter their financial and investment behavior toward investing in assets that are better positioned to manage climate risks and shape a more resilient financial system. The first step in this journey was the alteration of the global financial system by stimulating the nexus between the financial system and sustainable development. This step marked the birth of a sustainable finance approach which emerged as an alternative to the traditional conventional approach to remedy the challenges of prioritizing short-term returns at the cost of long-term value creation and marginalization of social and environmental effects.

The emergence of green financial instruments embedding climate resilience, promoting sustainability, and playing a role of a catalyst to low carbon economy(2) has prompted a dynamic shift of impactful investors' sentiments over eco-friendly investments. On the course of the past few years, investors awareness on the environmental impacts of businesses have grown tremendously as evidenced by the massive mobilization of capital towards eco-friendly projects depicting a continuous upward trend of green projects. The recent COP27, for example, showcased a pipeline of projects estimated at $120 billion requiring private sector investment to support poorer countries cut emissions and mitigate climate change. Holding the projections true, a continuous development of innovative financing mechanisms is crucial to meet

(1) https://www.ngfs.net/sites/default/files/media/2021/08/27/ngfs_climate_scenarios_phase2_june2021.pdf.

(2) Monasterolo, I., & Raberto, M. (2018). The EIRIN Flow-of-funds Behavioural Model of Green Fiscal Policies and Green Sovereign Bonds. Ecological Economics, 144, 228–243.

the projected targets, bring investment opportunities to impactful investors, and mobilizing funds to scale up a transition to a low carbon economy.

A wide range of instruments were introduced to combat climate change such as (green loans, CO2 trading, green bonds and green sukuk), however, green bonds stood out from all the rest. According to the literature, green bond is considered as an eco-friendly fixed-income instrument which excels in securing climate and sustainable finance with a potential of advancing efforts to spur the transition to a low carbon economy(3). An effective capitalization of green bonds can steer investment portfolios towards a green future and turn the prevailing challenges of climate change into opportunities.

In addition to financing low carbon projects, green bonds are known to bolster the resilience of investment portfolios to climate related risks in two ways. First, green bonds have the capacity to mitigate market volatilities and offer shelter to price oscillations in other markets(4). Second, under a comprehensive credit risk assessment by accounting for climate risks in investment decision making processes, green bonds are likely to outperform conventional peers and are better positioned to mitigate the climate risks. The deliberate design of green bonds to tap funds for sustainable projects such as energy efficiency, renewable energy, climate adaptation, green buildings, and sustainable transportation bolster the resilience to climate change. According to EU Science Hub, new green projects are directly associated with an 8% reduction in carbon emission when compared to non-green bond projects with an average reduction of 4% in carbon emissions for new and refinancing green bond projects in comparison to similar non-green bond projects.(5)

Against this backdrop, the modern portfolio theory which views portfolio optimization as a strategic process of integrating assets of different classes to offset portfolio risks is deeply engrained in the literature of safe-haven assets. In the context of green economy, research in green bond cross market relationships experienced a rapid expansion owing to the growing recognition of the hedging, diversification, and safe-haven attributes inherent in green bonds. In contrast to green bonds, research in green sukuk safe-haven prospect

(3) Reboredo, J. C., Ugolini, A., & Aiube, F. A. L. (2020). Network connectedness of green bonds and asset classes. Energy Economics, 86, 104629. https://doi.org/10.1016/j.eneco.2019.104629.

(4) Reboredo, J. C., Ugolini, A., & Aiube, F. A. L. (2020). Network connectedness of green bonds and asset classes. Energy Economics, 86, 104629. https://doi.org/10.1016/j.eneco.2019.104629; Naeem, M. A., Nguyen, T. T. H., Nepal, R., Ngo, Q. T., & Taghizadeh–Hesary, F. (2021). Asymmetric relationship between green bonds and commodities: Evidence from extreme quantile approach. Finance Research Letters, 43(October 2020), 101983.

(5) https://joint-research-centre.ec.europa.eu/jrc-news/green-bonds-support-carbon-emissions-reduction-research-finds-2021-02-02_en#:~:text=Analysis%20of%20the%20carbon%20emissions,the%20reduction%20is%20over%208%25.

is yet to gain momentum. Green sukuk, as the Shariah compliant equivalent of green bonds, target both impactful and Islamic investors by aligning green and Islamic ethical considerations under the auspices of Maqasid Shariah with an end goal of safeguarding ecological and social welfare.

Despite the similarities between green bonds and green sukuk in the use of proceeds and environmental objectives, distinct differences emerge between the two green assets such as the financial and legal structures. On top of adherence to green standards, green sukuk are subject to compliance to the principles of Shariah. Additionally, the green sukuk market is relatively small ($4.4 billion in H1 2022) compared to the green bond market valued at $2.2 trillion by the end of 2022. The niche market of green sukuk alongside its concentration in the Middle East and Southeast Asian countries are the two major contributors to the paucity of research in green sukuk. As such, this research is the first endeavor to assess the prospect of integrating green sukuk in investment portfolios for risk management purposes. The study seeks to answer three research questions. Do green sukuk offer hedging and diversification opportunities similar to green bonds despite the prevailing differences? How do green bonds and green sukuk perform against spillover effects from stocks and bitcoin? In terms of portfolio risk management, does either of the two assets offer a competitive advantage over its peers?

This backdrop vindicates our growing curiosity of comparing the effectiveness of green bond and green sukuk in hedging and portfolio diversification. To the best of our knowledge, a comparative study of the hedging and diversification capacities between green bonds and green sukuk is yet to be conducted. This study is significant in delineating the diversification potential of green sukuk in comparison to green bonds across different market conditions.

The rest of the study is organized as follows. Section 2 presents a review of the literature. Section 3 provides a description of the data and variables under study alongside a brief presentation of preliminary results. Section 4 describes the methodology implemented in our study. Empirical findings and the discussion of wavelet coherence and spillover indexes results are elaborated in Section 5 and 6 respectively. Section 7 performs robustness check of the methodology and findings. The study is concluded in section 8.

## 2. Review of the Literature

This study is closely related to the literature of markets interconnectedness with an objective of investigating the extent to which a volatility of returns in one instrument propagates to the returns of other asset(s)[6] to identify safe-haven and hedging assets across different market conditions. This study compares the diversification and hedge performance of green bonds and green sukuk against volatilities and spillover effects from the stock markets, bitcoin and fintech companies. This section is bifurcated into brief empirical reviews of the literature of green sukuk and green bonds.

### 2.1. Green Sukuk

The green Shariah-compliant alternative to traditional bonds in the capital markets is unquestionably a strong contender for portfolio diversification. With only one publication examining the co-movements of green sukuk with other sovereign debt instruments, the embryonic research on cross-market linkages between green sukuk has yet to acquire steam. Using a Multivariate Generalized Autoregressive Conditional Heteroscedastic-Dynamic Conditional Correlation (MGARCH-DCC) model, Narayan et al. (2022) assessed the interconnectedness between 5-year sovereign debt instruments of Indonesia in the form of bonds, sukuk and green sukuk, conventional stock market index and the Islamic index from the Jakarta stock exchange in the covid-19 pandemic era. The study reported an increase in volatility of the assets overtime particularly at the onset of the covid-19 pandemic. The study evinced the flight to quality attribute in sukuk and green sukuk amid investors' switch to sukuk and green sukuk from conventional and Islamic stocks.

### 2.2. Green Bonds

The interdependence between green bonds and other financial markets is well documented in the growing literature. Starting with the relationship between green bonds and stocks, a weak correlation is detected by most studies in literature attesting to green bonds' diversification potential for stock markets' investors [7]. Furthermore, the findings of Thai (2021), Nguyen et al. (2021) and Hung (2021) can be considered as a testimony for green bonds hedging ability against price oscillation from the stock market. The capacity of green bonds to serve as a safe-haven asset amid dramatic risk reduction capabilities was validated by the studies of Kuang (2021), Kocaarslan (2021), and Yousaf

(6) Kočenda, & Evžen. (2018). Survey of Volatility and Spillovers on Financial Markets. Http://Pep.vse.Cz/Doi/10.18267/j.Pep.650.Html, 27(3), 293–305. https://doi.org/10.18267/J.PEP.650

(7) Reboredo, J. C. (2018). Green bond and financial markets: Co-movement, diversification and price spillover effects. Energy Economics, 74, 38–50. https://doi.org/10.1016/j.eneco.2018.05.030; Ferrer, R., Shahzad, S. J. H., & Soriano, P. (2021). Are green bonds a different asset class? Evidence from time-frequency connectedness analysis. Journal of Cleaner Production, 292, 125988. https://doi.org/10.1016/j.jclepro.2021.125988

et al. (2022). The findings of these studies collectively position green bonds as a strategic asset sheltering price spillovers from the stock market over different market conditions. A few studies, however, reported that the diversification effectiveness of green bonds was limited to bullish market conditions. The correlation between green bonds and stocks weakens in bullish market but strengthened significantly post covid-19 pandemic(8) leading to a significant dissipation of green bonds hedging efficiency in extreme downturns (9).

With regards to bitcoin, the literature on the nexus between green bonds and bitcoin or the crypto-currency market is limited to a few studies. Hung (2021) found a bidirectional relationship between green bonds and Bitcoin. Furthermore, significant connectedness between the two assets was reported via Multilayer Perceptron Neural Network Non-linear Granger causality model inferring a potential hedging avenue in green bonds to price oscillations in Bitcoin. The results are in line with the findings of Thai (2021).

To the best of our knowledge, a comparative study of the hedging and diversification capacities between green bonds and green sukuk is yet to be conducted. This study is the first to explore the nexus of green bonds and stocks, and bitcoin in comparison to the relationship between green bonds and stocks and bitcoin. This study contributes to the rapid expansion of the literature of safe haven assets in the context of green finance(10) in four main fronts:

- First, to the best of our knowledge, our study is the first endeavor to empirically and comprehensively compare the hedging capacities of green bonds and green sukuk against stock markets and bitcoin spillover.
- Second, the study uses novel techniques such as the wavelet coherence to analyze markets' connectedness across different market conditions.
- Third, we complimented our wavelet analysis with the spillover index of Diebold and Yilmaz (2012) and Barunik and Krehlik (2018) to facilitate a thorough investigation of the hedging effectiveness of green bonds and green sukuk against spillover from stocks and bitcoin.

(8) Pham, L. (2021). Frequency connectedness and cross-quantile dependence between green bond and green equity markets. Energy Economics, 98, 105257. https://doi.org/10.1016/j.eneco.2021.105257

(9) Guo, D., & Zhou, P. (2021). Green bonds as hedging assets before and after COVID: A comparative study between the US and China. Energy Economics, 104(September), 105696.

(10) Pham, L. (2016). Is it risky to go green? A volatility analysis of the green bond market. Http://Dx.Doi.Org/10.1080/20430795.2016.1237244, 6(4), 263–291 ; Reboredo, J. C. (2018). Green bond and financial markets: Co-movement, diversification and price spillover effects. Energy Economics, 74, 38–50. https://doi.org/10.1016/j.eneco.2018.05.030; Nguyen, T. T. H., Naeem, M. A., Balli, F., Balli, H. O., & Vo, X. V. (2021). Time-frequency comovement among green bonds, stocks, commodities, clean energy, and conventional bonds. Finance Research Letters, 40(August 2020), 101739. https://doi.org/10.1016/j.frl.2020.101739.

- Finally, the findings of our study are of primary interest to speculators and investors operating across different investment frequencies and have vital implications for academia and policymakers to mobilize finance for climate change mitigation.

## 3. Data and Methodology

### 3.1. Data

This study uses daily data (Monday-to-Friday) encompassing the period of about 39 months dating from October 15, 2019, to December 31, 2022, to compare green bonds and green sukuk in diversification and hedging efficiency. The selection of this time-frame facilitates monitoring interconnectedness of the green sukuk index and green bonds with the stock markets, Fintech stocks and Bitcoin across different market conditions. The rationale of using daily data for analysis is to capture tick by tick fluctuations and effectively demonstrate the impact of shocks on the markets' interconnectedness. Daily prices in the form of bid prices (green sukuk) and closing prices for the rest of the dataset were fetched from Thompson Reuters database. The prices of the variables are either listed in US dollars or converted to US dollars (in the case of green sukuk). Data analysis is performed using continuously compounded daily returns by taking the difference in the logarithm percentage of two consecutive prices of the assets under study, expressed as:

$$r_{i,t} = ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \times 100$$

Figure 1 portrays prices and returns dynamics of markets under study. Volatilities in both price and return series are apparent in all markets. All markets were severely affected by the outbreak of the covid-19 pandemic evident to the short-lived downward trends in the assets' prices between March 2020 and May 2020.

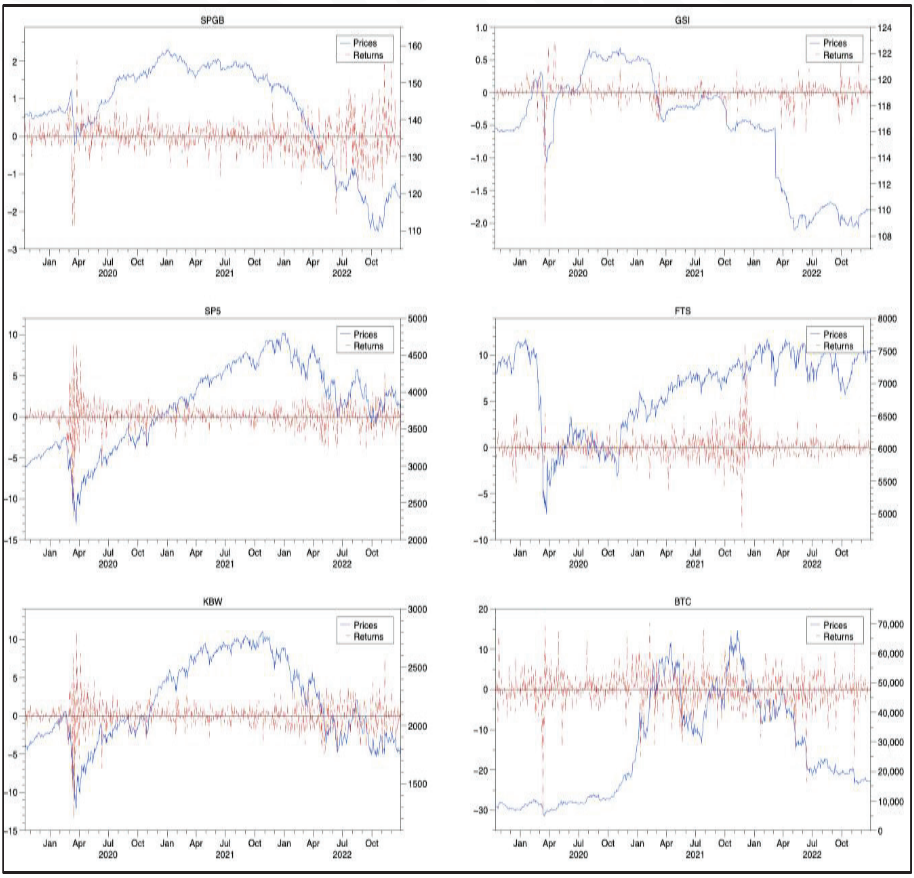



*Figure 1. Assets prices and returns dynamics.*

Notes: GSI is the Green sukuk index; SPGB- S&P Green Bond Index; KBW- KBW NASDAQ Technology Index; SP5- S&P500; FTS- FTSE100; and BTC- Bitcoin.

The Green Sukuk Index (GSI) is constructed following the market capitalization index methodology with minor adjustments to facilitate the integration of a higher number of green sukuk issuances which fulfill the following criteria:

a. Listed as 'green bond' or 'ESG bond' on Thompson Reuters database.

b. Certification (rated) by a leading rating agency in the country or region.

c. Compliance with Shariah requirements set by Shariah standard board such as the Accounting and Auditing Organization for Islamic Financial Institutions (AAOIFI).

The index is limited to Malaysian ringgit (MYR) denominated sukuk comprising of bid prices of 120 green sukuk issued by 10 private corporates in

Malaysia where the proceeds are mostly allocated towards energy efficiency projects as shown in table 1.

***Table 1. The structure of the Green Sukuk Index***

| Sukuk Name | Use of Proceeds | Issuance |
|---|---|---|
| Quantum Solar Park (semananjung) Sdn Bhd | Energy efficiency | 27 |
| Cypark Ref Sdn Bhd | Energy efficiency | 19 |
| Telekosang Hydro One Sdn Bhd | Energy efficiency | 15 |
| UiTM Solar Power Sdn Bhd | Energy efficiency | 15 |
| Sinar Kamiri Sdn Bhd | Energy efficiency | 14 |
| Tadau Energy Sdn Bhd | Renewable Energy Projects | 12 |
| PNB Merdeka Ventures Sdn Bhd | (Green constructions (buildings | 9 |
| Pasukhas Green Assets Sdn Bhd | Renewable Energy Projects | 7 |
| Edra Solar Sdn Bhd | Energy efficiency | 1 |
| Hsbc Amanah | Sustainable Development Projects | 1 |
| **Total** | | 120 |

*Source: Thompson Reuters*

The rest of the dataset comprises of daily closing prices of S&P Green Bond Index, KBW NASDAQ Financial Technology Index (KBW), S&P 500 and FTSE 100 and Bitcoin. The selection of S&P Green Bond Index as a proxy for the green bond market is based on the coverage of the index of a wide range of green bond markets worldwide. S&P Green Bond Index incorporates certified green bonds by Climate Bonds Initiative issued by sovereigns, multilateral organizations, and corporates. This study follows Pham (2021) and Tiwari et al. (2022) in selecting S&P Green Bond Index as a proxy for the green bond market. We incorporate two major stock indexes, namely: S&P 500 and FTSE 100 as proxies of the stock market which represent 500 and 100 publicly listed companies respectively. The two indexes comprise of heavily weighted companies with relatively high trading frequencies and volumes. As such, investors can easily invest in these indexes without facing any liquidity constraints.

KBW NASDAQ Financial Technology Index (KBW) was selected as a proxy of FinTech stocks. Using an equal weighted index, KBW was constructed from the synergy between Nasdaq and Keefe, Bruyette and Woods (KBW), which is a financial service investment bank, to track the performance of entities that integrates technological advancement in providing financial services and goods. Last but not least, given the proliferation of digital currencies in investment portfolios, Bitcoin spot prices represent the crypto-currency market amid its dominance not only in trading volumes and frequencies but also market capitalization. The selection of these variables is anticipated to generate meaningful results.

***Table 2. Descriptive Statistics and Preliminary tests***

| | SPGB | GSI | SP5 | FTS | KBW | BTC |
|---|---|---|---|---|---|---|
| Mean | -2.01 | -0.26 | 2.97 | -0.58 | -0.15 | 8.46 |
| Med | 0.00 | 0.00 | 7.92 | -6.50 | 3.39 | 11.52 |
| Min | -240.99 | -202.00 | -1276.52 | -866.68 | -1356.78 | -3093.14 |
| Max | 227.17 | 81.00 | 896.83 | 1151.24 | 1116.36 | 1653.22 |
| St. Dev | 44.16 | 15.22 | 152.72 | 122.65 | 182.75 | 426.94 |
| Cf. Var | -21.94 | -58.45 | 51.51 | -212.67 | -1255.01 | 50.49 |
| Skew | -31.07 | -335.82 | -79.93 | 125.67 | -51.33 | -72.03 |
| Kurt | 464.76 | 4436.61 | 1258.07 | 1559.03 | 862.10 | 585.60 |
| Obs | 837 | 837 | 837 | 837 | 837 | 837 |
| JB | 755.47 | 69375.00 | 5536.70 | 8587.70 | 2593.50 | 1251.00 |
| | 0.00*** | 0.00*** | 0.00*** | 0.00*** | 0.00*** | 0.00*** |
| ADF | -22.74 | -20.00 | -35.75 | -29.76 | -32.36 | -28.34 |
| | 0.00*** | 0.00*** | 0.00*** | 0.00*** | 0.00*** | 0.00*** |

Notes: The table shows the time series means, medians, minimums, maximums, standard deviations, coefficients of variance, skewness, and kurtosis of the main variable under study. JB and ADF test for normality (JB) and stationarity (ADF). ***, **, * denotes significance level at 1%, 5% and 10% respectively.

A summary of descriptive statistics is presented in table 2. GSI had the least average returns and the lowest unconditional volatility attributed to the buy and hold phenomenon of green sukuk prompting low trading frequencies of the green asset in underdeveloped green sukuk secondary markets. This is in line with the findings of Jones et al. (1994)it is the occurrence of transactions per se, and not their size, that generates volatility; trade size has no information beyond that contained in the frequency of transactions. Our results suggest that theoretical research needs to entertain scenarios in which (i of a positive relation between volatility and the number of transactions. In contrast, the findings reported BTC as the asset with the highest average returns and unconditional volatility amid its high risk. According to the absolute terms of the coefficients of variation, the riskiest asset was KBW followed by FTS and GSI. Except for FTS, the negative values of skewness infer a likelihood of extreme negative values in the sample period. Furthermore, the coefficients of kurtosis show all markets do not follow a normal distribution amid the existence of heavy tails in all markets.

Jarque-Bera test support the findings of abnormality in the data distribution at a significance level of 1%. The unit root tests are performed with neither a constant nor a trend at level form using the Augmented Dickey–Fuller (ADF) test where the optimal lag length was selected using the Akaike Information Criterion (AIC). ADF test results clearly indicate that all market returns are stationary (at 5% significance level). The selection of lag length for the unit root tests was based on the Akaike Information Criterion with no intercept and trend.

Table 3 portrays pairwise relation between investigated markets. A strong positive relationship was observed between SP5- KBW (93%), followed by KBW- BTC (41%) and SP5- BTC (40%). Overall, SPGB had a negative correlation with FTS and low positive correlations with the rest of the markets. As for GSI, the results remark negative correlation between GSI- FTS and GSI- BTC and low positive correlation with the rest of the dataset. The results imply that GSI is a better diversifier and hedge than SPGB in the sample period.

***Table 3. Correlation Matrix***

| | SPGB | GSI | SP5 | FTS | KBW | BTC |
|---|---|---|---|---|---|---|
| SPGB | 100% | | | | | |
| GSI | 21% | 100% | | | | |
| SP5 | 22% | 8% | 100% | | | |
| FTS | -1% | -2% | 4% | 100% | | |
| KBW | 25% | 8% | 93% | 3% | 100% | |
| BTC | 18% | -4% | 40% | -2% | 41% | 100% |

## 4. Methodology

### 4.1. Wavelet Coherence

The wavelet technique facilitates dynamics of time series assessment to visualize the variation of correlations between time series across multiple investment horizons presented by the wavelet scales [11]. According to Grinsted et al., (2004), the wavelet coherence is defined as:

$$R_n^s(S) = \frac{\left|S\left(s^{-1}W_n^{XY}(S)\right)\right|^2}{S(s^{-1}|W_n^x(s)|^2)\,.\,S(s^{-1}|W_n^Y(s)|^2} \tag{2}$$

with $0 \leq R_n^2(s) \leq 1$

where S is a smoothing operator, $W_n^y$ and $W_n^x$ denote the continuous wavelet transform of time series $x$ and $y$ respectively and $W_n^{xy}$ is the cross wavelet transform of the two-time series ( $x$ ) and ( $y$ ). The correlation coefficients in the wavelet coherence measure interconnectedness of two time series at each scale in the range of zero and one[12].

$$S\big(W(\tau,s)\big) = S_{scale}\left(S_{time}\big(W(\tau,s)\big)\right) \tag{3}$$

where S signifies smoothing in wavelet scale axis and time. This study follows the Morlet wavelet smoothing operator introduced by Torrence and Compo (1998) which is presented as:

$$S_{time}(W)_s = \left(W_n(s) * c_1^{\frac{-t^2}{2s^2}}\right)|._s;\ S_{time}(W)_s = \big(W_n(S) * c_2\Pi(0.6s)\big)|._n \tag{4}$$

where * denotes the convolution product, the normalization is demonstrated by $c1$ and $c2$ while Π represents the rectangle function. The factor of 0.6 is the empirically determined scale decorrelation length for the Morlet wavelet[13]. The phase difference is determined by a more complex polar form of wavelet coherency expressed as:

(11) Grinsted, A., Moore, J. C., & Jevrejeva, S. (2004). Application of the cross wavelet transform and wavelet coherence to geophysical time series. Nonlinear Processes in Geophysics, 11(5/6), 561–566. https://doi.org/10.5194/NPG-11-561-2004.

(12) Madaleno, M., & Pinho, C. (2012). International stock market indices comovements: a new look. International Journal of Finance & Economics, 17(1), 89–102. https://doi.org/10.1002/IJFE.448.

(13) Torrence, C., & Compo, G. P. (1998). A Practical Guide to Wavelet Analysis. Bulletin of the American Meteorological Society, 79(1), 61–78. https://doi.org/10.1175/1520-0477(1998)079.

$$\phi(a,t) = arctan\left\{\frac{\Im\left[S[a^{-1}W_{uv}(a,t)]\right]}{\Re\left[S[a^{-1}W_{uv}(a,t)]\right]}\right\} \tag{5}$$

in which $\Im$ and $\Re$ denote the imaginary parts and real parts of the complex variables respectively. An in-phase co-movement between time series at which time series $x$ leads y is denoted as $\emptyset\_xy \in (0,\pi/2)$. Alternatively, if $\emptyset\_xy \in (-\pi/2,0)$ the time series co-move with time series y leading $x$. An anti-phase relation between time series is expressed by the phase difference of $\pi$ $(-\pi)$ in which time series move in opposite directions. $\emptyset\_xy \in (-\pi,-\pi/2)$ and $\emptyset\_xy \in (\pi/2,\pi)$ denote the leading and lagging positions of $x$ respectively.

### 4.2. The Spillover Index

The assessment of interconnectedness between assets understudy is performed using the spillover indexes of Diebold and Yilmaz (2012) and Barunik and Krehlik (2018) (hereafter DY12 and BK18 respectively). DY12 undertakes forecasting error variance decompositions (FEVD) from a Generalized Vector Autoregressive models of Koop et al. (1996) and Pesaran and Shin (1998) that reflects a time series own variance or cross variance series. The KPPS-VAR model constitute the H-step-ahead FEVD as:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}\left(e_i'A_h\sum e_j\right)^2}{\sum_{h=0}^{H-1}\left(e_i'A_h\sum A_h'e_i\right)} \tag{6}$$

in which $\sum$ denotes the variance matrix for the error vector $e$, $\sigma\_jj$ stands for the standard deviation of the error term for the $j$th equation. $Q_{ij}(H)$ denotes the influence of one standard deviation shock to $x_j$ to the variance of the H-step-ahead forecast error of $x_i$, where the ratio of own variance impact or cross variance series impact is demonstrated by the main diagonal and off-diagonal factors respectively. The normalization of each FEVD in the Q(H) matrix can be estimated using the row sum expressed as:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N}\theta_{ij}^{g}(H)} \tag{7}$$

The normalization of FEVD is vital in evaluating the degree of interdependences between time series in the forms of the Total Spillover Index (TSI), Directional Spillover Index (DSI), Net Spillover Index (NSI) and Net Pairwise Spillover Index (NPSI). TSI measures time series contribution of spillover to the total forecast error variance expressed as:

$$TSI(H) = \frac{\sum_{i,j=1,i\neq j}^{N} \theta_{ij}(H)}{\sum_{i,j=1}^{N} \theta_{ij}(H)} \times 100 = \frac{\sum_{i,j=1,i\neq j}^{N} \theta_{ij}(H)}{N} \times 100 \qquad (8)$$

in which TSI is an off-diagonal sum of the ratios of the forecast error variances of all $x\_i$ because of shocks in $x\_j$, where all $i \neq j$.

The DSI measures the spillover received by vector $i$ from all vectors $j$ defined in equation 9 in addition to the spillover transmitted by vector $i$ to all vectors $j$ as expressed in equation 10.

$$DSI_{i.}(H) = \frac{\sum_{j=1,j\neq i}^{N} \theta_{ij}(H)}{\sum_{i,j=1}^{N} \theta_{ij}(H)} \times 100 = \frac{\sum_{j=1,i\neq j}^{N} \theta_{ij}(H)}{N} \times 100 \qquad (9)$$

$$DSI_{.i}\,(H) = \frac{\sum_{j=1,j\neq i}^{N} \theta_{ij}(H)}{\sum_{i,j=1}^{N} \theta_{ji}(H)} \times 100 = \frac{\sum_{j=1,i\neq j}^{N} \theta_{ij}(H)}{N} \times 100 \qquad (10)$$

The NSI calculates the difference between asset (vector $i$) transmission and reception of spillover where positive (negative) values indicate vector $i$ is a net sender (receiver) of spillover. NSI is defined as:

$$NSI_{i}(H) = DSI_{.i}(H) - DSI_{i.}(H) \qquad (11)$$

Finally, NPSI captures the difference between gross volatility spillover from vector $i$ to vector $j$ and vise-versa to determine a net receiver and source of spillover between two time series. Equation 12 defines the NPSI as:

$$\begin{aligned} S_{ij}^{g}(H) &= \left( \frac{\tilde{\theta}_{ji}^{g}(H)}{\sum_{i,k=1}^{N} \theta_{ik}^{\sim g}(H)} - \frac{\tilde{\theta}_{ij}^{g}(H)}{\sum_{j,k=1}^{N} \theta_{jk}^{\sim g}(H)} \right) \times 100 \\ &= \left( \frac{\tilde{\theta}_{ji}^{g}(H) - \tilde{\theta}_{ij}^{g}(H)}{N} \right) \times 100 \end{aligned} \qquad (12)$$

## 5. Wavelet Results

The wavelet coherence results are portrayed in a heat map where the co-movements of time series are measured on a scale of 01-. While the -axis displays the time frame of the sample, the -axis depicts wavelet scales which reflect different investment horizons. A red (blue) zone denotes high (low) correlation between two time series. A rightward (leftward) arrow denotes a positive (negative) relationship. When the arrow points right-down or left-up, it signifies that the first variable in the equation leads or influences the latter, and vice versa. If the arrow's direction is completely horizontal or vertical, the lead-lag relationship between the time series remains indeterminate. Monte Carlo simulations determine the statistical significance of wavelet coherency, with 95% confidence indicated by red zones within the black contours.

The dynamic connections between GSI with SP5, FTS, KBW and BTC are presented in figure 2a through 2d. Overall, a weak coherency is observed throughout the sample period, particularly between GSI and FTS as depicted in figure 2b. Small pockets of temporal high correlations are observed in the short and medium terms. However, the lead-lag relationship is vague in the absence of clear directions of the arrows. Distinctive red zones reflecting high correlation between markets emerge in low frequencies between GSI-SP5, GSI-KBW and GSI-BTC as shown in figure 2a, 2b and 2c respectively between February 2020 and July 2020 amid the outbreak of the covid-19 pandemic. In this period, GSI lead SP5, KBW and BTC in in-phase movement. In the case of GSI-BTC, GSI manifested a high coherency with BTC between September 2021 and February 2022 as shown in figure 2d. The arrows are pointing up-left indicating that the two assets are moving in in anti-phase movement where GSI leads BTC.

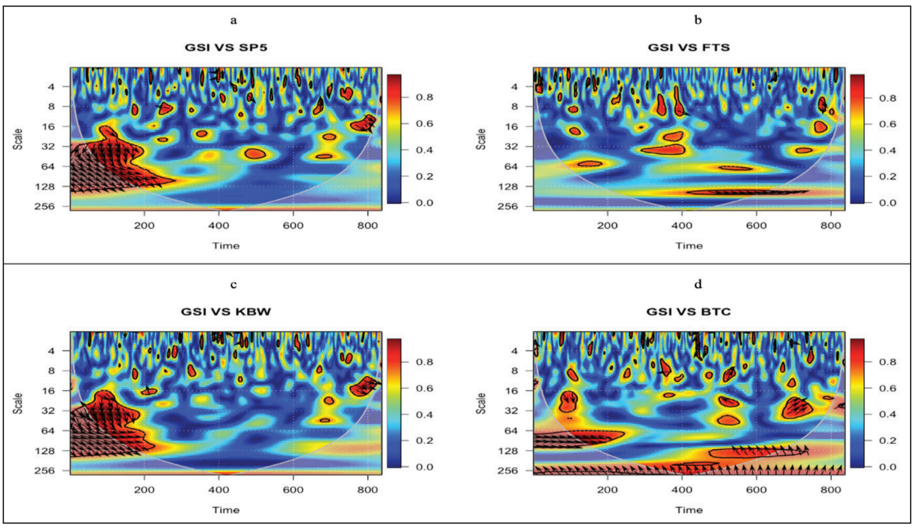



*Figure 2. Wavelet coherency between GSI and other assets.*

Notes: SPGB stands for S&P Green Bond Index; KBW- KBW NASDAQ Financial Technology Index; SP5- S&P500; FTS- FTSE100; and BTC- Bitcoin. Sample period is presented on the horizontal axis covering a period between Oct 15, 2019 - Dec 31, 2022, where (100 = Mar 3, 2020, 200 = Jul 21, 2020, 300 = Dec 8, 2020, 400 = Apr 27, 2021, 500 = Sep 14, 2021, 600 = Feb 1, 2022, 700 = Jun 21,2022, and 800 = Nov 8, 2022). The vertical axis denotes three investment frequencies: short term (48- days), medium term (832- days) and long term (32+ days).

Figure 3a through 3d visualizes the wavelet coherency between SPGB and SP5, FTS, KBW and BTC. While the predominant tonality of the coherence between SPGB and FTS is low as shown in figure 3b, some intervals of low coherence are scattered in the short and medium terms with undetermined lead-lag relationship between the two time series. Figure 3a and 3c exhibit multiple zones of high coherence between SPGB and SP5 and KBW respectively in all frequencies. Pockets of high correlations are apparent at the onset of the covid-19 pandemic where SPGB poses the leading role in in-phase movement and post Feb 2022 till the end of the sample period in the medium and long terms in a mixed lead-lag relation. In high frequencies (short-term), regions of high correlations are dispersed across various time intervals with no clear lag/lead relationship between the two-time series. As for the causal relationship between SPGB and BTC, figure 3d depicts the dominance of a weak relationship between the two assets. A short-lived high coherency is observed at the outbreak of the covid-19 pandemic in the low and medium frequencies where SPGB leads BTC in a positive co-movement. Other zones of moderate to high correlations are dispersed in all frequencies in figure 3.

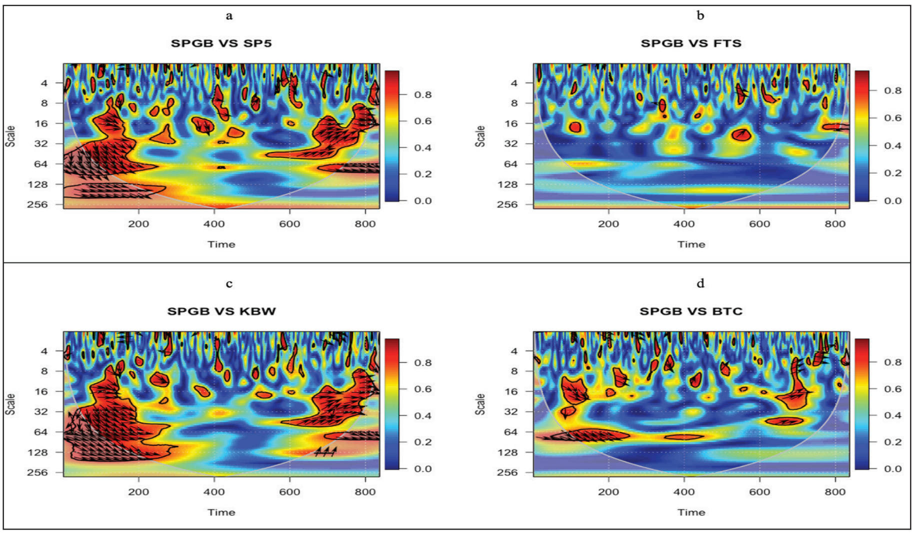



*Figure 3. Wavelet coherency between SPGB and other assets.*

Notes: SPGB stands for S&P Green Bond Index; KBW- KBW NASDAQ Financial Technology Index; SP5- S&P500; FTS- FTSE100; and BTC- Bitcoin. Sample period is presented on the horizontal axis covering a period between Oct 15, 2019 - Dec 31, 2022, where (100 = Mar 3, 2020, 200 = Jul 21, 2020, 300 = Dec 8, 2020, 400 = Apr 27, 2021, 500 = Sep 14, 2021, 600 = Feb 1, 2022, 700 = Jun 21,2022, and 800 = Nov 8, 2022). The vertical axis denotes three investment frequencies: short term (48- days), medium term (832- days) and long term (32+ days).

The comparison between the coherency of GSI and SPGB as presented by the wavelet results implies the superiority of GSI in portfolio diversification. GSI and SPGB can be strategic diversifiers and hedges against price oscillation of FTS in different market conditions throughout the sample period. As for SP5 and KBW, the performance of GSI in offering diversification and hedge advantages to investors of multiple horizons is superior to SPGB. However, the high correlations between GSI and SP5 and KBW at the onset of the covid-19 pandemic prompted dissipation of diversification and hedging advantages particularly to long term investors. Thus, investors should be attentive to market dynamics and must refrain from combining GSI and SP5 and KBW under the same investment portfolio in this period. In a BTC portfolio, arguably SPGB performed slightly better than GSI. Patches of high correlation were scattered across all frequencies of the sample period. Thus, the diversification and hedging potential of both GSI and SPGB dissipated in these periods.

## 6. Spillovers results

### 6.1. Static Spillover Results

This study uses a daily vector autoregressive model of order 1 as recommended by the Schwarz criterion via generalized variance decompositions of the 100-days-ahead forecast to assess return spillover of selected assets. It does so following the generalized FEVD framework of Diebold and Yilmaz (2012). The static spillover index is shown in Table 4. Directional spillovers are represented by the sum of off-diagonal column and off-diagonal row. The «to others» row in the dataset displays an asset's contribution of spillover effects to other assets, while the «from others» column represents the spillover effect from other assets. Own-assets spillover of returns is captured in the diagonal cells. Net directional spillover is the difference between «to others» and «from others» directional spillover. A market with a positive net value is a net transmitter of spillover while a negative net value asset is a net receiver. Total spillover is the off-diagonal sum of the ratios of the forecast error variances shown in the lower right corner.

*Table 4. Static Spillover Index DY12*

| Panel A | GSI | SP5 | FTS | KBW | BTC | FROM |
|---|---|---|---|---|---|---|
| GSI | 96.48 | 1.07 | 0.08 | 1.93 | 0.45 | 0.70 |
| SP5 | 0.34 | 49.73 | 0.09 | 41.96 | 7.88 | 10.05 |
| FTS | 0.04 | 0.15 | 99.60 | 0.13 | 0.07 | 0.08 |
| KBW | 0.37 | 42.8 | 0.07 | 48.53 | 8.23 | 10.29 |
| BTC | 0.21 | 12.08 | 0.17 | 12.72 | 74.82 | 5.04 |
| TO | 0.19 | 11.22 | 0.08 | 11.35 | 3.33 | **26.17** |
| NET | -0.51 | 1.17 | 0.00 | 1.06 | -1.71 | |
| **Panel B** | **SPGB** | **SP5** | **FTS** | **KBW** | **BTC** | **FROM** |
| SPGB | 72.10 | 11.07 | 0.13 | 13.00 | 3.70 | 5.58 |
| SP5 | 3.56 | 48.1 | 0.08 | 40.6 | 7.65 | 1.038 |
| FTS | 0.04 | 0.15 | 99.61 | 0.13 | 0.07 | 0.08 |
| KBW | 4.16 | 41.15 | 0.07 | 46.66 | 7.95 | 10.67 |
| BTC | 3.14 | 11.76 | 0.16 | 12.38 | 72.55 | 5.49 |
| TO | 2.18 | 12.83 | 0.09 | 13.22 | 3.88 | **32.20** |
| NET | -3.40 | 11.792 | 0.01 | 2.55 | -1.61 | |

Notes: The underlying variance decompositions are calculated with the VAR of order 1 suggested by Schwarz criterion using generalized variance decompositions of the 100-days-ahead forecast. The study employed the generalized VAR spillover framework of DY12 to identify FEVDs. The Static Spillover results of GSI and SPGB are reported in panel A and B respectively. Sample: Oct 15, 2019 - Dec 31, 2022.

Panel A and B of table 4 present DY12 static spillover results of GSI and SPGB with SP5, FTS, KBW and BTC. The total spillover (TS) of GSI and SPGB in panel A and B is 26.17% and 32.30% respectively. Accordingly, the return forecast error variance decomposition acquired from other assets within panel

A and B is estimated at 26.17% and 32.30% respectively. Overall, a weak to moderate interconnectedness between the assets is observed in table 4 amid a low to moderate TS inferring to a potential venue for diversification. Given the TS of GSI in panel A is lower than of SPGB in panel B, GSI is likely to be a better diversifier and hedge than SPGB when combined with SP5, FTS, KBW and BTC. The contribution of GSI spillover to other assets and vice-versa is negligible at 0.19% and absorbing 0.7% from the system. SPGB absorption of spillover from the system is slightly higher at 5.58% while contributing by 2.18%. Once again, the findings confirm the diversification preeminence of GSI. In terms of net directional return spillover, the results of DY12 report both GSI and SPGB as net receivers of return spillover by 0.51% and-3.4% respectively supporting the risk diversification capacities of GSI and SPGB.

Next we use the frequency decomposition technique of Baruník and Křehlík (2018) to assess markets connectedness across different scales. The first band corresponds to movements from 1- 8 days while the second and third bands reflect movements from 8–32days and 32 days–infinity respectively. The decomposition process highlights investing opportunities across multiple horizons to a wide range of investors. The TS in panel A and B of table 5 experienced a significant decline as we approached the lower frequencies. The highest TS was recorded in scale 1 of panel B of table 5 which correlates to fluctuations between 18- days. A sharp drop in TS in scale 2 and 3 implies that the transmission of shocks within the system is highly anticipated to happen up to 8 days from a turbulent incident. Shocks to any asset within the system are perceived to be a short-lived contagion during extreme market conditions. The results of net directional spillover show that net directional spillover tend to be the furthest from zero in the highest frequencies [14]. GSI And SPGB were net recipients of spillover in all scales. GSI and SPGB demonstrated diversification potential given the insignificant values of net spillovers across the scales throughout the period under study. The results of DY12 and BK18 are in line with the findings of wavelet coherence.

(14) Liow, K. H. (2015). Volatility spillover dynamics and relationship across G7 financial markets. The North American Journal of Economics and Finance, 33, 328–365. https://doi.org/10.1016/J.NAJEF.2015.06.003

*Table 5. Static Spillover Index BK18*

| | | Scale 1 | Scale 2 | Scale 3 |
|---|---|---|---|---|
| Panel A | GSI | -0.34 | -0.13 | -0.05 |
| | SP5 | 1.03 | 0.10 | 0.04 |
| | FTS | 0.01 | 0.00 | 0.00 |
| | KBW | 0.78 | 0.21 | 0.07 |
| | BTC | -1.48 | -0.18 | -0.05 |
| | TS | 23.33 | 2.18 | 0.66 |
| Panel B | SPGB | -2.18 | -0.93 | -0.29 |
| | SP5 | 1.87 | 0.44 | 0.13 |
| | FTS | 0.02 | 0.00 | 0.00 |
| | KBW | 1.79 | 0.58 | 0.18 |
| | BTC | -1.50 | -0.09 | -0.02 |
| | TS | 27.84 | 3.34 | 1.02 |

Notes: BK18 scales correspond to wavelet frequencies. Scale 1 of BK18 corresponds to band 3.14-0.39 depicting spillovers in the short term (1–8 days), Scale 2 corresponds to band (0.390.10-) depicting spillovers in the medium term (832- days), Scale 3 corresponds to band (0.100.05-) denoting spillover in the long run (32days-infinity). Sample: Oct 15, 2019 - Dec 31, 2022.

### 6.2. Dynamic rolling window analysis

While the static results are insightful in determining the average performance, it is highly unlikely that a single constant value would apply over the whole sample. As such, the evaluation of dynamics of return and its decomposition in time and frequency domains is crucial to understand cross-markets interconnectedness. The study adopts 50-days rolling windows and a forecast horizon of 100-ahead to compare the diversification and hedge attributes of GSI and SPGB across different market conditions. In this section, the study examines dynamic TS, dynamic net spillover and dynamic net pair-wise spillover.

#### *6.2.1. Dynamic Total Spillover*

Figure 4 portrays DY12 dynamic total spillovers of the system within the two markets. Figure 4 shows the TS of GSI is highly volatile where the lowest connectedness (21%) between markets was remarked in January 2021. The highest TS recorded in this system was close to 65% in February 2020.

On average, the total connectedness oscillates between 30% and 42%. The outbreak of the covid-19 pandemic intensified market connectedness which is reflected by a temporary peak (65%) in TS in February and March of 2020.

Similar results are observed in the TS of SPGB the TS hit the peak at the onset of the covid-19 pandemic (67%) and was the lowest in January 2021 (23%). For the rest of the period, TS oscillates between 28% and 48%. All in all, TS tells us two things. First, a temporal intensity in market interconnectedness is observed by TSI at the outbreak of the covid-19 epidemic in the short run. As such, short term investors should steer clear of GSI and SPGB. Second, a similar trend is perceived in the TSI of GSI and SPGB. However, the performance of GSI in portfolio diversification is marginally better amid the low TS values across the sample period. These results are in line with the DY12 static results in table 4.

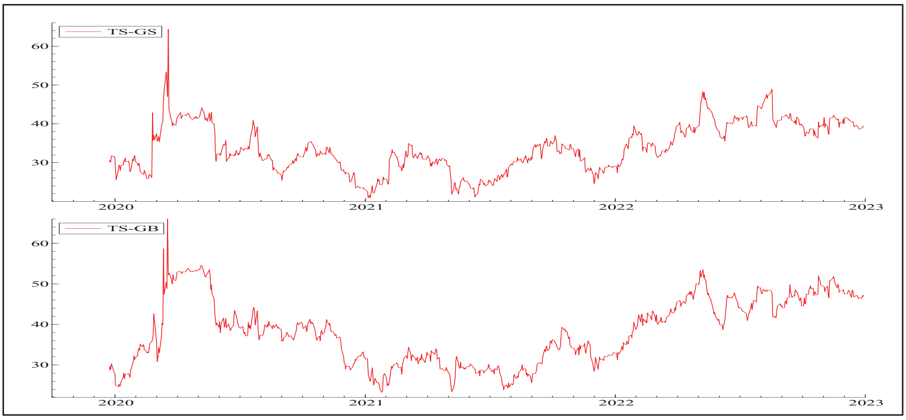



*Figure 4. DY12 Total Spillover Dynamics*

The TS of GSI and SPGB calculated by BK18 in figure 5 reveals essential information of dynamic overall connectedness in the two systems. First, high volatilities in TS are depicted in the high frequencies of GSI and SPGB. The TS in scale 1 fluctuates between 22% - 35% in GSI and 25% - 46% in SPGB. The findings imply that the fluctuations in the TS of DY12 are primarily driven by the high frequencies. Second, the gravity of the covid-19 epidemic is manifested in sharp fluctuations in markets' connectedness with a short-lived transmission of spillovers within the system. Investing in GSI or SPGB will not result in any diversification benefits for short term investors in this period. Third, the low scales of BK18 demonstrate less volatilities and a weak TS (>3%) within the two systems. Thus, long term investors are likely to benefit from diversification opportunities by combining GSI or SPGB with the other assets. Fourth, GSI slightly outperformed SPGB in all scales of BK18 in portfolio diversification.

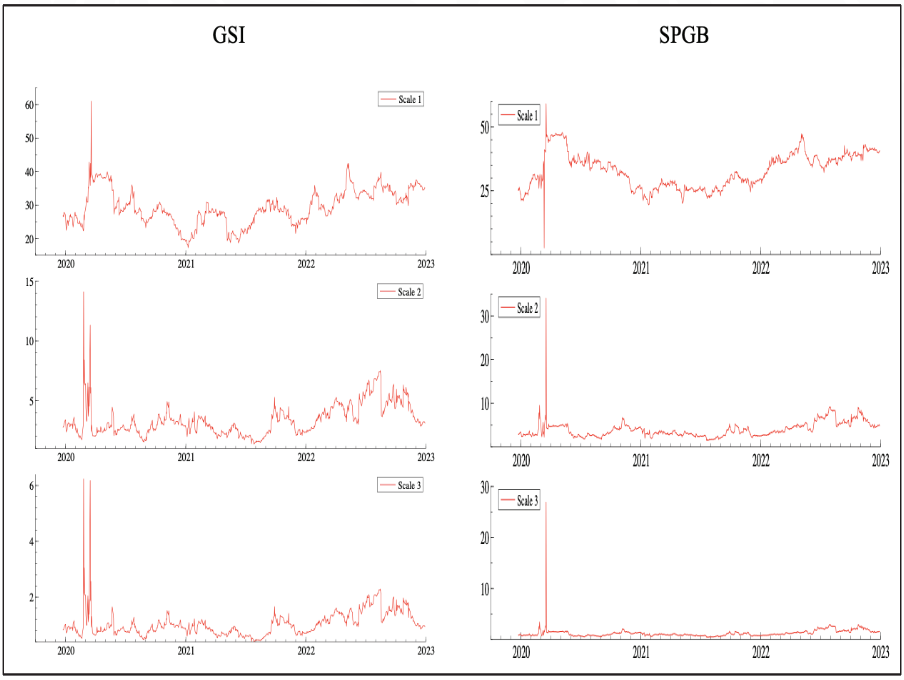



*Figure 5. BK18 Dynamic Total Spillover*

Notes: Scale 1 of BK18 corresponds to band 3.14- 0.39 depicting spillovers in the short term (1–8 days), Scale 2 corresponds to band 0.39- 0.10 depicting spillovers in the medium term (832- days) while Scale 3 corresponds to band 0.10- 0.05 demonstrating spillover in the long run (32 days-infinity). Sample: Oct 15, 2019 – Dec 31, 2022.

### *6.2.2. Dynamic Net Spillover*

DY12 net directional spillovers of GSI and SP5, FTS, KBW and BTC are plotted in figure 6. GSI performed as a net receiver of spillover for most of the investigated period with a short-lived transmission of spillover in the wake of covid-19 pandemic. On the contrary, the market with the highest transmission of spillover in panel A of figure 6 was SP5. Likewise, SPGB in figure 6 remained a net recipient of spillover from SP5, FTS, KBW and BTC for most of the sample period interspersed with series of net transmission of spillover on the onset of covid-19. The highest transmitter of spillover in panel B of figure 6 was KBW.

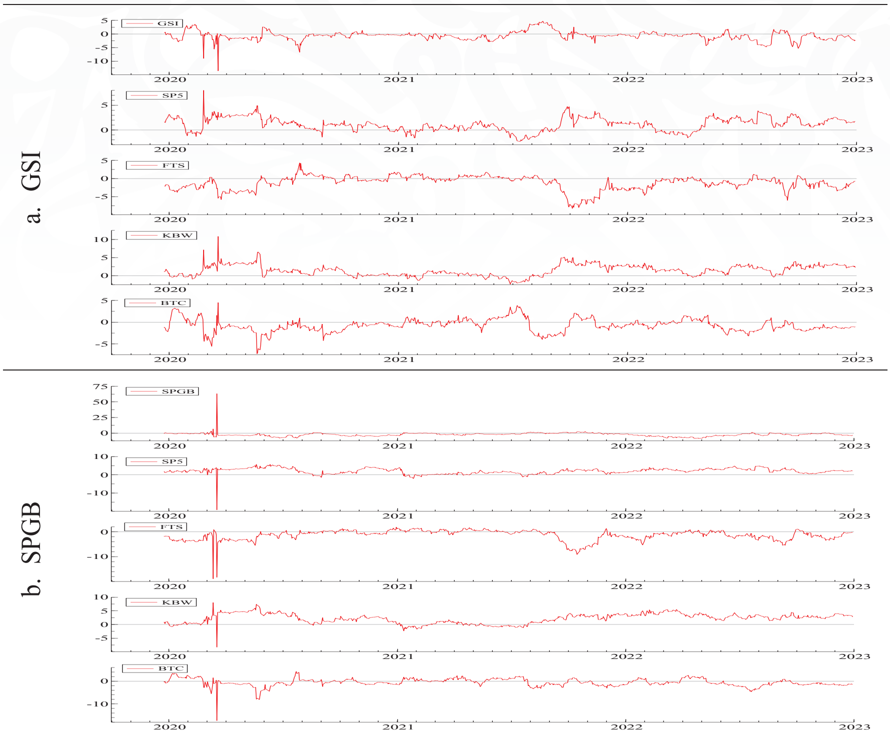



*Figure 6. DY12 Dynamic Net Spillover*

Notes: GSI stands for the Green Sukuk Index; SPGB- S&P Green Bond Index; KBW- KBW Nasdaq Financial Technology Index; BTC- Bitcoin; S&P- S&P500; FTS- FTSE100. Sample: Oct 15, 2019 – Dec 31, 2022.

Figure 7 reports the BK18 net spillover plots of GSI. Scale 1, 2 and 3 in panels a, b and c reflect the short, medium, and long terms respectively. In figure 7a, GSI was consistently a net receiver of spillover throughout the sample timeframe. At the onset of covid-19 pandemic, GSI experienced a rise in net spillover shifting GSI to a source of spillover momentarily. Similarly, GSI was a net transmitter of spillover between June and July of 2022. Similar patterns can be observed in scale 2 and three but at a lower degree (values) of net spillover. SP5 was the net transmitter of spillover within the system in the higher frequency as shown in figure 7a. In the medium and low frequencies, KBW emerged as the source of spillover as reported in figures 7b and 7c respectively. Overall, a thorough examination of figure 7 reveals the dynamic behavior of markets during significant events illustrated by a temporary fall in net spillover of returns of all markets during the covid-19 pandemic outbreak.

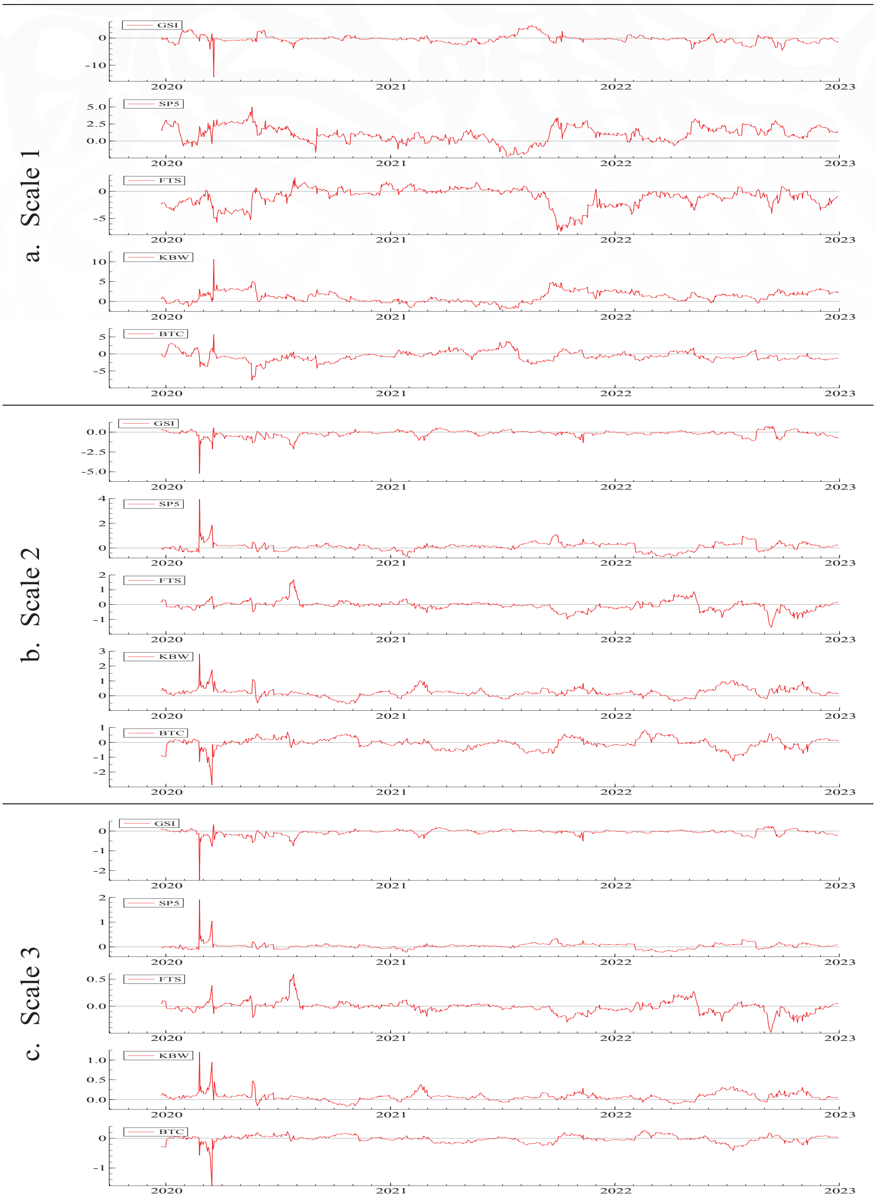


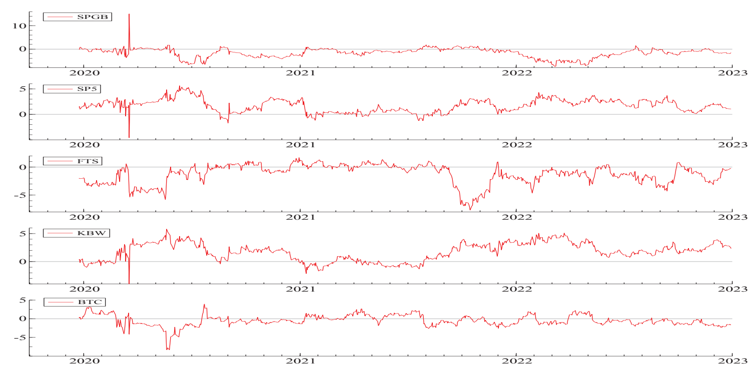

*Figure 7. GSI BK18 Dynamic Net Spillover*

Notes: GSI stands for the Green Sukuk Index; KBW- KBW Nasdaq Financial Technology Index; BTC- Bitcoin; S&P- S&P500; FTS- FTSE100. Scale 1 of BK18 corresponds to band 3.14- 0.39 depicting spillovers in the short run (1–8 days), Scale 2 corresponds to band 0.39- 0.10 depicting spillover in the medium run (832- days) while Scale 3 corresponds to band 0.10- 0.05 depicting spillover in the long run (32days- infinity). Sample: Oct 15, 2019– Dec 31, 2022.

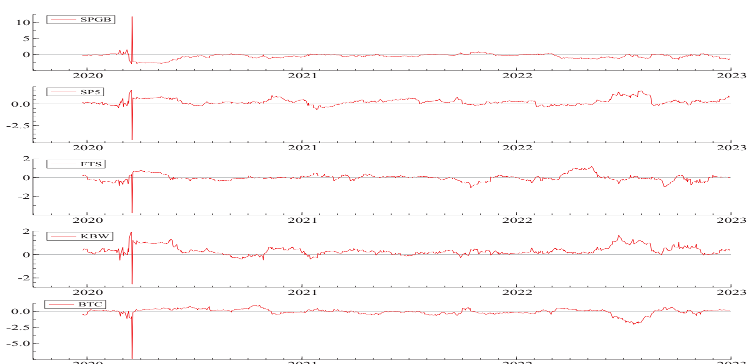
Figure 8 depicts BK18 net spillover returns of SPGB. All markets experienced momentary changes in net spillover at the onset of covid-19 pandemic. In this period, GSI shifted from a net receiver to a net transmitter of spillover before experiencing a sudden drop in net spillover. GSI performed as a net receiver across the sample period post March 2020 as shown in figures 8a, 8b and 8c. Once again, KBW was the highest transmitter of spillover in the system in all investment horizons as demonstrated by figures 8a, 8b and 8c.

These findings are in line with table 4 and table 5 where the highest net spillover in all markets were remarked in the high frequencies of scales 1,2 and 3 which explain the volatilities and the high values of net spillover in DY12 plots in figure 6. For once, the findings show the superiority of SPGB over GSI in portfolio diversification. Nonetheless, the persistence of both GSI and SPGB as net receivers of spillover suggest that contribution of the two indexes to markets' interdependence, particularly in the long run, is negligible and the volatilities in GSI and SPGB have a minimal impact on the contagion effect within the systems in the long run.

a. Scale 1




b. Scale 2



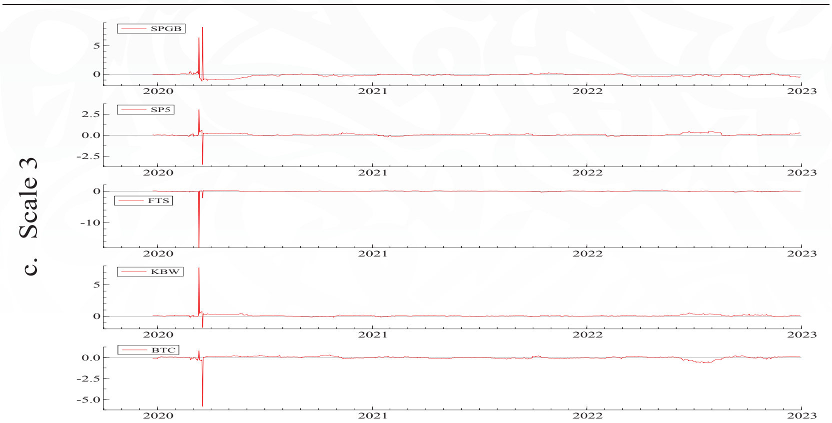



*Figure 8. SPGB BK18 Dynamic Net Spillover*

Notes: SPGB stands for S&P Green Bond Index; KBW- KBW Nasdaq Financial Technology Index; BTC- Bitcoin; S&P- S&P500; FTS- FTSE100. Scale 1 of BK18 corresponds to band 3.14- 0.39 depicting spillovers in the short run (1–8 days), Scale 2 corresponds to band 0.39- 0.10 depicting spillover in the medium run (832- days) while Scale 3 corresponds to band 0.10- 0.05 depicting spillover in the long run (32days- infinity). Sample: Oct 15, 2019– Dec 31, 2022.

### *6.2.3. Dynamic Net Pair-wise Spillover*

The following section illustrates the empirical findings of net pairwise directional spillover. A negative net pairwise between two assets (for instance GSI and SP5) indicates that the former (GSI) is a net transmitter of spillover and while the latter is deemed to be a source of net spillover if the value of the net pairwise spillover is positive. With that in mind, the net pairwise connectedness between GSI and other markets was highly volatile with GSI being positive for most of the sample period. Loosely speaking, according to figure 9a, GSI is a net receiver of spillover from all markets except for a few short-lived intervals such as the onset of the covid-19 pandemic and mid 2021 where GSI was a source of spillover to SP5, FTS and BTC as portrayed in figure 9a. Overall, the net pairwise spillovers between GSI and other markets mostly oscillate between 1 and -1 as shown in figure 9a. In the context of SPGB, similar results are observed in net pairwise relationship between SPGB and other assets in figure 9b. SPGB performed as a net recipient of spillover from all markets throughout the sample period. A noteworthy observation shown in figure 9b is the short-lived performance of SPGB as a net transmitter to all markets at the onset of the covid-19 pandemic.

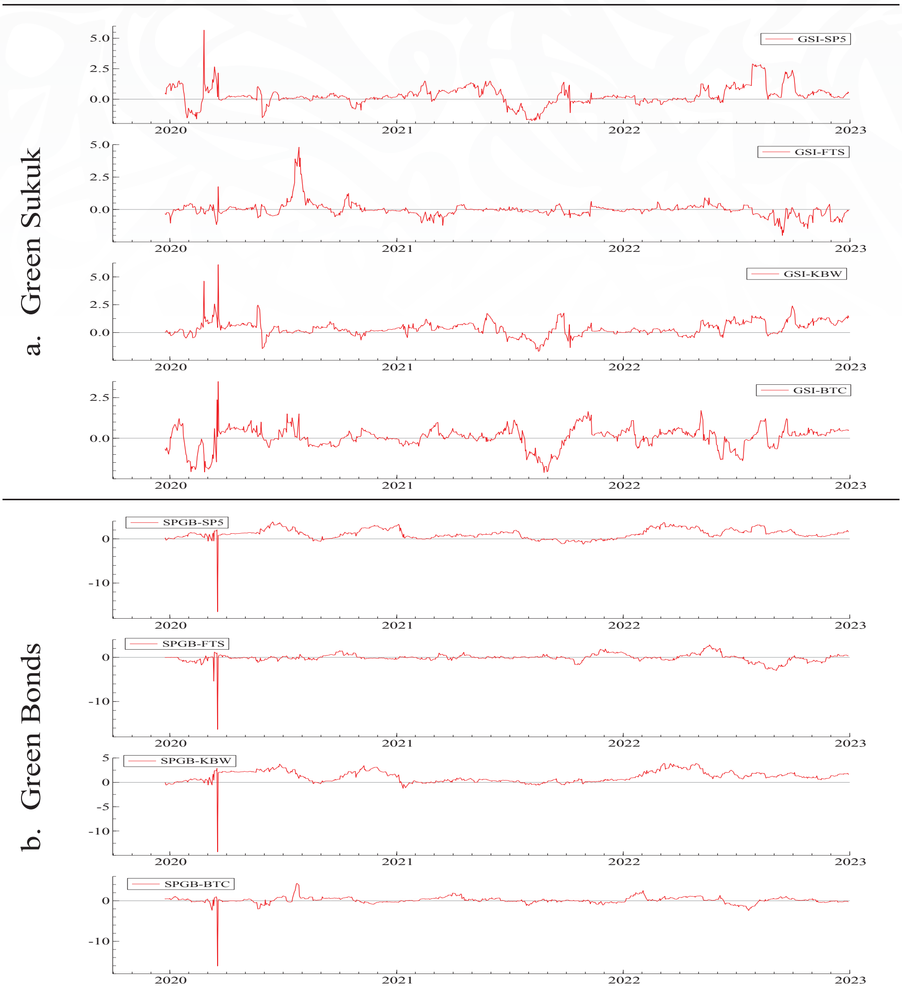



*Figure 9. DY12 Dynamic Net Pair-wise Spillover*

Notes: GSI stands for; SPGB- S&P Green Bond Index; KBW- KBW Nasdaq Financial Technology Index; BTC- Bitcoin; S&P- S&P 500 Index; FTS- FTSE 100 INDEX. Sample: February 15, 2019 – December 31, 2022.

BK18 net pairwise relationships between GSI and SPGB with other assets are presented in figure 10. Three key observations are noted from figure 10. First, the net pairwise connectedness of GSI and SPGB with all markets was highly dynamic, particularly in the short term, where GSI and SPGB remained persistent net receivers from all markets in all scales for most of the sample time. Fluctuations in net pair-wise spillover are more noticeable in GSI.

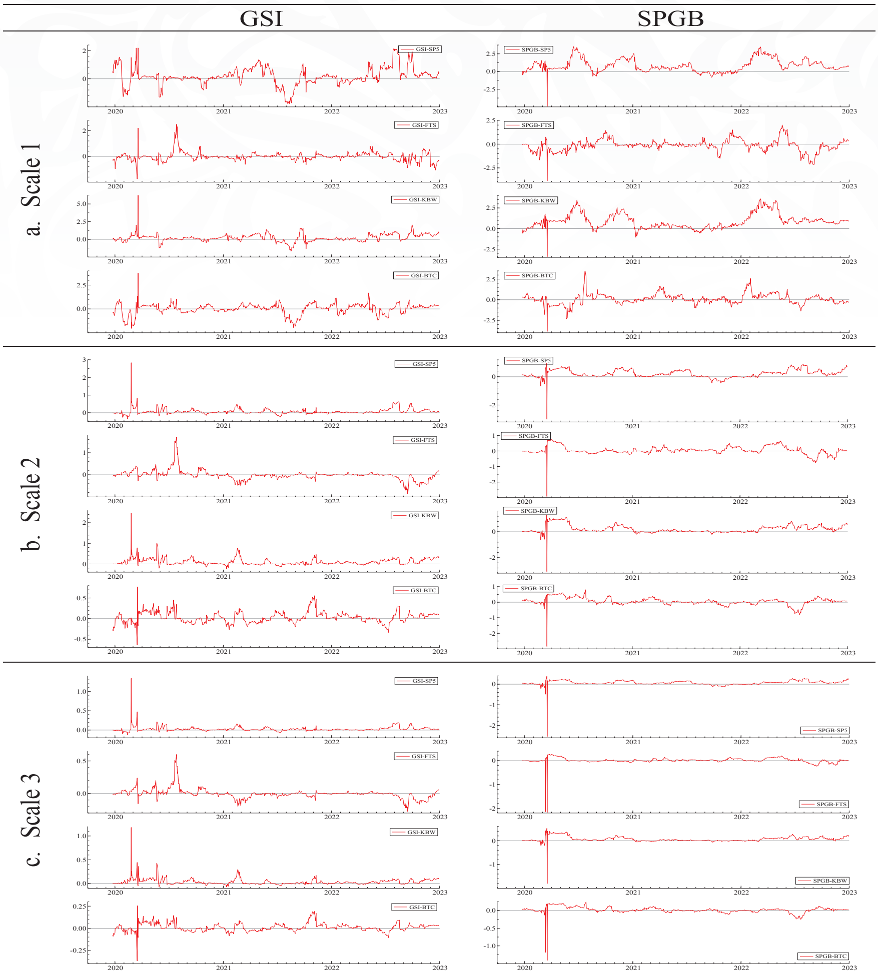



*Figure 10. BK18 Dynamic Net Pair-wise Spillover*

Notes: GSI is the Green Sukuk Index; SPGB- S&P Green Bond Index; KBW- KBW Nasdaq Financial Technology Index; BTC- Bitcoin; S&P- S&P500; FTS- FTSE100. Scale 1 of BK18 corresponds to band 3.14- 0.39 depicting spillovers in the short run (1–8 days), Scale 2 corresponds to band 0.39- 0.10 depicting spillover in the medium run (832- days) while Scale 3 corresponds to band 0.10- 0.05 depicting spillover in the long run (32days- infinity).

Second, in events of bad news (shocks) such as the covid-19 pandemic pair wise relationship experience some temporal changes in net pairwise spillover. GSI and SPGB tend to shift to net transmitters of spillover momentarily as depicted by all scales of GSI and SPGB in figure 10a, 10b, and 10c. During the covid-19 pandemic, the impact of the pandemic on market interconnectedness intensity is apparent in SPGB in all markets. Third, the plots of BK18 net pairwise spillover in figure 10 are in line with DY12 plots in figure 9 and highlight the similarities between the two indexes influenced by rapid and high fluctuations in the short horizons of BK18 and DY12 plots. Accordingly, the contribution of high frequencies is higher than of the medium and long terms. As we move to low frequencies, net pairwise spillover tends to dramatically decrease and oscillate about zero.

To sum up, net pairwise spillover findings are insightful in investment decision making. The persistent feature of GSI and SPGB as net receivers of spillover especially in high frequencies enlighten short-term investors of the risk of combining GSI or SPGB with other assets in the same investment portfolio since the predictive power of GSI and SPGB prices on the respective assets is insignificant. Not to mention, the less influence of GSI and SPGB on SP5, FTS, KBW and BTC than the other way around. As a result, GSI and SPGB are not ideal in offering short-term investors with any diversification opportunities. On the contrary, the oscillation of net pairwise spillover around zero between GSI and SPGB and other assets imply the existence of diversification potential in the long run (15).

## 7. **Robustness Check**

The robustness of the results is validated using alternative VAR orders, rolling windows, and forecast horizons to evaluate DY12 dynamic gross return spillovers. Starting with alternate VAR orders, DY12 TS of GSI and SPGB we calculated using VAR order 9 suggested by Akaike's Information criterion (AIC) and Final Prediction Error criterion (FPE). The trend of the TS was identical to the original one used in the study calculated using VAR order 1 based on SC and HQ. Second, we used a rolling window 100 days instead of the original 50-days to investigate the existence of any significant divergences in total spillover. We observed a similar trend of connectedness in the systems despite the existence of minor fluctuations in rolling windows with relative less days. Despite small variations in rolling windows with relative fewer days, a similar pattern of connectedness is observed in the systems of GSI and SPGB. Finally, we estimated a lower forecast horizon of 50-ahead instead of 100-ahead to confirm the robustness of the forecast horizon results. Identical trends are observed in forecast horizons. To conclude, the findings indicate

(15) Tiwari, A. K., & Sahadudheen, I. (2015). Understanding the nexus between oil and gold. Resources Policy, 46, 85–91. https://doi.org/10.1016/J.RESOURPOL.2015.09.003

the robustness of our analysis and unbiases in selection of VAR order, rolling windows and forecast horizon and as demonstrated in figure 11.

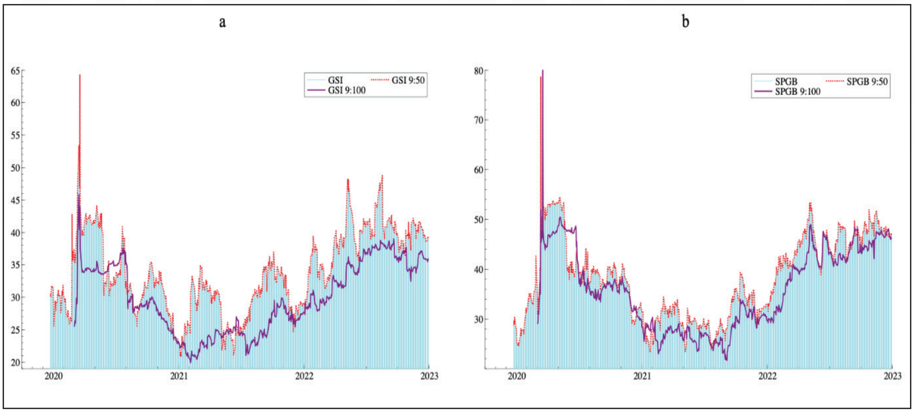



*Figure 11. DY12 TS via alternate rolling windows, VAR and Forecast horizons.*

Notes: GSI refers to the Green Sukuk Index; SPGB- S&P Green Bond Index. 9 is the alternate VAR order as suggested by Akaike's Information criterion (AIC) and Final Prediction Error criterion (FPE). 50 and 100 refer to the rolling windows. Sample: Oct 15, 2019 – Dec 31, 2022.

## 8. Conclusion and Policy Recommendations

In this study, we attempt to compare the diversification and hedging capacities inherent in green sukuk and green bonds and their potential to offset high market volatilities and spillover across different investment frequencies via the wavelet coherence and the spillover index methodologies. The wavelet results depict intensification in co-movements between GSI and SPGB and SP5, KBW and BTC, at the onset of the covid pandemic subjugating short-lived series of high correlation. The findings imply the absence of short-term diversification benefits of integrating GSI and SPGB in any investment portfolio other than FTS in extreme market downturns. Additionally, the findings of wavelet coherence portray the superiority of GSI over SPGB in portfolio risk management. The results of DY12 and BK18 spillover indexes imply a transmission of shocks within the systems is highly anticipated to happen up to eight days from a turbulent incident. The deterioration of markets' interconnectedness in the low frequencies of both systems should alert investors of GSI and SPGB long term hedging and diversification properties. The findings of dynamic rolling window infer that changes in GSI market to have minimal impact to the contagion effect in the event of turbulent markets at least in the long term. The findings of TS reveal a relatively lower connectedness of markets within the GSI system in comparison to SPGB. Thus, GSI has a slightly better performance in overall market connectedness. The spillover index and net pair-wise spillover indexes results, however, prove marginal supremacy of SPGB in terms of diversification and hedging capacities. Overall, these results support the findings of wavelet coherence.

The findings of this study point out some prominent implications for investors, academia, and policymakers. It is important for investors to understand that the relationship between GSI and SPGB with the selected assets is heterogenous across multiple horizons. Accordingly, hedging and diversification decisions should reflect different investment horizons. For policymakers, understanding markets dynamics, shocks and spillovers can enhance disclosure of risk receivers and transmitters which facilitate formulating and designing policies to ensure market efficiency, financial stability, and promotion of green assets. To facilitate the development of green finance, particularly green sukuk and green bond investments, more efforts need to be directed towards promoting an enabling ecosystem with globally coordinated standards, green taxonomies, and incentives. Finally, from an academic point of view, this study can stimulate research and provide a better understanding of the influence of prevailing market conditions on the ferocity of markets' connectedness to predict future trends and volatilities between green sukuk and other markets.

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