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Full length Article

## In search of safe haven assets during COVID-19 pandemic: An empirical analysis of different investor types

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### ABSTRACT

This study assesses the role of gold, crude oil and cryptocurrency as a safe haven for traditional, sustainable, and Islamic investors during the COVID-19 pandemic crisis. Using Wavelet coherence analysis and spillover index methodologies in bivariate and multivariate settings, this study examines the correlation of these assets for different investment horizons. The findings suggest that gold, oil and Bitcoin exhibited low coherency with each stock index across almost all considered investment horizons until the onset of the COVID-19. Conversely, with the outbreak of the pandemic, the return spillover is more intense across financial assets, and a significant pairwise return connectedness between each equity index and hedging asset is observed. Hence, gold, oil, and Bitcoin do not exhibit safe-haven characteristics. However, by decomposing the time-varying co-movements into different investment horizons, we find that total and pairwise connectedness among the assets are primarily driven by a higher-frequency band (up to 4 days). It indicates that investors have diversification opportunities with gold, oil, and Bitcoin at longer horizons. The results are robust over different types of equity investors (traditional, sustainable, and Islamic) and various investment horizons.

### 1. Introduction

The COVID-19 outbreak has created turmoil in the global financial markets. The Dow Jones Industrial Average (DJIA) index, for instance, recorded a decline of more than 30% in March 2020 in response to the global pandemic. In fact, the impact of COVID-19 on stock markets was more severe than any other pandemic in history, including the 1918 Spanish flu (Baker et al., 2020). This sharp decline has jeopardized the portfolio of equity investors worldwide, not only traditional but also other clusters of investors, such as sustainable and Islamic. However, the underlying cause of the COVID-19 crisis is more complicated than experienced with previous crises. Government measures such as lockdown and closing of borders to contain the pandemic have greatly affected economies (Goodell, 2020). In June 2020, the International Monetary Fund (IMF) announced through the World Economic Outlook (WEO) that the global annual economic growth projection will fall to 4.9%, a decline of 1.9% from the WEO forecast in April 2020, which makes

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the COVID-19 crisis the worst recession since the great depression in 1929, much worse than the 2007 global financial crisis (IMF, 2020).

The ongoing COVID-19 crisis has led to huge losses and uncertainty among investors.<sup>1</sup> This unforeseen situation has induced a flight-to-quality, a phenomenon where investors rebalance their portfolios during troubled financial times, among investors to move their investment to a safer asset (Caballero and Krishnamurthy, 2008). Baur and McDermott (2010) showed that investors most probably seek a haven when faced with extreme adverse market shocks. Thus, what assets can be relied upon as a safe haven during the COVID-19 pandemic crisis? To be classified as a safe haven, an asset must hold its value in stormy or adverse market conditions. Traditionally, several assets were popularly considered a safe haven. Many believe that gold is an ideal safe haven instrument for investors, especially with the experience of the 2007 global financial crisis when the gold price rose sharply when all other asset classes suffered huge losses (Baur and McDermott, 2010; Beckmann et al., 2015). Among other assets often considered a safe haven are bonds (Ciner et al., 2013), foreign exchange (Ranaldo and Söderlind, 2010), crude oil (Elie et al., 2019), and cryptocurrency (Bouri et al., 2020).

Meanwhile, the assets managed under socially responsible investing (SRI) principles have grown exponentially across the globe. According to the report on US Sustainable, Responsible and Impact Investing Trends (US SIF, 2018), professionally managed sustainable and impact investing trend in the United States had reached \$12 trillion, an 18-fold increase from 1995 when the US SIF started to measure US SRI assets. The report also mentions that the number of SRI assets represents 26% of the total professionally managed assets in the United States, similar to the *Shariah*-compliant (Islamic) equity segment. The Malaysia International Islamic Financial Centre (MIFC, 2018) reported that the asset under management of global Islamic funds rose to \$70.8 billion in 2017 from \$47 billion in 2008. Hence, with numerous investors from these two clusters of investments with different objectives, the appropriate safe-haven assets for them during the COVID-19 crisis are also worth investigating.

SRI investing involves any investment strategy that considers both the investor's financial objectives and the investment's impact on environmental, social, and governance (ESG) performance (Aysan et al., 2021a, b; Muñoz et al., 2014). However, the screening criteria for Islamic investing are based on religious beliefs and practices. Qualitative criteria focusing on firms engaged in alcohol, gambling, tobacco, and weapons activities, help Islamic investing in excluding businesses engaged in immoral activities. From this perspective, Islamic investing can be considered a subcategory of SRI (Azmi et al., 2019). Besides, Islamic investing excludes companies depending on quantitative criteria that set upper thresholds for leverage and interest income. Therefore, Islamic investing is subject to a restricted and underdiversified investable universe (Hussein and Omran, 2005), which makes hedging activities more valuable. The literature and industry practice have no consensus on what assets are the best safe-haven instruments. Hence, this study reevaluates the validity of several potential safe-haven assets during the COVID-19 pandemic.

Furthermore, the pandemic-related volatility and associated market risk have increased the demand for diversifying investments and using hedging strategies (Goodell and Goutte, 2021b). This study considers three types of investments traditionally considered safe-haven assets in the literature: gold, crude oil, and Bitcoin (see also Ji et al., 2020). We examine the correlation of these potential hedging assets with the equity index for traditional, sustainable, and Islamic investors for different investment horizons during the COVID-19 period.

Thus, this study makes several significant contributions to the literature. First, this is perhaps the first study to comprehensively examine the validity of various potential safe-haven assets for different types of equity market investors (traditional, sustainable, and Islamic) and consider the length of their investment horizons. Hence, we contribute to the existing empirical literature by studying the correlation between hedging asset returns (gold, oil, Bitcoin) and equity market returns and investigating different investor types on whether the hedging assets offer diversification benefits during the pandemic. Oil and gold are the most commonly traded commodities, and their price movements can have substantial repercussions for financial markets and vice versa (Gharib et al., 2021). Bitcoin has also gained attention among investors to be considered a hedging tool because of its independence from sovereign authority and its tradability supported by a weak correlation with the equity market, making it a potent diversification instrument (Shahzad et al., 2020). Therefore, it is crucial to analyze the co-movement and causality between these hedging assets and financial markets, and how the COVID-19 pandemic has affected their dependence structure. From this perspective, understanding the effect of the pandemic on the potential hedging assets could guide assets managers in the three markets (traditional, sustainable, and Islamic) in changing their positions during the still unfolding pandemic and other similar global public health hazards in the future.

Second, our methodological approach comprises the application of both Wavelet coherence analyses and spillover indices of Diebold and Yilmaz (2012) and Baruník and Křehlík (2018) - called DY12 and BK18, respectively - in a multivariate setting. The application of Wavelets allows us to examine the evolution of correlation patterns in time and for different frequencies in a bivariate setting without resorting to an ad hoc specified time or frequency settings. This approach decomposes time-varying co-movements into different investment horizons, which in turn facilitate tailored hedging strategies to different types of investors with varying investment horizons.<sup>2</sup> In addition to the Wavelet approach, this study uses the DY12 return spillovers approach to examine the connectedness between each equity type (designed to accommodate different investor views) and the three potential safe-haven assets. The

<sup>1</sup> COVID-19, however, has not affected all investors equally. Staszkievicz et al. (2020) indicated that financial markets in Europe and South America responded to the COVID-19 crisis quicker than Asia and North America. Furthermore, it appears that the impact of the pandemic on the financial markets of each country depends on the size of the economy and the efficiency of the financial market.

<sup>2</sup> The Wavelet coherence method has been extensively used in the price co-movement literature, among them are studies by Vacha and Baruník (2012) (among energy commodities), Dewandaru et al. (2014) (Islamic and conventional indices), Madaleno and Pinho (2014) (equity and oil prices), and Nagayev et al. (2016) (Islamic equity and commodities).

DY12 framework helps in analyzing the transmission of returns across each equity index and the three hedging assets and capture directional spillovers from and to each equity index and safe-haven assets.

The data acquired from the DY12 approach are limited to the time domain, so this study reports a recently extended version proposed by BK18 that also includes the connectedness across assets in the frequency domain. Using the DY12 and BK18 methodologies in a multivariate setting, this study deeply analyses the co-movement of the chosen pairs between each type of equity and the three potential safe-haven assets derived from the Wavelet approach. Understanding the transmission dynamics of prices from a contributor market to a recipient market is particularly relevant during crises, that is, when diversification is the most essential (Hkiri et al., 2017).

Our findings from the Wavelet coherence analysis indicate that the connection of the three hedging assets (gold, oil and Bitcoin) vary across time and investment horizons. However, during the COVID-19 pandemic, few patches of high coherence are dispersed between each equity index and hedging vehicle across different investment horizons. Hence, during the crises when there is financial markets transmission risk across assets, no gold, oil, or Bitcoin exhibits safe-haven characteristics. Our findings from return connectedness using DY12 and BK18 indicate that for each system, alternatively designed for the hedging purposes of different types of investors (i.e., conventional, sustainability, and Islamic), the higher frequency band (1-4 days) drives connectedness. It indicates that each type of investor has diversification opportunities with gold, oil and Bitcoin in the long term. Furthermore, we observed strengthening of the total spillover since the onset of the COVID-19 pandemic within each system, which is again mainly driven by high-frequency components. Finally, a significant pairwise return connectedness between each equity index and hedging asset is observed with the outbreak of the pandemic (a large negative short-lived swing that bounces back), again mainly driven by the high-frequency band.

This study is presented as follows: Section 2 summarises the empirical studies on gold, crude oil, and Bitcoin as a safe-haven instrument. Section 3 describes the dataset and methodology used in this study. Section 4 presents our findings, and Section 5 presents the conclusions.

## 2. Literature Review

The COVID-19 pandemic has led to huge risks faced by equity investors.<sup>3</sup> It has further worsened with the co-movement of different assets during the crisis, which might further jeopardize their portfolios. Studies have shown that assets from different classes tend to move in the same direction during the crisis. Piplack and Straetmans (2010) found increasing co-movements between four types of asset classes (i.e., stocks, government bonds, T-bills, and gold) in the US market during crises, which may be explained by an exogenous factor such as oil shocks or monetary policy shifts. Co-movement is observed among and between different assets markets. Didier et al. (2012) found a co-movement between the stock market returns of the United States and 83 countries during the 2007 global financial crisis, which was largely driven by financial linkages. Therefore, the co-movement phenomenon makes it imperative to assess which assets are proven to have safe-haven properties during market turmoil, such as the COVID-19 pandemic.

To objectively evaluate which assets qualify as a safe-haven instrument during the COVID-19 crisis, we must first understand the definition of safe-haven itself. Baur and Lucey (2010) define a safe-haven asset as a place of safety or shelter for investors to protect wealth in the event of adverse market conditions. Such an asset offers investors a cover (positive return) when all other assets suffer losses during the market downturn. This study considers the following three popular candidates of safe-haven assets: gold, crude oil, and Bitcoin.

### 2.1. Gold

During the 2007 global financial crisis, gold has proven its value as the prominent safe-haven asset, especially for equity investments. Baur and Lucey (2010) stated that gold is not correlated with other assets, making it an ideal haven. Moreover, gold is assumed to have the characteristic of a zero-beta asset with no market risk (McCown and Zimmerman, 2006). Gold offers investors additional protection than other safe-haven assets, such as bonds, including protection from risks such as inflation, currency, and default (Baur and McDermott, 2016). However, gold also possesses some undesirable properties as price volatility, less liquidity, and high storage costs.

Baur and McDermott (2016) provided a behavioral interpretation of why investors prefer to hold gold over bonds as a safe-haven asset. They highlighted that under stressful conditions, investors focus more on positive information than negative. Hence, the past positive experience of gold during market turmoil dominates investors' perception more than its negative characteristic as a risky asset. Furthermore, the local thinking concept proposed by Bear et al. (2020), that is, under a stressful condition where investors lack the time and resources to seek alternative assets, they choose simple possibilities and choose the "what comes to mind" asset. Most often, owing to an earlier experience, gold becomes a natural alternative.

Several empirical studies have investigated the role of gold as a hedge and safe-haven instrument during economic downturns. Coudert and Raymond (2011) found that gold is qualified as a safe-haven asset for stock indices in France, Germany, the UK, and the US during market recessions and bear markets between 1978 and 2009. Moreover, the conditional correlations between gold and equities are lower on average in economic downturns than during upswings. Anand and Madhogaria (2012) examined the dynamic relationship between stocks and gold price in six developed and developing countries (India, China, the US, the UK, Germany and Japan) from January 2002 to December 2011. They showed that in developed countries (i.e., the US, the UK, Germany and Japan), stock prices Granger cause gold price, while the opposite relationship is observed for developing countries (India and China). Besides being a

<sup>3</sup> Rizvi et al. (2020) documented that fund managers have responded to the COVID-19 outbreak by moving from high-risk to low-risk investment strategy. They have also switched from high risk to relatively less sensitive sectors and countries with fewer COVID-19 cases.



hedging tool for the investment portfolio, gold is also popular as a hedge option for inflation. However, [Zhu et al. \(2018\)](#) revealed that since 1997 in the UK and 2003 in the United States, gold has lost its role as a hedge for inflation. Further, they argued that gold only acts as an inflation hedge during periods of high inflation and inflation expectations.

[Bredin et al. \(2015\)](#) investigated the consistency of gold as a hedge and safe-haven asset for investors with heterogeneous investment horizons using Wavelet analysis, considering both calendar time and investment horizon. Using daily data of equity, bond and gold prices from January 1980 to December 2013 from the US, the UK and Germany markets, their finding shows low codependence among gold, equities and bonds, on average, of the four observed markets. Hence, their study supported the notion of gold as a hedging instrument for investment horizons for up to 1 year. On the role of gold as a safe-haven instrument during market turmoil, their study examined three market downturns of economic contractions in the early 1980s, the Black Monday crash in 1987, and the 2007 global financial crisis. They found that gold consistently acts as a safe haven for equities up to 1 year during financial crises. However, gold did not perform as a safe-haven asset during the economic contraction in the early 1980s, where it displayed a positive relationship with US equities. To evaluate gold's role as both hedging and safe-haven instrument, [Beckmann et al. \(2015\)](#) augmented the smooth transition regression (STR) using an exponential transition function that separates the regression into two regimes. The first regime accounts for the average period to test whether gold is a hedge for equities, while the second regime accounts for periods specified as extreme market turmoil to test whether gold is a safe haven for stock markets. Their study included a huge data set of 18 individual markets running long term from January 1970 to March 2012 using monthly data. They found that gold acts as a safe-haven asset, but its effectiveness depends on specific market conditions.

This long-claimed status of a safe-haven instrument must be tested, especially during the COVID-19 crisis, which exhibits an anomaly in gold price behavior compared with that in the 2007 global financial crisis. Gold price experienced a hike from February to early March 2020, leaving the stock investors hopeful that gold would be their safety net. However, it plunged more than 10% in March 2020 before it went up again drastically to a higher price than before the COVID-19 era. Several studies have attempted to test whether gold is a viable safe-haven asset for investors during COVID-19. [Cheema et al. \(2020\)](#) found that gold is a weak safe-haven asset in all ten largest countries covered in their research during the COVID-19 pandemic, except for Canada. A potential explanation is that investors have probably lost their trust in gold because of extreme losses on gold price from 2011 to 2015. [Corbet et al. \(2020\)](#) documented similar results for the Chinese stock market; that is, gold has not served as a hedging or safe-haven asset for the equity market during the COVID-19 crisis.

## 2.2. Crude oil

Other commodities can also potentially carry safe-haven properties during the turmoil in the financial market. The hedging and safe haven properties of commodities are due to the intrinsic value they hold. Several studies have found a low ([Bhardwaj et al., 2015](#)) or even negative ([Gorton and Rouwenhorst, 2006](#)) correlation between commodities and other assets, thus justifying diversification of portfolio as a good hedging option ([Bhardwaj et al., 2015](#); [Gorton and Rouwenhorst, 2006](#)). However, the recent trend of financialization has increased co-movement between commodities and stock markets. Financial investors enter and exit the commodities market, depending on their market sentiment rather than on commodity fundamentals ([Silvennoinen and Thorp, 2013](#)). [Silvennoinen and Thorp \(2013\)](#) also found the increase in correlation between US stocks with the commodity futures, rising toward 0.5 in 2009 from a level close to zero in the 1990s. Thus, whether commodities are still a good hedging tool and a safe haven option for equity investors need to be investigated.

Crude oil is one of the most referred commodities, apart from gold, studied as a hedging and safe-haven tool. Crude oil is a prominent commodity traded globally, and it plays a significant role for macroeconomic factors, such as exchange rates, inflation and economic growth ([Junttila et al., 2018](#)). Several studies have also documented the linkages between crude oil and equity valuation (e. g., [Apergis and Miller, 2009](#); [Ciner, 2013](#)). The effect of crude oil prices on the stock market depends on whether the changes in oil prices are a result of the supply and demand shock in the global market, suggesting a time-varying relationship with equity markets ([Park and Ratti, 2008](#)). Considering that crude oil is a significant input factor in production, an increase in oil price decreases expected cash flows and, hence, reduces the stock price. However, for the net exporting oil countries, an increase in oil prices enhances economic growth and increases the stock price ([Jiménez-Rodríguez and Sánchez, 2005](#)). For instance, [Miller and Ratti \(2009\)](#) found a negative relationship between crude oil price and the stock market in selected OECD countries from January 1971 to March 2008. However, a positive relationship between crude oil and the stock market is usually found in net exporting oil countries such as the Gulf Cooperation Council ([Aroui et al., 2015](#)).

Several studies have evaluated crude oil's hedging properties to confirm whether it is a robust safe-haven asset for equity investors. [Ciner et al. \(2013\)](#) found that the oil market does not act as a safe-haven asset for the stock market. However, it could serve as a safe haven during some specific periods, such as the first Gulf War in the 1990s and the 2007 global financial crisis. During the COVID-19 pandemic, crude oil prices have experienced sharp volatility, mainly because of two major forces: the price war between Russia and Saudi Arabia and the ongoing pandemic ([CNBC, 2020](#)). The global lockdown measures adopted by most countries to contain the coronavirus spread have severely affected the oil price, following transportation and industrial shutdown. The oil price in the United States even turned negative for the first time in history ([BBC, 2020](#)). Whether the oil is still a good safe haven during the recent market downturn is, thus, debated. [Devpura and Narayan \(2020\)](#) reported that COVID-19 cases and deaths contributed between 8% and 22% to daily crude oil price volatility.

In view of the COVID-19 announcement, [Salisu et al. \(2020\)](#) found that the probability of having negative crude oil price returns is higher during the pre-COVID-19 announcement period than during the post-announcement period. [Prabheesh et al. \(2020\)](#) found that the COVID-19 pandemic has strengthened the relationship between crude oil price return and the stock market in four major net oil-importing Asian countries, thereby making it an unsuitable hedging tool. [Filis et al. \(2011\)](#) examined the time-varying correlation between the stock market and oil prices in oil-importing and oil-exporting countries. The study finds no time-varying correlation

between the importer and exporter countries but found variation in the correlation in response to significant demand-side oil price shocks caused by business cycle or world crisis. Gharib et al. (2021) found a common bilateral effect of bubbles in crude oil and gold markets from March to April 2020, corresponding to the COVID-19 outbreak. However, this study differs from the previous literature as it focuses on the impact of the COVID-19 pandemic on the oil market and examines whether oil is a good hedging tool for various stock investors.

### 2.3. Bitcoin

Cryptocurrency is another popular asset claimed to have safe-haven characteristics. Bitcoin, one of the leading cryptocurrencies globally, was introduced in 2008 as a decentralized digital currency. Bitcoin is often proclaimed to be digital gold because of its detachment and independence from the traditional financial market (Conlon et al., 2020; Courtois et al., 2014). Bitcoin is considered a safe haven due to its independence from monetary policy, role as a store of value, and limited correlation with traditional assets (Conlon and McGee, 2020). Symitsi and Chalvatzis (2019) showed that Bitcoin offers significant diversification benefits within traditional asset portfolios, including exchange rate and stocks. However, when considering an alternative investment, other important factors should be considered during the crisis period. Bitcoin is less liquid, more volatile and costlier to transact than other assets even under normal market conditions (Smales, 2019).

Several empirical studies evaluated the hedging and safe-haven attributes of Bitcoin during market turmoil. Using Wavelet-based quantile-in-quantile regressions Bouri et al. (2017) found that Bitcoin acts as an effective hedge against uncertain market environments. Stensås et al. (2019) also uncovered that Bitcoin acts as strong safe haven during extremely uncertain periods. Uddin et al. (2020) revealed that Bitcoin is a good diversification asset for Islamic (Dow Jones Islamic index) and sustainable investors (FTSE 4 Good index) for specific investment horizons (16–32 days, 64–256 days).

In contrast, some studies have indicated that Bitcoin is a risky asset that does not provide hedging or a safe haven benefit to investors' portfolio. For example, Conlon and McGee (2020) found that Bitcoin did not act as a safe haven asset during the COVID-19 crisis. It even increased the downside risk of the portfolio as the crisis progressed, indicating that investors with Bitcoins in their portfolio faced substantial additional losses. This finding negates the safe-haven hypothesis of Bitcoin. Mensi et al. (2020) showed that the co-movement between Bitcoin and equity (both conventional and Islamic) increases with the investment horizon, indicating that the hedging benefits eventually dissipate. Cheema et al. (2020) found that Bitcoin is not an effective hedging tool for all ten countries in their dataset, except for Japan and India; instead, *Thether* was found to be a strong safe-haven asset during the COVID-19 period. These findings are also supported by (Goodell and Goutte (2021a, b). Mariana et al. (2020), however, found that Bitcoin and Ethereum are safe-haven assets for a short period during the COVID-19 pandemic, which is proven by its negative correlation with the S&P500 index. Similarly, Aysan et al. (2021a, b) showed that cryptocurrencies (including Bitcoin) offer investors opportunities to balance portfolio risk during the pandemic.

Overall, the literature provides mixed evidence on the use of Bitcoin as a hedging tool and safe-haven asset. The finding also varies across regions, time, and investment horizons.

## 3. Research Methodology

### 3.1. Data

This study analyzes the dynamic links as well as spillover effects between global equities (conventional, Islamic, and sustainable), commodities (gold and crude oil), and cryptocurrency (Bitcoin). The dataset consists of daily closing prices (in USD) of these assets and initially covers the period from January 1, 2016, to January 29, 2021. The data are obtained from Thomson Reuters DataStream. The price series are transformed into daily returns by taking the natural logarithm of the ratio of two successive asset prices (Arouri et al., 2011). Table 1 describes the variables used in the study.

Table 2 provides descriptive statistics of the three equity markets (i.e., conventional, sustainability, and Islamic) and three hedging assets (i.e., gold, oil, and Bitcoin). The average returns are positive for all equity markets and hedging assets. During the sample period, the highest and lowest average returns were observed for Bitcoin and oil markets, respectively. Unconditional volatility, measured by the standard deviation of daily returns, is the lowest for the gold market but largest for the oil market. Furthermore, the values of skewness and kurtosis observed in oil returns indicate that the returns in the oil market have a high probability of losses.

Since the outbreak of the COVID-19 pandemic, Bitcoin has reached multiple peaks and has been showing a continuous upward trend. This upward trend confirms the previous findings of the risk management properties of Bitcoin under global economic uncertainty (Dyhrberg, 2016; Bouri et al., 2017). While the cryptocurrency ecosystem was dominated by retail investors, it has increasingly attracted institutional investors, such as pension schemes and investment funds (Urquhart, 2021). Specifically, Bitcoin is becoming increasingly popular. The pandemic has accelerated the use of cryptocurrencies, especially by major payment service providers and central banks (Urquhart, 2021; Ostroff, 2020). Simultaneously, the world's central banks have been engaging with massive lending programs to limit the financial implications of the pandemic. This has fueled concerns of an inflationary momentum that will be difficult to dispel. From this perspective, next to gold, investments such as Bitcoin are being considered an effective hedge against inflationary pressures, given that the supply of Bitcoin is algorithmically limited (Wang et al., 2020; Wu et al., 2019). In contrast, the COVID-19 pandemic has battered the oil market more than any other. In April 2020, the oil prices suffered a historic crash, reaching subzero levels because of both demand shocks (COVID-19 related) and supply shocks (OPEC+ group could not reach an agreement in March 2020).

**Table 1**  
Description of variables.

Variable	Description	TRDS Code
CON	Dow Jones Global Index	DOWGBL\$
SUS	Dow Jones Sustainability Index	DJSWDC\$
ISL	Dow Jones Islamic Index	DJIMKT\$
GLD	Gold (Handy & Harman, USD per troy oz)	GOLDHAR
OIL	Crude Oil (Brent, Spot, USD per barrel)	EIAEBRT
BIT	Bitcoin (USD to Bitcoin exchange rate)	BTCTOU\$

Notes: All the times series are converted into logarithmic returns with base *e*. Frequency: daily. Sample period: January 1, 2016 - January 29, 2021. Observations: 1326 (prices), 1325 (log returns). Source of data: Thomson Reuters DataStream (TRDS).

**Table 2**  
Descriptive statistics and correlation matrix.

A. Statistics	CON	SUS	ISL	GLD	OIL	BIT
Mean	0.030	0.036	0.050	0.042	0.031	0.330
Median	0.055	0.070	0.070	0.011	0.041	0.280
Minimum	-10.907	-10.604	-9.639	-5.265	-64.370	-49.397
Maximum	8.487	7.694	7.916	5.133	41.202	23.840
St.Deviation	1.006	0.993	0.982	0.880	3.693	4.724
C.Variation	33.991	27.408	19.533	20.737	117.900	14.327
Skewness	-1.629	-1.624	-1.307	-0.082	-3.099	-0.875
Kurtosis	26.660	24.863	23.678	8.107	93.196	15.084
B. Correlation	CON	SUS	ISL	GLD	OIL	BIT
CON	<b>100%</b>	96 %	92 %	12 %	35 %	18 %
SUS	96 %	<b>100 %</b>	94 %	13 %	33 %	18 %
ISL	92 %	94 %	<b>100%</b>	16 %	31 %	18 %
GLD	12 %	13 %	16 %	<b>100%</b>	5%	17 %
OIL	35 %	33 %	31 %	5%	<b>100%</b>	7%
BIT	18 %	18 %	18 %	17 %	7%	<b>100%</b>

Notes: CON stands for DJ Global Index, SUS – for DJ Sustainability Index, ISL – for DJ Islamic Index, GLD – for Gold, OIL – for Crude Oil, BIT – for Bitcoin exchange rate. All time series are converted into logarithmic returns with base *e*. Frequency: daily. Sample period: January 1, 2016 – January 29, 2021. Observations: 1326 (prices), 1325 (log returns). Source of data: TRDS.

3.2. Methods

3.2.1. Wavelet coherence

Wavelets are useful for decomposing ('de-noising') the original time series into different frequencies (scales). Wavelet coherence, proposed by Grinsted et al. (2004) and Aguiar-Conraria and Soares (2011), is a multidimensional (3-D) analysis tool based on a continuous wavelet transform (CWT). It allows tracking the dynamic links between pairs of assets (bivariate framework) over different investment horizons. Compared with the other econometric approaches that analyze time-series data on time and frequency domains separately, the Wavelet coherence approach allows for tracking the co-movement between the variables on time and frequency simultaneously. Wavelet coherence is a non-parametric tool useful for measuring the dynamic links between two variables, identifying the structural breaks and shifts, and gauging the causal links at different scales (Nagayev et al., 2016).

Wavelet coherence is calculated as follows (Grinsted et al., 2004):

$$R_n^2(s) = \frac{|S(s^{-1}W_n^{XY}(s))|^2}{S(s^{-1}|W_n^X(s)|^2) \cdot S(s^{-1}|W_n^Y(s)|^2)} \tag{1}$$

where S is a smoothing operator. The convolution in time and scale is used for smoothing.

$$S(W) = S_{scale}(S_{time}(W_n(s))) \tag{2}$$

where  $S_{scale}$  and  $S_{time}$  indicate smoothing on the Wavelet scale and time, respectively. The Morlet Wavelet is used as a smoothing operator as proposed by Torrence and Webster (1999):

$$S_{time}(W)_s = \left( W_n(s) * c_1 \frac{e^{-\frac{t^2}{2s^2}}}{s} \right) \Big|_s; S_{time}(W)_s = (W_n(s) * c_2 \Pi(0.6s)) \Big|_n \tag{3}$$

where  $c_1$  and  $c_2$  represent normalization constants, and  $\Pi$  stands for the rectangle function. Factor 0.6 is the scale decorrelation length for the Morlet Wavelet (Torrence and Compo, 1998).

The coefficients of Wavelet coherence fall in the range between zero and one [ $0 \leq R_n^2(s) \leq 1$ ]. It measures the local linear association between a pair of assets at each scale.  $W_n^{XY}(s)$  specifies the cross-wavelet power and indicates the time-scale space with high common power. It can be treated as the local covariance between the variables at each scale. The cross-wavelet power of  $x(t)$  and  $y(t)$  series is calculated as:

$$W_n^{XY}(s) = W_n^X(s)W_n^{*Y}(s) \tag{4}$$

where  $W_n^X(s)$  and  $W_n^{*Y}(s)$  are the continuous Wavelet transforms of two assets  $x(t)$  and  $y(t)$ , respectively. The character \* indicates a complex conjugate.

The phase differences in Wavelet coherence denote the lead-lag relationship between two variables. The phase is measured as:

$$\varphi_n^{XY}(s) = \tan^{-1} \left( \frac{I\{S(s^{-1}W_n^{XY}(s))\}}{R\{S(s^{-1}W_n^{XY}(s))\}} \right) \tag{5}$$

where  $I$  represents the imaginary parts and  $R$  represents the real parts of the smooth power spectrum.

Wavelet coherence results are presented in the form of a heat map, with red (blue) zones representing strong (weak) correlations. The strength of the co-movement is defined within the range 0 - 1. Arrows on the heatmap allow us to identify the direction as well as a lead-lag relationship between the examined return series. Arrows pointing to the right (left) side indicate a positive (negative) correlation. Arrows pointing right-down or left-up indicate that the first asset leads the second one, and vice versa. However, if the arrows are positioned precisely at 3 or 9 o'clock, neither of the variables is lagging. The black contours around the red zones denote the 95% confidence level. The y-axis represents different scales (frequencies), whereas the x-axis indicates the time dimension. The gray region on the edge of the heat map is a cone of influence showing the area affected by the boundary assumptions in which the results are statistically insignificant (at the 95% confidence level). Overall, the regions representing a weak or negative co-movement between the assets in the time-frequency space suggest the desired diversification benefits for investors.<sup>4</sup>

### 3.2.2. Spillover index

This study also adopted the spillover index approach of Diebold and Yilmaz (2012), called DY12, to identify the direction of transmissions between asset returns. The method helps in estimating the static and dynamic relationships between assets and classifying them as net transmitters and net recipients of shocks. The spillover index is measured using the forecast-error variance decomposition (FEVD) in the generalized vector autoregressive (VAR) framework, developed by Koop et al. (1996) and Pesaran and Shin (1998). Unlike the orthogonalised FEVD, the generalized FEVD does not depend on the ordering of variables in the VAR (Kinkyo, 2020). By introducing shock to one variable in the model, we estimate the response of other variable(s) to that shock. To identify whether an asset is a net transmitter (positive value) or a net receiver (negative value) of shocks, we calculate the net spillover index, which is the difference between "TO" and "FROM" spillover values.

Following DY12, we model the asset returns as an N-variable VAR. For each asset  $i$ , the shares of its forecast-error covariance are added because of the shocks in another asset  $j$ , for all  $j \neq i$ . To obtain the spillover index, we sum across all four assets - each type of equity with gold, oil and Bitcoin - ( $i = 1, \dots, N|N = 4$ ) the contribution of spillovers to the total forecast-error variance, which is the total of all non-diagonal elements in the forecast error variance matrix. The main advantage of the FEVD method is its invariance to the ordering of the variables as the shocks to each variable are not orthogonalized. Assume the following stationary covariance of four variables VAR(p):

$$x_t = \sum_{i=1}^p \varphi_i x_{t-i} + \varepsilon_t \tag{6}$$

where  $x_t$  is the  $4 \times 1$  vector of asset returns,  $\varphi$  is a  $4 \times 4$  autoregressive parameter matrix and  $\varepsilon_t$  the vector of error terms that are assumed to be serially uncorrelated.

If the VAR system is covariance stationary, its moving average representation (MA) is given by  $x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$ , where the  $4 \times 4$  coefficient matrix  $A_i$  obeys a recursion of the form  $A_i = \varphi_1 A_{i-1} + \varphi_2 A_{i-2} + \dots + \varphi_p A_{i-p}$  where  $A_0$  is the  $N \times N$  identity matrix and  $A_i = 0$  for  $i < 0$ . The MA representation is then used to forecast the future H-steps ahead of the vector of independent variables.

Koop et al. (1996) and Pesaran and Shin (1998) proposed the following H-step-ahead FEVD based on the generalised impulse responses as follows:

$$\theta_{ij} \left( H \right) = \frac{\sigma_{ij}^{-1} \sum_{h=0}^{H-1} (e_i' A_h P e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \sum_{k=1}^4 A_k' e_i)} \tag{7}$$

where  $\theta_{ij}(H)$  is the contribution of a one-standard-deviation shock to  $x_j$  to the variance of the H -step ahead forecast error of  $x_i$ ,  $\sigma_{ij}$  is the

<sup>4</sup> For further details, please refer to Grinsted et al. (2004).

standard deviation of the error term for the  $j$  th equation,  $\Sigma$  is the variance matrix of the vector errors  $\varepsilon$ , and  $e_i$  is an  $N \times 1$  selection vector with 1 for the  $i$  th element and 0 otherwise. The spillover index yields an  $N \times N$  matrix  $\theta(H) = [\theta_{ij}(H)]$ , where each entry reveals the contribution of variable  $j$  to the forecast-error variance of variable  $i$ . Own-variable and cross-variable contributions are contained in the main diagonal and off-diagonal elements, respectively, of the  $\theta(H)$  matrix. Each entry in the  $\theta(H)$  matrix is normalised by the row sum to ensure that the row sum is equal to 1. Using the normalised FEVD,  $\tilde{\theta}_{ij}(H)$ , we construct the total spillover, directional spillover, and net spillover indexes.

The total spillover index (TSI) measures the contribution of spillovers across all four assets to the total forecast-error variance. The TSI is calculated as follows:

$$TSI(H) = \frac{\sum_{i,j=1, i \neq j}^N \tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ij}(H)} \times 100 = \frac{\sum_{i,j=1, i \neq j}^N \tilde{\theta}_{ij}(H)}{N} \times 100 \tag{8}$$

where TSI is the sum of the off-diagonal elements of the matrix obtained from a standard variance decomposition exercise in any VAR system relative to the number of variables. The sum of the diagonal elements relative to the number of variables, however, is a measure of how much of the forecast error variances are explained by own shocks.

The directional spillover index (DSI) captures the spillovers received by asset  $i$  from all other assets  $j$  as follows. Similarly, one can also capture the directional spillovers transmitted by asset  $i$  to all other assets. The DSI provides a decomposition of TSI to those coming from (or to) a particular asset. The first directional spillover ("From" directional spillover) is calculated as follows:

$$DSI_i(H) = \frac{\sum_{j=1, j \neq i}^N \tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ij}(H)} \times 100 = \frac{\sum_{j=1, j \neq i}^N \tilde{\theta}_{ij}(H)}{N} \times 100 \tag{9}$$

The second DSI ("To" DSI) is similarly measured as

$$DSI_i(H) = \frac{\sum_{j=1, j \neq i}^N \tilde{\theta}_{ji}(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ji}(H)} \times 100 = \frac{\sum_{j=1, j \neq i}^N \tilde{\theta}_{ji}(H)}{N} \times 100 \tag{10}$$

The net spillover index (NSI) measures the net contribution of asset  $i$  to all other assets and is calculated as the difference between the "To" directional spillover index and the "From" directional spillover index, i.e.:

$$NSI_i(H) = DSI_i(H) - DSI_i(H) \tag{11}$$

To capture the time-varying nature of the spillover index,  $NSI_i(H)$ , we apply a rolling-window methodology.

Finally, we use the method of Baruník and Křehlík (2018), called BK18, who extended the model of DY12 by measuring the interconnectedness on the time-frequency domain.<sup>5</sup> This technique is used to complement the time-frequency framework of Wavelet coherence.

## 4. Empirical Findings

### 4.1. Wavelet coherence

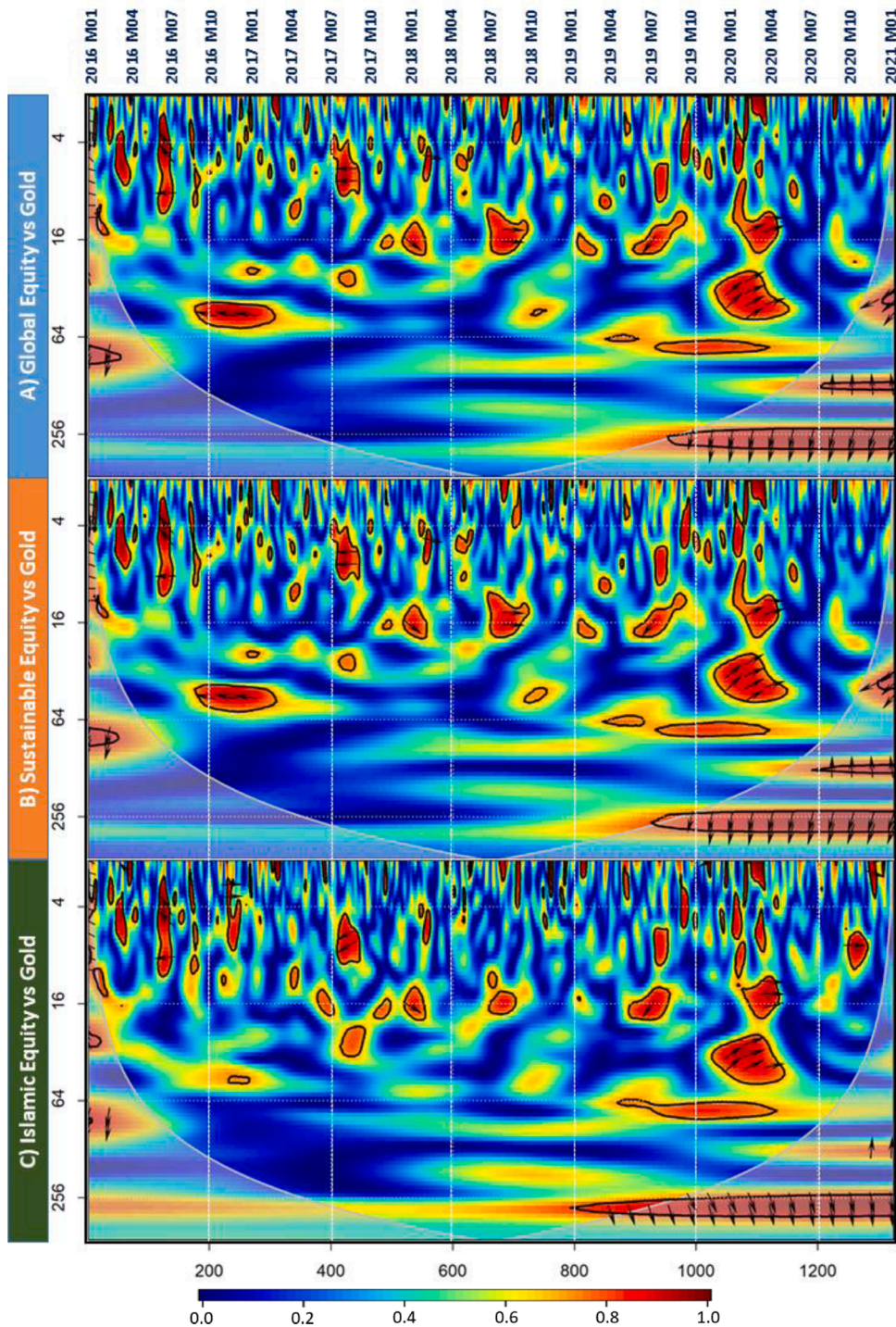
The application of Wavelets helps in examining the co-movement between various equity markets (conventional, sustainability, and Islamic) and the three commonly used hedging assets (i.e., gold, crude oil, and Bitcoin). Specifically, this study focuses on the dynamic correlations between each separate equity market and the three hedging assets in the time and frequency domains. This approach assists in evaluating whether the hedging assets provide diversification opportunities in time and across different investment horizons to conventional, sustainable, and Islamic investors. Hence, this time-frequency representation helps examine whether the co-movement dynamics of yields have been affected during the COVID-19 pandemic. The values for the 5% significance level represented by the black contour line are derived from Monte Carlo simulations.<sup>6</sup>

Figs. 1–3 show the estimated Wavelet coherence for various equity markets and hedging assets, showing a time-varying relationship for all examined pairs of indices across different frequencies. Frequencies or investment horizons are displayed on the vertical

<sup>5</sup> Please refer to Diebold and Yilmaz (2012) and Baruník and Křehlík (2018) for a detailed description of the techniques.

<sup>6</sup> The statistical significance using wavelet power analysis is derived based on "the empirical (chi-squared) distribution for the local wavelet power spectrum of a white or red noise signal using Monte Carlo simulation analysis" (Torrence and Compo, 1998; Gallegati et al., 2014).

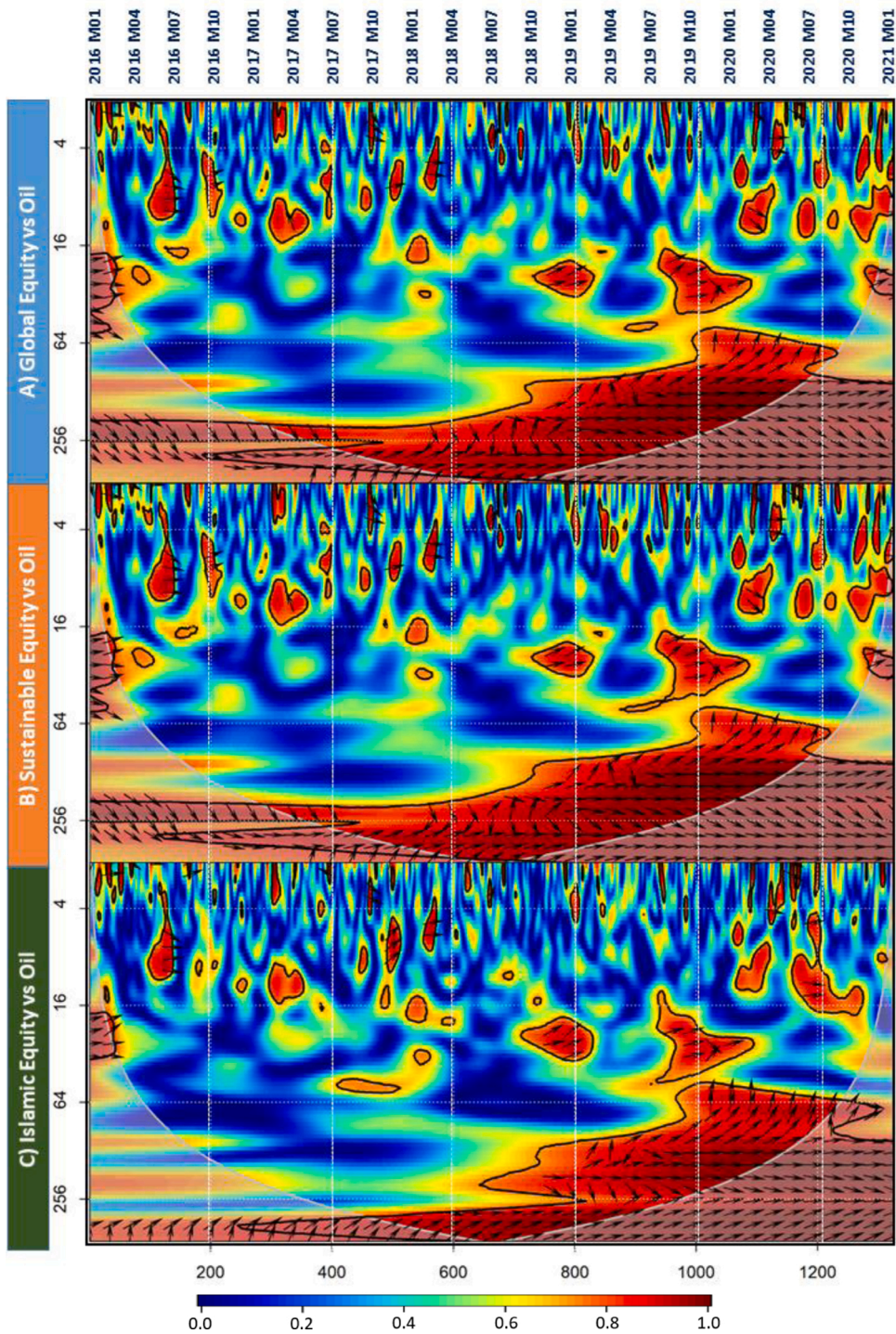




**Fig. 1.** Equities vs Gold.

*Notes:* Wavelet coherence output. The number of Monte Carlo randomizations = 1000. The strength of the relationship is defined within the range 0 to 1. Arrows on the heat map indicate the direction and a lead-lag relationship between the examined series. Arrows heading to the right (left) side suggest a positive (negative) correlation. Arrows pointing right-down or left-up reveal that the first variable leads the second one, and vice versa. However, if arrows are positioned precisely at 3 or 9 o'clock, there is no lead-lag relationship between the variables. The black contours around the red zones denote the 95% confidence interval. The y-axis represents different scales (frequencies), whereas the x-axis shows the time dimension. The light gray region on the edge of the heat map is a cone of influence indicating the area affected by boundary assumptions in which the results are statistically insignificant at the 95% confidence interval. The outputs are produced using R package “*biwavelet*” of Gouhier et al. (2019). *Sample period:* January 1, 2016 - January 29, 2021.

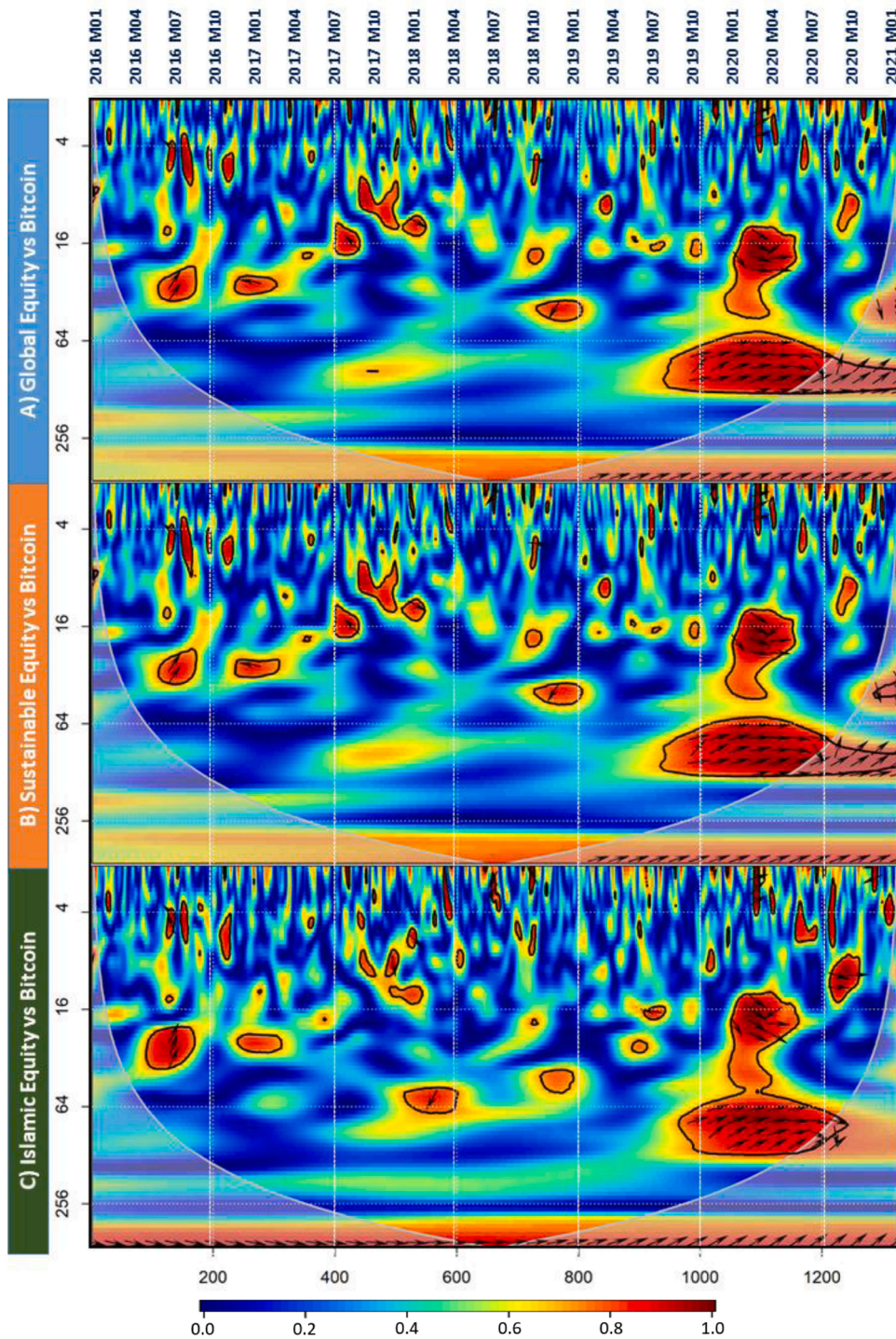




**Fig. 2.** Equities vs Oil.

*Notes:* Wavelet coherence output. The number of Monte Carlo randomizations = 1000. The strength of the relationship is defined within the range 0 to 1. Arrows on the heat map indicate the direction and a lead-lag relationship between the examined series. Arrows heading to the right (left) side suggest a positive (negative) correlation. Arrows pointing right-down or left-up reveal that the first variable leads the second one, and vice versa. However, if arrows are positioned precisely at 3 or 9 o'clock, there is no lead-lag relationship between the variables. The black contours around the red zones denote the 95% confidence interval. The y-axis represents different scales (frequencies), whereas the x-axis shows the time dimension. The light gray region on the edge of the heat map is a cone of influence indicating the area affected by boundary assumptions in which the results are statistically insignificant at the 95% confidence interval. The outputs are produced using R package “*biwavelet*” of Gouhier et al. (2019). *Sample period:* January 1, 2016 - January 29, 2021.





**Fig. 3.** Equities vs Bitcoin.

*Notes:* Wavelet coherence output. The number of Monte Carlo randomizations =1000. The strength of the relationship is defined within the range 0 to 1. Arrows on the heat map indicate the direction and a lead-lag relationship between the examined series. Arrows heading to the right (left) side suggest a positive (negative) correlation. Arrows pointing right-down or left-up reveal that the first variable leads the second one, and vice versa. However, if arrows are positioned precisely at 3 or 9 o'clock, there is no lead-lag relationship between the variables. The black contours around the red zones denote the 95% confidence interval. The y-axis represents different scales (frequencies), whereas the x-axis shows the time dimension. The light gray region on the edge of the heat map is a cone of influence indicating the area affected by boundary assumptions in which the results are statistically insignificant at the 95% confidence interval. The outputs are produced using R package “*biwavelet*” of Gouhier et al. (2019). *Sample period:* January 1, 2016 - January 29, 2021.

axis, from a single day up to 256 days (approximately one market year). Conversely, time is displayed on the horizontal axis, covering the entire sample period. The color code for the strength of correlation ranges from blue (low coherency between the series) to red (high coherency between the series). Consequently, both the frequency and time intervals where the pairs significantly move together can be identified. Arrows in the Wavelet coherence plot represent the phase differences. Two time series are in phase (anti-phase) when the arrows are pointed rightward (leftward), which indicates that they move in the same (opposite) direction. Arrows pointing right-down ( $\searrow$ ) or left-up ( $\swarrow$ ) show that the first time series leads the second one, whereas arrows pointing right-up ( $\nearrow$ ) or left-down ( $\nwarrow$ ) indicate that the first time series is led by the second one.

The connection between each stock index and the three hedging assets varies across time and investment horizon. A visual inspection reveals that gold (see Fig. 1) was weakly related to the three indices across all frequencies but mostly at lower frequencies (longer investment horizons). Bredin et al. (2015) and Beckmann et al. (2015) suggested that gold serves as a hedging asset. The onset of the COVID-19 pandemic, however, has shown an increase in the correlation. Moreover, information on the phases (represented by arrows) shows that the relationship between gold and the three equity indices was not homogeneous across scales before and during the COVID-19 period. For holding periods less than 64 days, as the arrows point up and to the right, gold prices are found to lead the three indices at the beginning of the pandemic. However, the correlation between the gold prices and the indices vanishes once economies recover.

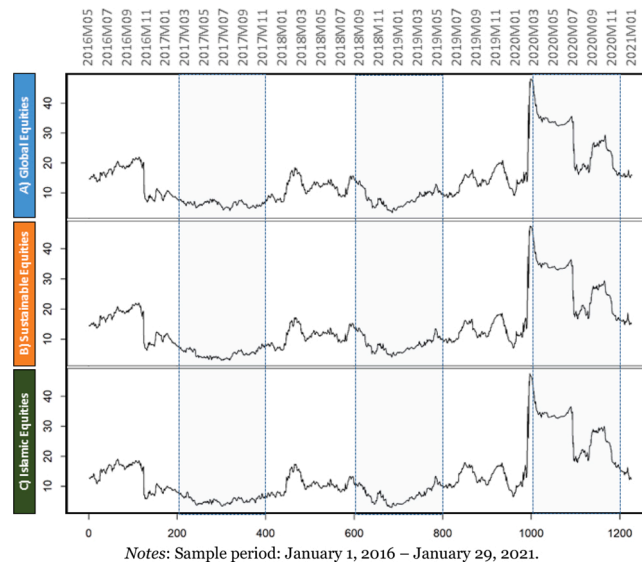
In the case of oil (Fig. 2), low coherency dominates in the short-run (up to 16 days) on average, suggesting that oil can be considered a short-horizon hedge for the three equity indices. For this horizon, the number of small pockets of high coherency can be observed during the study sample period that the pairs are in phase (arrows pointing rightward), and that each equity index leads the oil price. For investors with a holding period between 8 and 16 days, the co-movement pattern between oil and both the conventional and sustainable index becomes more apparent at the onset of the crisis, while the co-movement between oil and Islamic index becomes strong during the pandemic phase. For investors with a holding period between 16 and 64 days, two distinct pockets of high coherency are found between oil and the three indices. The first, and smaller of the two, is detected in the middle of the sample period (i.e., from October 2018 to February 2019), while the second is noticed close to the outbreak of the pandemic. Beyond this investment horizon, an extended period of positive coherency, observed for increasing frequencies as the pandemic approaches, exists between each equity index and oil price. Upward facing arrows signify that while each equity index has a long-horizon positive relationship with oil, oil prices lead the fluctuations in equity prices. Hence, oil's hedging ability for each equity index is completely dissipated for longer horizons.

**Table 3**

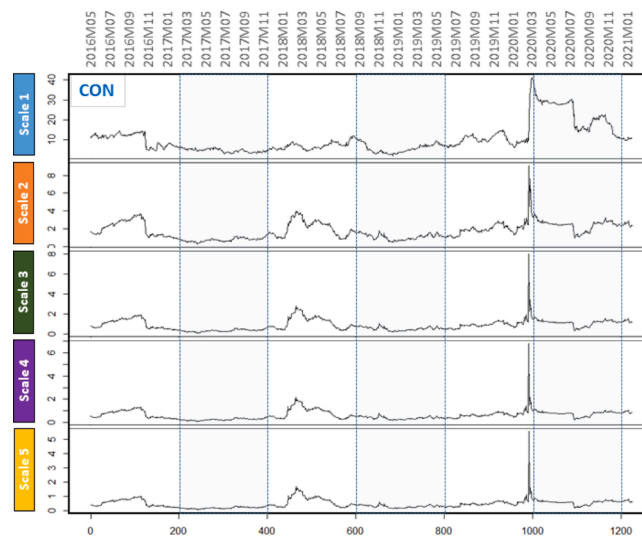
Net and overall spillovers (static, all equities) - DY12 and BK18 outputs.

A) Global Equities	Net CON	Net GLD	Net OIL	Net BIT	Overall
DY12	0.24	-0.02	-0.07	-0.15	9.37
Scale 1	0.39	0.09	-0.25	-0.23	7.49
Scale 2	-0.07	-0.05	0.08	0.03	0.92
Scale 3	-0.04	-0.02	0.05	0.02	0.44
Scale 4	-0.02	-0.02	0.03	0.02	0.29
Scale 5	-0.02	-0.02	0.02	0.02	0.22
B) Sustainable Equities	Net SUS	Net GLD	Net OIL	Net BIT	Overall
DY12	0.26	0.00	-0.13	-0.14	8.96
Scale 1	0.41	0.11	-0.32	-0.20	7.31
Scale 2	-0.06	-0.05	0.09	0.03	0.81
Scale 3	-0.04	-0.03	0.05	0.02	0.39
Scale 4	-0.02	-0.02	0.04	0.01	0.26
Scale 5	-0.03	-0.02	0.03	0.01	0.19
C) Islamic Equities	Net ISL	Net GLD	Net OIL	Net BIT	Overall
DY12	0.25	-0.03	-0.11	-0.12	8.75
Scale 1	0.28	0.09	-0.20	-0.17	7.14
Scale 2	-0.02	-0.05	0.04	0.03	0.79
Scale 3	-0.01	-0.03	0.02	0.02	0.38
Scale 4	-0.01	-0.02	0.02	0.01	0.25
Scale 5	-0.01	-0.01	0.02	0.00	0.19

Notes: CON stands for DJ Global Index, SUS – for DJ Sustainability Index, ISL – for DJ Islamic Index, GLD – for Gold, OIL – for Crude Oil, and BIT – for Bitcoin exchange rate. This table summarizes the results from DY12 and BK18 and presents the static Net and Overall spillovers for all types of equities under study with Bitcoin, oil and gold. The sum of all values from different bands produced by BK18 should be equal to the DY12 value. The positive value suggests that the asset is the net exporter of shocks, and the negative value is for the net importer of shocks. Scale 1 corresponds to BK18's band  $3.14 - 0.79 = 1-4$  days, Scale 2 = band  $0.79 - 0.39 = 4-8$  days, Scale 3 = band  $0.39 - 0.20 = 8-16$  days, Scale 4 = band  $0.20 - 0.10 = 16-32$  days, Scale 5 = band  $0.10 - 0.00 = 32+$  days. Sample period: January 1, 2016 – January 29, 2021.



**Fig. 4.** Overall spillovers (DY12).  
Notes: Sample period: January 1, 2016 – January 29, 2021.



**Fig. 5.** Overall frequency spillovers - Global equities (BK18).  
Notes: CON stands for DJ Global Index. Scale 1 = band 3.14 - 0.79 = 1–4 days, Scale 2 = band 0.79 - 0.39 = 4–8 days, Scale 3 = band 0.39-0.20 = 8–16 days, Scale 4 = band 0.20 - 0.10 = 16–32 days, Scale 5 = band 0.10 - 0.00 = 32+ days. Sample period: January 1, 2016 – January 29, 2021.

The relationship with Bitcoin (see Fig. 3) shows that the coherency between each stock index and Bitcoin is negligible across all considered investment horizons until the onset of the COVID-19 pandemic. Thus, Bitcoin is an efficient hedge for each type of investor, especially during tranquil periods. With the outbreak of the pandemic, we observe heightened co-movements between Bitcoin and each type of equity for the frequency band 16–64 days. Each type of equity leads Bitcoin as the arrows point right-down for this investment horizon. However, the high level of co-movement between Bitcoin and equities dissipates during the pandemic for this investment horizon. At the onset of the pandemic, a positive relationship is detected for the frequency band 64–128 days. Hence, Bitcoin does not act as a safe-haven asset during the COVID-19 crisis, which confirms the findings of Conlon and McGee (2020) and Corbet et al. (2020).

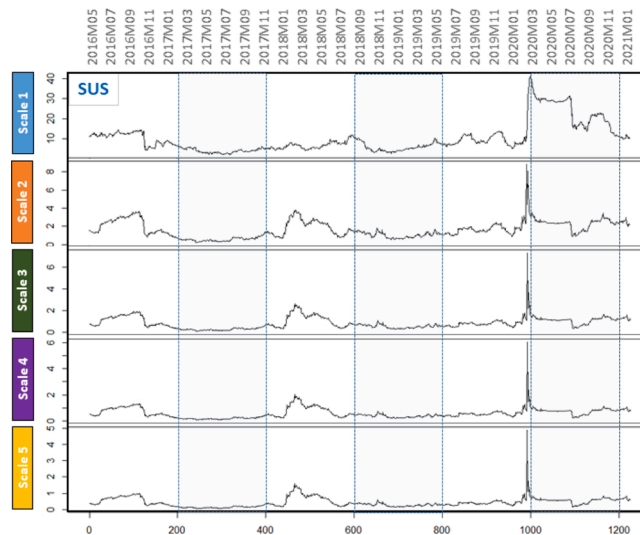


Fig. 6. Overall frequency spillovers - Sustainable equities (BK18).

Notes: SUS – DJ Sustainability Index. Scale 1 = band  $3.14 - 0.79 = 1-4$  days, Scale 2 = band  $0.79 - 0.39 = 4-8$  days, Scale 3 = band  $0.39 - 0.20 = 8-16$  days, Scale 4 = band  $0.20 - 0.10 = 16-32$  days, Scale 5 = band  $0.10 - 0.00 = 32+$  days. Sample period: January 1, 2016 – January 29, 2021.

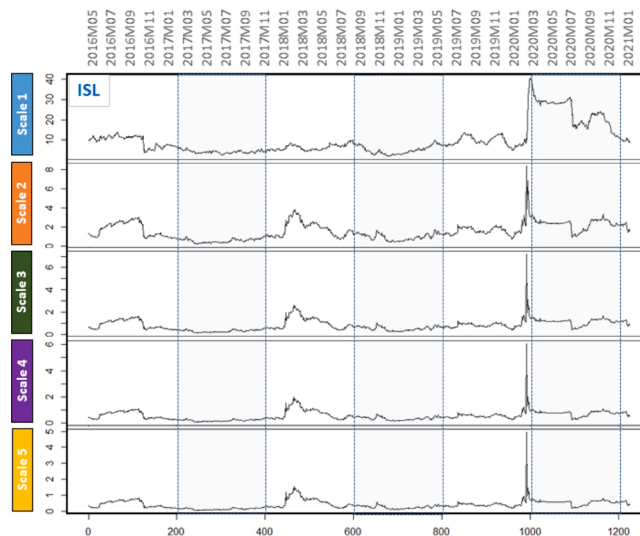


Fig. 7. Overall frequency spillovers - Islamic equities (BK18).

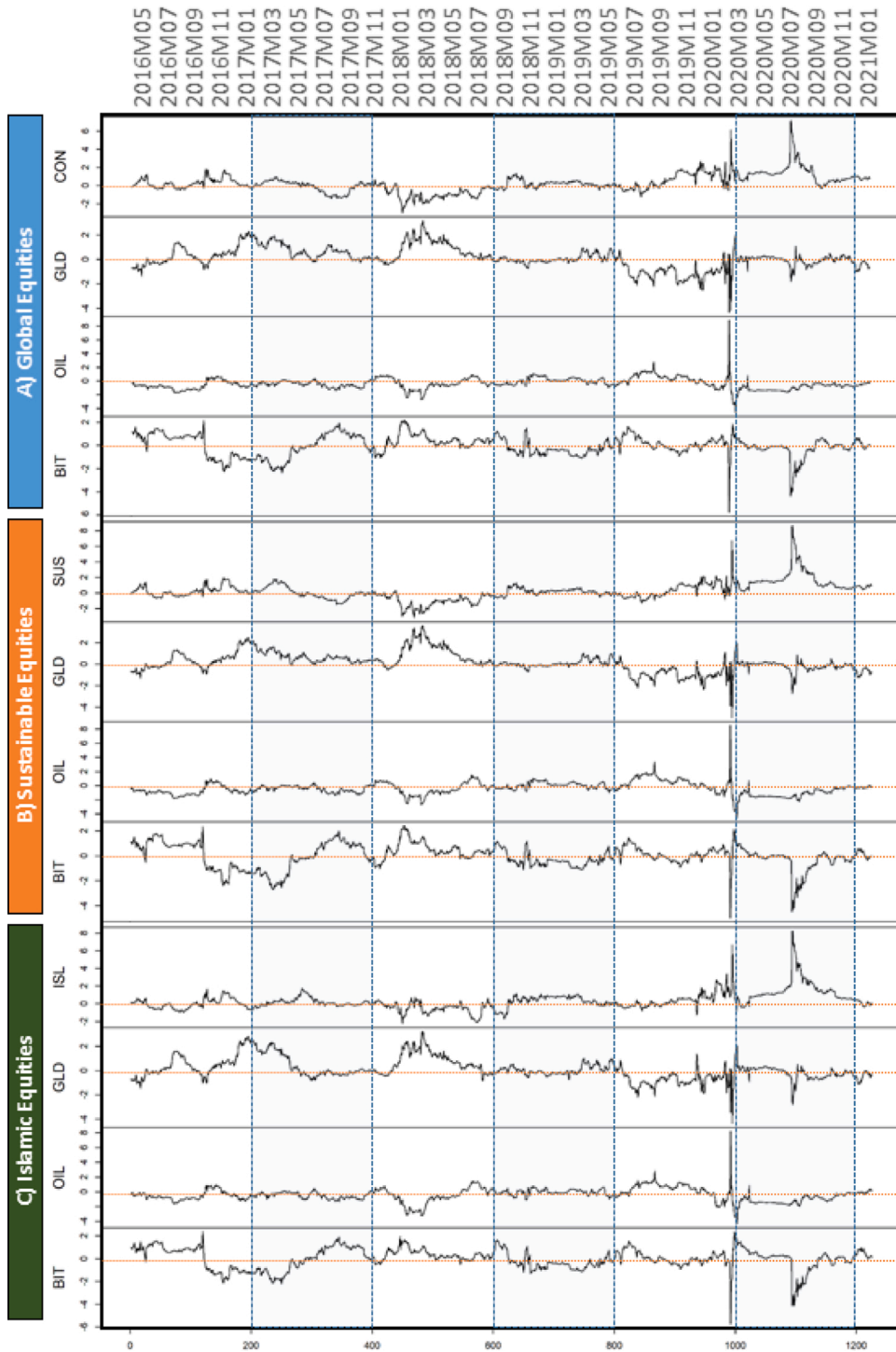
Notes: ISL – DJ Islamic Index. Scale 1 = band  $3.14 - 0.79 = 1-4$  days, Scale 2 = band  $0.79 - 0.39 = 4-8$  days, Scale 3 = band  $0.39 - 0.20 = 8-16$  days, Scale 4 = band  $0.20 - 0.10 = 16-32$  days, Scale 5 = band  $0.10 - 0.00 = 32+$  days. Sample period: January 1, 2016 – January 29, 2021.

Until the outbreak of the COVID-19 pandemic, the level of coherency between each index and safe-haven assets was low, for different investment horizons, except for the relationship between each equity index and oil, where a positive relationship is observed at longer investment horizons. However, with the COVID-19 outbreak, small patches of high coherency are dispersed between each equity index and the hedging vehicles across different investment horizons.

The higher correlation is short-lived and related to economic lockdown and pandemic confinement measures<sup>7</sup>. Hence, independent of investor type, the original portfolio strategy should be revisited by developing a hedging strategy that focuses more on gold and

<sup>7</sup> Siddiqui et al. (2020) found that the comovement concentration in the stock market occurs at a short-time scale (even only 2 days) as the impact of COVID-19 enlarged during the second half of March 2020. Okorie and Lin (2021) also reveal a significant but short-lived contagion effect in the stock market during the COVID-19 pandemic crisis.

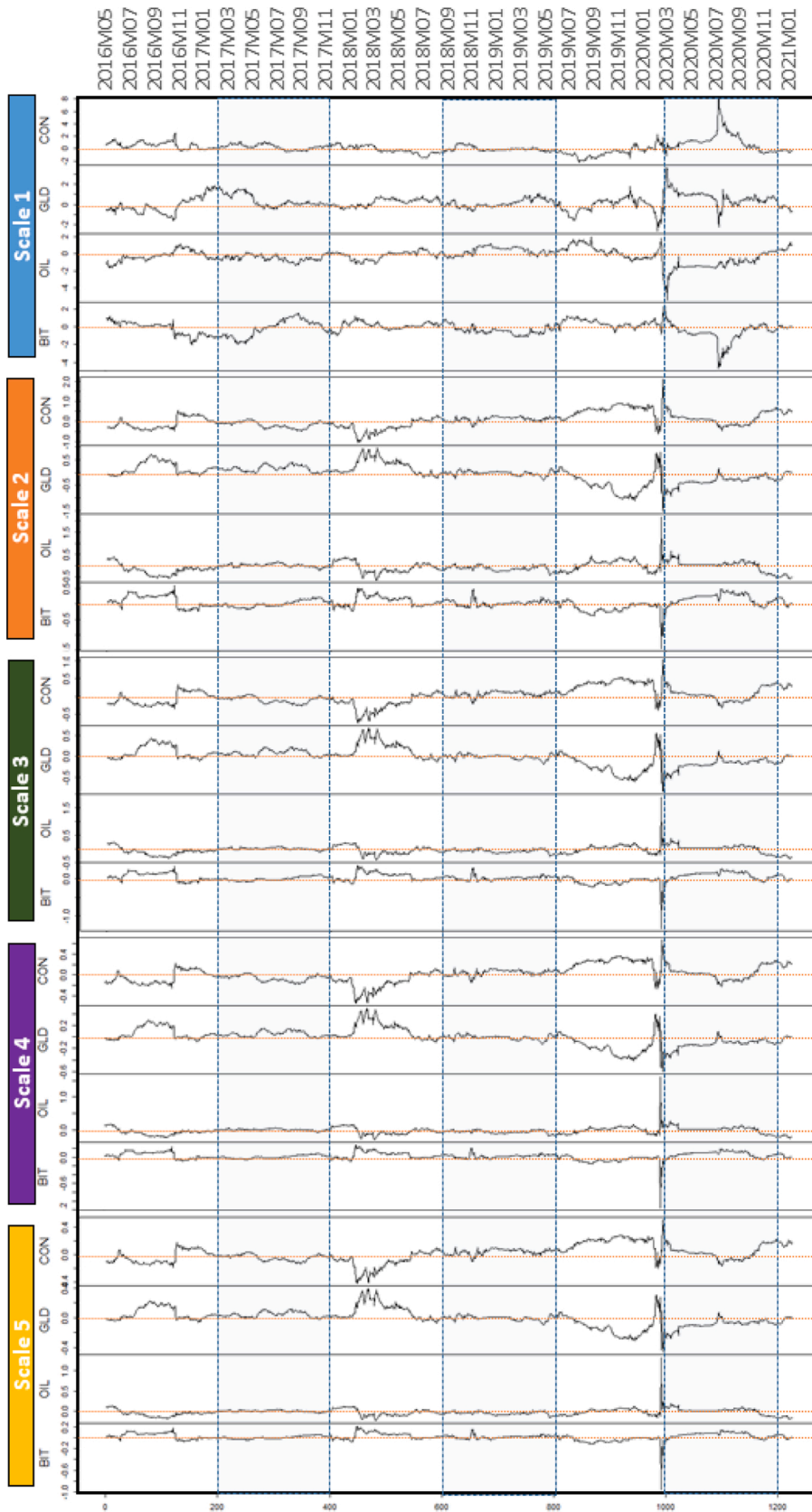




**Fig. 8.** Net spillovers (DY12).

Notes: CON stands for DJ Global Index, SUS – for DJ Sustainability Index, ISL – for DJ Islamic Index, GLD – for Gold, OIL – for Crude Oil, and BIT – for Bitcoin exchange rate. Sample period: January 1, 2016 – January 29, 2021.





(caption on next page)

**Fig. 9.** Net frequency spillovers - Global equities (BK18).

Notes: CON stands for DJ Global Index, GLD – for Gold, OIL – for Crude Oil, and BIT – for Bitcoin exchange rate. Scale 1 = band 3.14 - 0.79 = 1–4 days, Scale 2 = band 0.79 - 0.39 = 4–8 days, Scale 3 = band 0.39 - 0.20 = 8–16 days, Scale 4 = band 0.20 - 0.10 = 16–32 days, Scale 5 = band 0.10 - 0.00 = 32+ days. Sample period: January 1, 2016 – January 29, 2021.

Bitcoin. Having a passive hedging strategy with oil is particularly problematic, given its high correlation with equity markets for longer investment horizons. Nevertheless, our findings also show that COVID-19 has had a weak structural impact on the comovement between equity markets and hedging assets. It implies that investors should not make drastic changes to their exposure to hedging assets during market stress.

#### 4.2. Static connectedness

Table 3 presents the net directional and overall static spillover index for each equity market and the three hedging assets based on the DY12 for the time domain, and the BK18 for the frequency domain. For the DY12 spillovers, a low overall connectedness is observed between each equity index and the three hedging assets. The overall connectedness of global, sustainable and Islamic equities with the three hedging assets is 9.37%, 8.96%, and 8.75%, respectively. This finding is also similar to the DY12 spillover index between stocks, bonds, commodities and Bitcoin. The results suggest that gold, oil, and Bitcoin provided diversification benefits for each type of equity investor over the sample period.

The spillover analysis shows that the three stock indices contribute the most to balance the system with hedging assets. Within the systems, Bitcoin and oil are the largest net receivers of spillovers. The frequency decomposition of spillovers, following Barunik and Krehlik (2018), complements the frequency analysis of the Wavelet coherence approach. The first band corresponds to movements up to 4 days, the second from 5 to 8 days, the third from 9 to 16 days, the fourth from 17 to 32 days, and the last for 33 days and more. As in the Wavelet coherence approach, these frequency bands allow evaluation of the connectedness of each equity index with the three hedging assets over different horizons. The BK18 method allows identifying the whole spectrum of information transmission within each system at varying horizons.

We observe that the total spillover from the highest frequency band (1–4 days) contributes the most to the total connectedness within each system, as shown by Tiwari et al. (2018). For this horizon, the total connectedness of global, sustainable, and Islamic equities with the three hedging assets is 7.49%, 7.31%, and 7.14%, respectively.

The contribution from the lower frequencies to the total connectedness drops abruptly, suggesting that the total spillover is rarer for longer investment horizons. It implies that each system processes information rapidly; therefore, shocks to any asset are largely transmitted to other assets within four days. Across frequencies, the net contribution of the three equities to their respective system is the largest in the highest frequency band (1–4 days), while the three equities become net receivers beyond this horizon. The contribution of gold within each system varies across frequencies. While gold is a net-transmitter in the highest frequency band, it becomes a net-receiver in every other frequency band. In contrast, Bitcoin and oil are the largest net receivers in the highest frequency band while becoming a net transmitter in every other frequency band.

The study results suggest that the overall connectedness within each system, alternatively designed for the hedging purposes of different types of investors, is mainly a short-run phenomenon, suggesting that each type of investor has relatively better diversification opportunities at longer horizons.

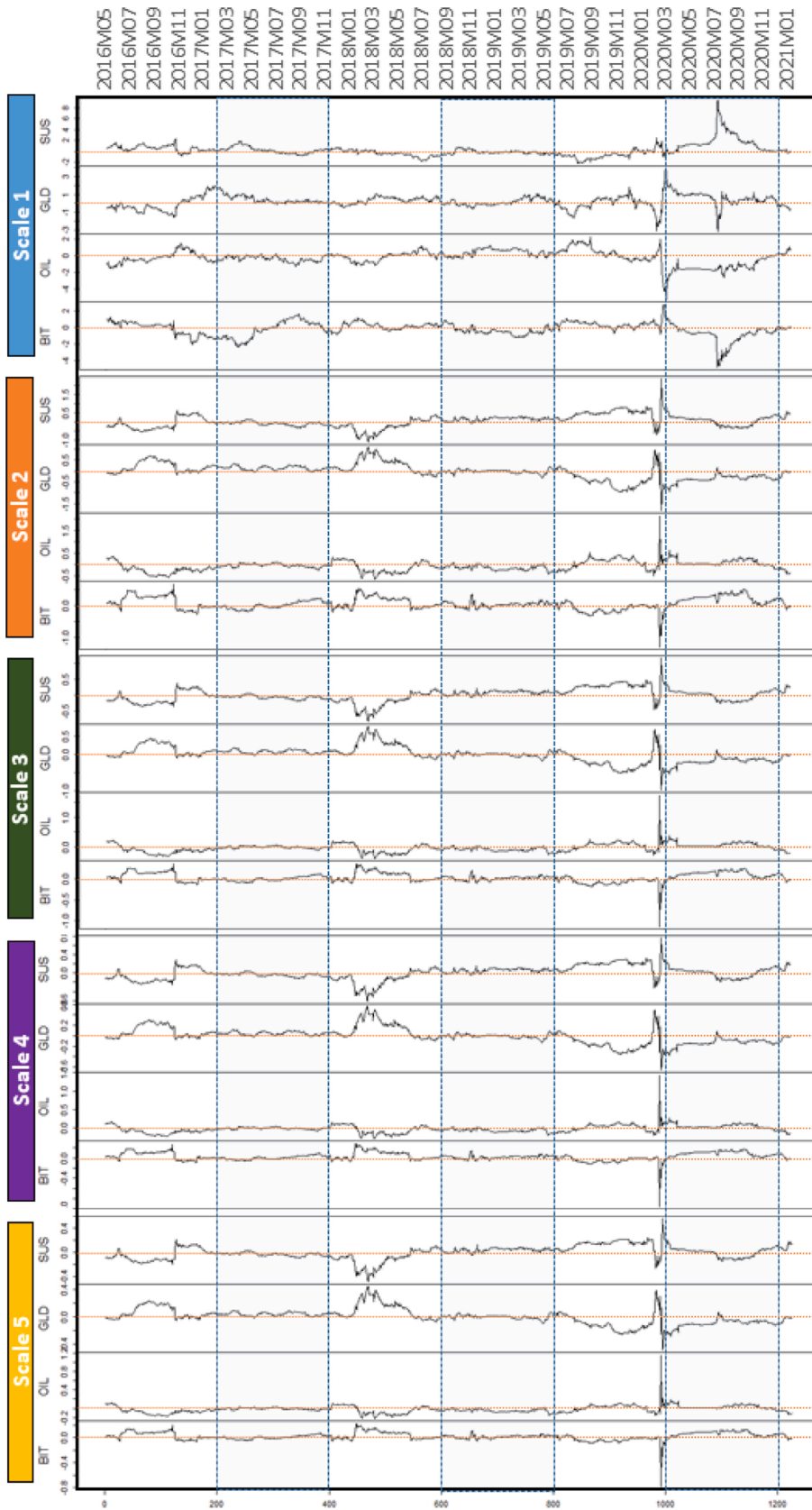
#### 4.3. Dynamic connectedness

To examine the results in depth, the time dynamics of the overall return spillovers are examined using the approaches of both DY12 and BK18. Fig. 4 presents the overall connectedness of the three systems based on DY12 and built around the conventional, sustainable and Islamic markets.

The overall connectedness of the three systems, formed in the function of equity type and three hedging assets, shows similar dynamic behavior over the sample period. Thus, the three overall spillover indices were relatively stable and varied between 5% and 20% until they reached a short-lived peak of approximately 50% at the onset of the COVID-19 crisis. These results are consistent with DY12, who found that the overall spillover varied between 5% and 25% from 2000 until the 2007 global financial crisis. The strengthening of the overall spillover in March 2020 stems mainly from the economic uncertainty and financial volatility caused by the COVID-19 pandemic, which led investors to reprice risk at the global scale. Several other studies also find high co-movement and contagion, which shows a structural break in the international transmission of financial shocks during crises (Bekaert et al., 2014; Chiang et al., 2007; Corsetti et al., 2005; Hartmann et al., 2004).<sup>8</sup>

Figs. 5–7 show that the overall connectedness over time and across frequencies demonstrates a similar pattern between the three systems for each frequency band at the peak in March 2020. Furthermore, the overall spillovers are mostly driven by high-frequency components, suggesting that most transmission occurs in the very short-run (1–4 days), implying that markets rapidly process information. This finding also indicates that each type of investor (global, sustainable, and Islamic) is more certain about the stability of the respective systems in the long run.

<sup>8</sup> Elsingher et al. (2006) also supported the notion of contagion effect during the crises in the banking system.



(caption on next page)

**Fig. 10.** Net frequency spillovers - Sustainable equities (BK18).

Notes: SUS stands for DJ Sustainability Index, GLD – for Gold, OIL – for Crude Oil, and BIT – for Bitcoin exchange rate. Scale 1 = band 3.14 - 0.79 = 1–4 days, Scale 2 = band 0.79 - 0.39 = 4–8 days, Scale 3 = band 0.39 - 0.20 = 8–16 days, Scale 4 = band 0.20 - 0.10 = 16–32 days, Scale 5 = band 0.10 - 0.00 = 32+ days. Sample period: January 1, 2016 – January 29, 2021.

Further, the analysis focuses on the time-varying net directional return spillovers within each system of equity and the three hedging assets. This process helps in identifying the net transmitters and receivers of spillovers within each system. Fig. 8 presents the time dynamics of the net directional return spillovers (from DY12) across all variables within each system. The DY12 approach showed that the time dynamics of net directional spillovers oscillated around zero before the pandemic, while a substantial time variation was observed during the pandemic. Importantly, equity indices within each system emerge as net transmitters of return spillovers in the long run during the pandemic, while the three hedging assets are net receivers of return spillovers. These findings can be interpreted as the first sign that equity markets are key in influencing the hedging assets during the pandemic.

Figs. 9–11 present the time-frequency dynamics of the net directional spillovers (based on BK18). Our findings reveal that the linkages are mainly driven by the highest frequency band (1 - 4 days), beyond which the interlinkages decline with each subsequent longer time frame. Besides, within each system, the net spillovers are low before the outbreak of the pandemic. With the pandemic, we observe once again a high degree of interconnection within each system of equity and hedging assets. Within each system, independent of the frequency bands, equity indices appear to be, on average, net transmitters of return spillovers. While Bitcoin is a net receiver in the highest frequency band, it becomes a net transmitter for other frequency bands. Although less significant, oil shows the same transmission pattern across frequencies as Bitcoin. Gold is a net transmitter of return spillovers to other assets in the highest frequency band during the pandemic while becoming the net receiver in lower frequency bands.

From the dynamic net pairwise directional connectedness (based on DY12) results in Fig. 12, we can determine the key transmitters and receivers of return spillovers in each system in a bivariate setting. The positive domain of net pairwise directional spillovers indicates that the equity within each system serves as a net receiver, while the negative domain shows that the equity acts as a net transmitter (Geng et al., 2020; Umar et al., 2019). Furthermore, the net pairwise connectedness between each stock index and hedging assets oscillates around zero until the index mainly enters the negative domain during the pandemic, which indicates that the stock indices are net return transmitters with each of the three hedging assets. Specifically, the peak in the net transmission from stock indices to hedging assets was extremely short-lived in March 2020, while the second temporary peak was observed in August 2020. Another interesting finding is that the shocks from stock returns have a relatively less impact on the oil market than gold and Bitcoin.

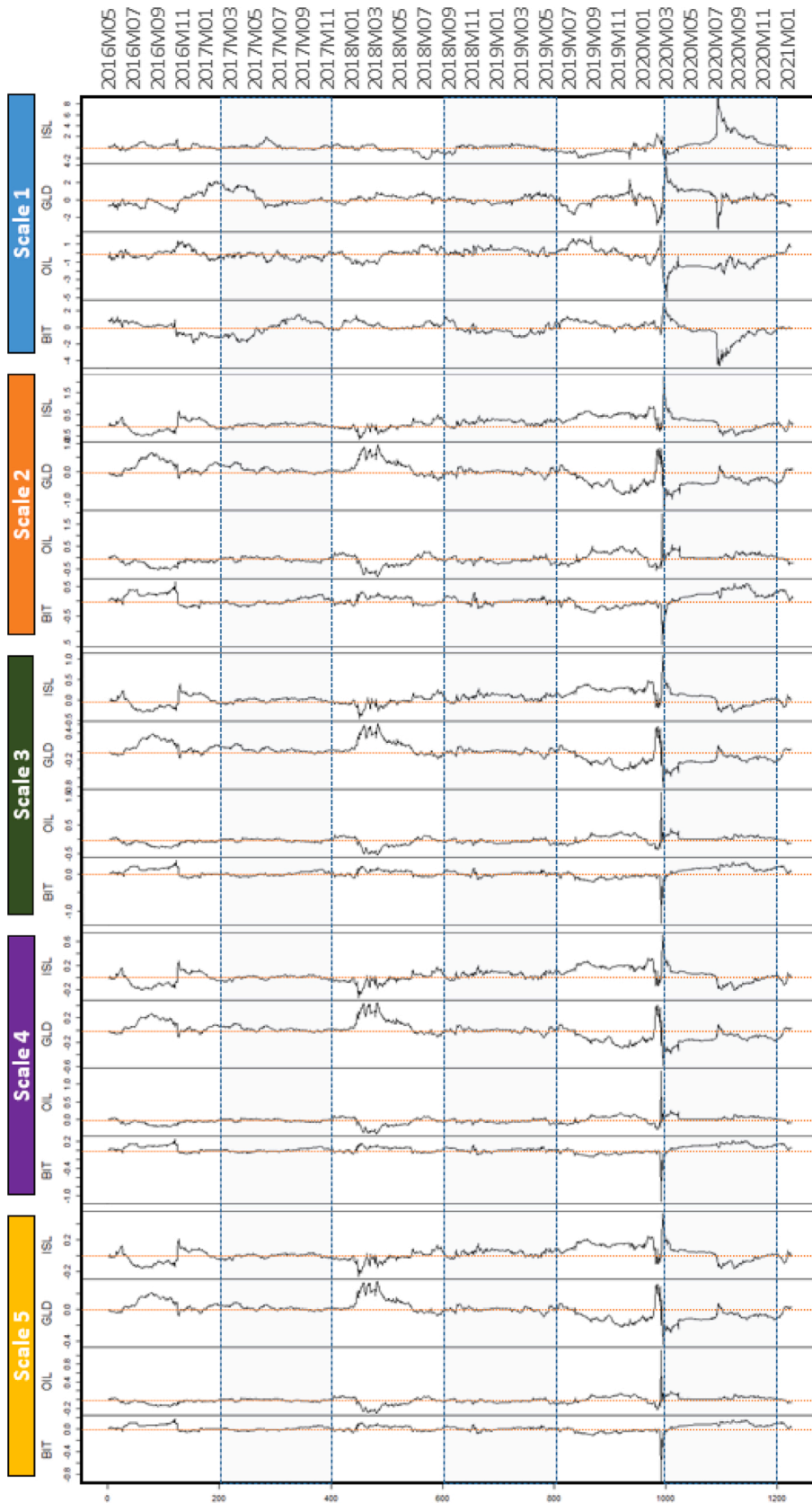
Fig. 13 shows that the DY12 net pairwise directional return connectedness in each system is mainly driven by the highest frequency band, consistent with our previous findings. These results again confirm the importance of integrating frequency dynamics into the DY12 approach.

Our analysis shows little to no difference in the effect that each hedging asset has on the three observed equity investors. This finding further supports the notion that the Islamic, socially responsible, and the conventional stock market has a strong co-movement. Paltrinieri et al. (2019), in their 10-year study, found a cointegration between these three types of equity indices, as well as a co-movement with mutual casualties of major economic factors, such as oil prices and market volatility. Other studies, such as Ho et al. (2014) and Rizkiah and Da'rain (2016), found a similar phenomenon. Nonetheless, studying the effect of the difference of hedging assets on each of these investor types is still important because there are fundamentally different principles in the filtering processes of asset selection that could affect future performance.

Overall, consistent with the Wavelet coherence analyses, we found that connectedness between equity markets and hedging assets has increased at the beginning of the COVID-19 pandemic. Moreover, we found that the connectedness is mainly driven by the high-frequency band. This observation implies that different equity investors should not alter their investment strategy in hedging assets, provided they have longer-term investment horizons.

## 5. Conclusion

The ongoing COVID-19 pandemic crisis has caused considerable losses to equity investors across the world. Hence, finding safe-haven assets is an urgent and important matter to protect equity investors from further downside risk during this market turmoil. Potential assets traditionally perceived to have safe-haven properties, such as gold, crude oil, and cryptocurrencies, may lose their hedging properties because of the nature of the underlying forces of the current pandemic. Therefore, their role as a safe-haven asset during COVID-19 must be reevaluated. Extending the literature on this topic, our study applies the Wavelet coherence analysis and DY12- and BK18-based spillover indices in bivariate and multivariate settings. Specifically, we examine the correlation between the three equity indices (traditional, sustainable, and Islamic) for different investment horizons and the prices of the three potential safe-haven assets (gold, crude oil, and Bitcoin) from January 2017 to January 2021.



(caption on next page)



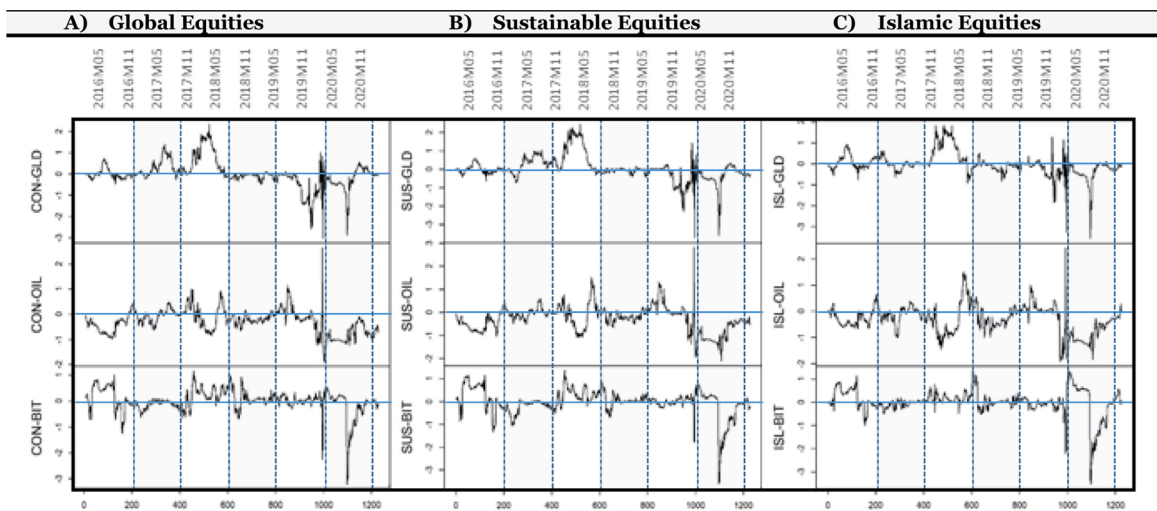
**Fig. 11.** Net frequency spillovers - Islamic equities (BK18).

Notes: ISL stands for DJ Islamic Index, GLD – for Gold, OIL – for Crude Oil, and BIT – for Bitcoin exchange rate. Scale 1 = band 3.14 - 0.79 = 1–4 days, Scale 2 = band 0.79 - 0.39 = 4–8 days, Scale 3 = band 0.39 - 0.20 = 8–16 days, Scale 4 = band 0.20 - 0.10 = 16–32 days, Scale 5 = band 0.10 - 0.00 = 32+ days. Sample period: January 1, 2016 – January 29, 2021.

The Wavelet results show that the connection between the three equity indices and the three hedging assets varies across time and investment horizons. Gold is found to correlate weakly with all three indices across all horizons, especially in the longer horizon. Oil shows a low coherence for a short investment horizon (up to 16 days), while its hedging ability completely dissipates for longer horizons. The coherence between Bitcoin and the three equity indices was negligible across all investment horizons before the COVID-19 period. However, a heightened co-movement is found between the three indices and all three potential safe-haven assets at the onset of the COVID-19 period.

The results from the DY12 Spillover Index further emphasize this inference. The overall static connectedness between the equity indices and the three hedging assets is considerably low (approximately 9% for the three indices). The total connectedness within each system is mainly a very short-term phenomenon. This suggests that the three hedging assets offer diversification benefits for each type of equity investor, especially at longer investment horizons. Overall, the three potential safe-haven assets (gold, crude oil, and Bitcoin) offer hedging properties for different investment horizons of all three types of equity investors. However, their role as a safe-haven asset during the current COVID-19 crisis needs further confirmation.

Our results have practical implications for different types of investors with different investment horizons, as they need time-horizon information on the co-movement and causality to implement diversification and hedging strategies effectively. Briefly, investors may still consider gold as a hedging instrument for a longer period; however, it does not serve as a hedging tool during short-term turmoil, such as the COVID-19 pandemic. Alternatively, oil does not show any hedging property in the long term, while Bitcoin even shows a strong co-movement during the crisis period. However, it is recommended to closely monitor the movement of each asset in one’s portfolio during the turbulent periods, although the underlying cause of crisis might be different in each case, which might lead to different market reactions.



**Fig. 12.** Pairwise spillovers (DY12).

Notes: CON stands for DJ Global Index, SUS – for DJ Sustainability Index, ISL – for DJ Islamic Index, GLD – for Gold, OIL – for Crude Oil, BIT – for Bitcoin exchange rate. Sample period: January 1, 2016 – January 29, 2021.



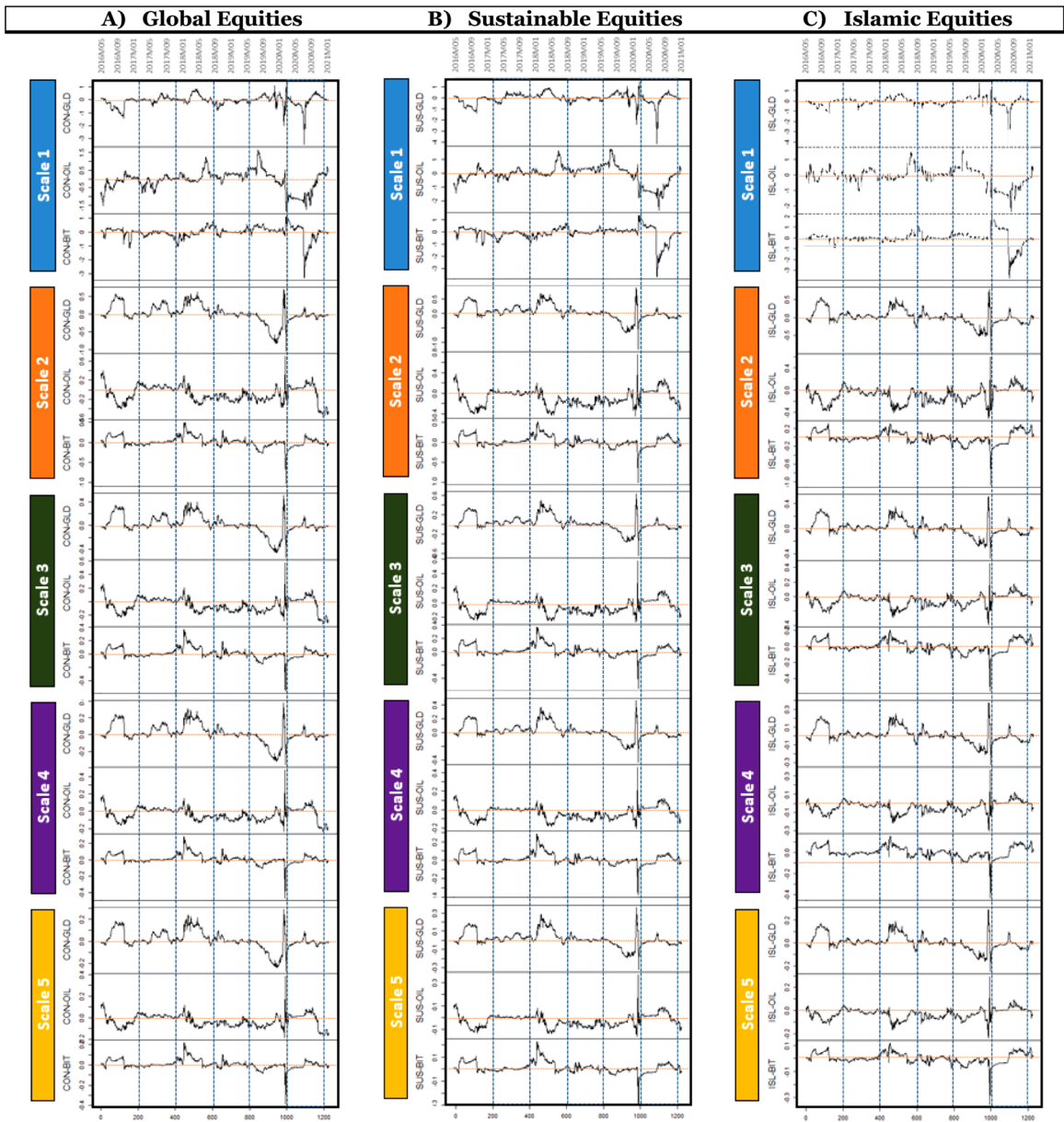


Fig. 13. Pairwise frequency spillovers (BK18).

Notes: CON stands for DJ Global Index, SUS – for DJ Sustainability Index, ISL – for DJ Islamic Index, GLD – for Gold, OIL – for Crude Oil, and BIT – for Bitcoin exchange rate. Scale 1 = band  $3.14 - 0.79 = 1-4$  days, Scale 2 = band  $0.79 - 0.39 = 4-8$  days, Scale 3 = band  $0.39 - 0.20 = 8-16$  days, Scale 4 = band  $0.20 - 0.10 = 16-32$  days, Scale 5 = band  $0.10 - 0.00 = 32+$  days. Sample period: January 1, 2016 – January 29 2021.

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