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REVISITING THE DYNAMIC CONNECTEDNESS, SPILLOVER AND HEDGING OPPORTUNITIES AMONG CRYPTOCURRENCY, COMMODITIES, AND ISLAMIC STOCK MARKETS

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ABSTRACT

The study investigates the dynamic interconnections and opportunities for hedging among cryptocurrency, commodity, and Islamic stock markets using DCC-GARCH and Spillover connectedness models. Using daily data covering the Russia-Ukraine war and COVID-19 outbreak from December 1, 2019 to April 15, 2022, we document weak and frequently negative correlation between Bitcoin and Islamic stock markets. Thus, Bitcoin could be viewed as a haven from Islamic stock market losses. The results also indicate that Bitcoin's diversification benefits are normally steady and increase considerably during turbulence. Furthermore, the net return spillovers from the Bitcoin market remain above zero during most of the study period. We also find that utilizing Bitcoin as a hedge during the COVID-19 pandemic phase leads to higher expenses. The outcomes of this investigation are expected to carry substantial ramifications for Indonesian investors and portfolio managers who adhere to Shariah law since they will enable them to comprehend the advantages of diversifying portfolios across various periods of stock holding or investment horizons.

Keywords: Bitcoin, COVID-19, Connectedness, Financial market, Russia-Ukraine war, Spillover.
JEL classification: E51; G11; G15; G23; O16; O33.

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I. INTRODUCTION

The world's financial markets are interlinked due of improvements in ICT (information, communication, and technology), as well as financial innovations and the removal of international financial restraints (Andrada-Félix et al., 2022; Balli et al., 2020; Elsayed et al., 2022; Raza Rabbani et al., 2024). The financial markets worldwide are getting more susceptible to contagion effects coming from outside the host country (Corbet et al., 2020; Costa et al., 2022; Jin & An, 2016). The Covid-19 outbreak, the East Asian Crisis of 1997, the 2007-2008 Global Financial Crisis, and the 2010-2012 European Sovereign Debt Crisis all had an impact on all the countries (Mensi, Al Rababa'a, et al., 2021; Sharma, 2022). As a result, investing must be diversified to mitigate the risks connected with financial markets (Naeem et al., 2023; Dharani et al., 2022). Commodities in general can play this role because they have the least resemblance to financial assets (Balcilar et al., 2021; Trabelsi, 2019). This is because the fundamental forces of supply and demand frequently dictate commodity pricing (Asadi et al., 2023; Wen & Wang, 2021; Shaik et al., 2023a). In fact, commodities' resiliency in times of crisis can be linked to the current increase in investments in the commodity market (Asadi et al., 2023; El Khoury et al., 2023; Hasan et al., 2023). Consequently, a portfolio comprised of valuable metals, financial assets, energy, cryptocurrency, commodities, and Islamic financial assets may be considered less risky. As a result, we look into how spillovers affect financial assets, precious metals, commodities, digital currency, and Islamic stocks.

The most recent researches (analyzed within the literature review segment) that focus on the spillovers within the stock or commodity markets or only consider time-domain effects are those by Afzal et al. (2023); El Khoury et al. (2023); Ghabri et al. (2022); Khalfaoui et al. (2023); Mensi et al. (2021); Mensi, Al Kharusi, et al. (2022); Mensi, Al Rababa'a, et al. (2022); Pham & Do (2022); Samitas et al. (2022); Trichilli & Boujelbéne (2023). The bulk of past research also examine topics like the European debt crisis, the global financial crisis, and the COVID-19 problem that occurred before and during the pandemic (Ahmed, 2010; Chazi & Syed, 2010; Sharma, 2022; Hassan & Raza Rabbani, 2023). We add to the current body of literature by investigating the transmission of return spillovers among commodities, cryptocurrencies, and Islamic equities markets, while accounting for both the Covid-19 pandemic and the Russia-Ukraine conflict timeframes. We enhance the literature by investigating the transmission of return spillovers across both commodities and financial markets, as well as considering the COVID-19 outbreak and the period of the Russia-Ukraine war. Given the collapse of the stock and oil markets during the period in issue, it is critical to include the Covid-19 crisis phase. To accomplish this, we employ Bitcoin from the cryptocurrency space, daily closing prices sourced from the Morgan Stanley Capital Index (MSCI) for Islamic stock indices in Russia, United States and Ukraine, as well as spot prices for commodities such as West Texas Intermediate (WTI) crude oil, gold, wheat, and palladium that are actively traded in each commodity class under consideration.

Several empirical studies have been undertaken to investigate the spillovers between the financial and commodity markets (Balcilar et al., 2021; Shaik et al., 2023b; Ben Amar et al., 2023; Ji et al., 2020; Mo et al., 2022; Reboredo et al., 2021; Sharma, 2022; Wu et al., 2023). Hammoudeh et al., (2009) investigate the transmission of spillover effects across crude oil, valuable metals, and the US exchange rate. The study discovers strong volatility transmission between gold and oil returns using the GFEVD (Generalized Factor Error Variance Decomposition) and IRF (Impulse Response Functions).

Using the GARCH model, Narayan & Sharma (2011) study the relationship between the price of crude oil and firm returns for 560 US-listed companies on the NYSE. The authors demonstrate how different enterprises' returns are affected differently by crude oil shocks. Mensi, Al Rababa'a, et al., (2022), examine the return transmission of shocks and volatility between the S&P-500 and commodities prices using the VAR-GARCH approach. Their findings suggest that the oil and gold markets are significantly impacted by a shock to the S&P-500. Creti et al., (2013) apply the DCC-GARCH method to study how the correlation between equities and 25 commodities changed from 2001 to 2011.

From a methodological standpoint, the most current works on the relevant subject are by Bouri et al. (2021), Le et al. (2021) and Wu et al., (2023). Using the DCC-GARCH model, Bouri, Lei, et al., (2021) investigate the safe-haven characteristics of numerous commodities vs stocks across time and among different frequencies. Contrarily, Palanska (2018) examines the prices of crude oil, corn, cotton, gold, and the S&P 500 from January 2002 through December 2015 using the DY-12 spillover paradigm without taking the Covid-19 crisis era or frequency-based analysis into consideration.

Using spillover's measures of DY-12 and BK-18 across different time frames and frequencies, we examine return spillovers comprehensively, including overall, directional, and pairwise analyses in crude oil, gold, wheat, and palladium, Islamic stocks, and Bitcoin. Contrary to Bouri, Gabauer, et al., (2021), who use a wavelet coherence paradigm to analyze bivariate interactions, the DY-12 and BK-18 metrics of spillover can capture multi-variate correlations. The spillover measures additionally indicate the impact of a shock on one or more variables on others over a period of days. Spillover measurements can therefore, in a sense, quantify causal links (Khalfaoui et al., 2023).

Recent studies have focused on Islamic equity and Bitcoin's function against traditional assets as a safe-haven during the COVID-19 outbreak (Barson et al., 2022; Ghabri et al., 2022; Huynh et al., 2020; Trichilli & Boujelbéne, 2023; Yousaf et al., 2023). Therefore, the current study tries to support the idea that Bitcoin is superior to gold in terms of portfolio variety (Ghabri et al., 2022; Yang et al., 2022). This is due to the sharp increase in investment risk brought on by the pandemic-related extremely volatile stock market conditions experienced globally (Bouri et al., 2020; Trichilli & Boujelbéne, 2023). As a result, to reduce the risk involved with their portfolios, investors seek alternative assets like Bitcoin and Islamic equities (Disli et al., 2021; Ghabri et al., 2022). Bitcoin appears to have short-term haven properties before and throughout the outbreak, according to Yang et al., (2022), despite being more volatile than gold and the S&P 500. More particular, they reach the conclusion that gold serves as a favored asset for portfolio diversification over Bitcoin for risk-averse investors in China, while the opposite holds true for risk-seeking investors (Cui & Maghyereh, 2023).

Theoretical and practical links between cryptocurrencies and Islamic stock markets have been identified in recent works by Ghabri et al., (2022); Li & Meng, (2022); Muneeza et al., (2023); Trichilli & Boujelbéne, (2023) and Yousaf et al., (2023). Mensi, Al Kharusi, et al., (2022) speculate that this link may be less direct and more indirect. Inflation, foreign exchange rates, and monetary aggregates are the three ways that Bitcoin influences global stock markets and monetary system (Ghabri et al., 2022; Soni & Nandan, 2022). They believe that the acceptance of Bitcoin has the potential to replace conventional currency or take over one or more of its functions (Chkili et al., 2021). This event leads to a decrease in the circulating money supply, killing the quantity theory of money (Tiwari et al., 2022; Trichilli & Boujelbéne, 2023).

The study adds to the existing literature in multiple aspects. The article examines the dynamic interconnection and hedging potential between cryptocurrencies, commodities, and Islamic stock markets. Our results have substantial implications for investors who design long-term investment portfolios to fulfill their financial objectives. It focuses on the relationship between the Islamic stock market and commodities and cryptocurrencies. This study also investigates the degree of connection of a network to assess whether conventional investments operate as information net transmitters or net receivers for commodities, Islamic stock markets, and cryptocurrency investments. As a result, it provides an additional comprehension of the dynamic interconnectedness and hedging opportunities that exist between cryptocurrency, commodities, and Islamic stock markets. This article investigates financial interconnectedness by comparing cryptocurrency volatility spillovers to Islamic stock markets and commodities markets such as West Texas Intermediate (WTI) crude oil and spot gold, wheat, and palladium prices. The diversity of Islamic stock markets is driving this inquiry. Because of their geographic diversity, Russia, Ukraine, and the United States are three of the countries represented. Furthermore, we compute hedging ratios and structural break ratio are poised to offer tangible support to investment portfolio managers. This research, to our knowledge, is the initial endeavor to incorporate all of these criteria to a global analysis of the stock and commodity markets during the COVID-19 crisis and the Russian-Ukrainian conflict. Finally, the findings on the relative volatility of Islamic asset portfolios versus conventional assets could be valuable for policymakers assessing how commodity and financial innovation development affects the capital market, as well as market participants diversifying risk with innovative assets.

The following sections include the remaining portions of this investigation. Section 2 describes the data and methodology for determining volatility connectivity. In Section 3, an examination of the outcomes and discussion of the findings is offered. Section 4 is concluded with a brief analysis of the implications of the conclusion.

II. DATA AND ECONOMETRIC METHODOLOGY

2.1. Data Sources and Descriptive Statistics

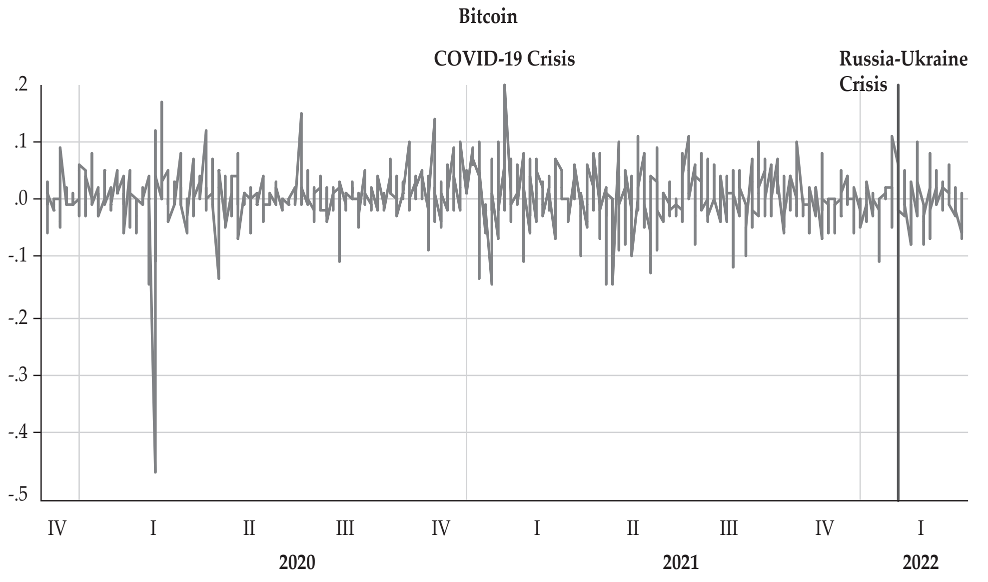
We use daily closing price information from the Morgan Stanley Capital Index (MSCI) for the Islamic stock indices in Russia, Ukraine, and the United States. We also consider Bitcoin, West Texas Intermediate (WTI) crude oil, gold, wheat, and palladium spot prices. The study period is from December 1, 2019, through April

15, 2022, and includs the Russian-Ukrainian War and the COVID-19 outbreak. All the series are extracted from Datastream. We compute the daily compounded returns by comparing the logarithmic values of two consecutive prices.

Figure 1 depicts the daily time progression of Bitcoin, Islamic stock markets, and main commodities returns. The graph depicts extreme movements beginning January 1, 2020, because of the COVID-19 epidemic. The onset of the Russia-Ukraine Crisis causes the second structural split, which causes concern in cryptocurrency, commodities, and Islamic stock markets. This result can be attributed to the fact that the European Union and United States put economic and financial sanctions on Russia during the Russia-Ukraine crisis. Europe and the United States have barred certain Russian financial institutions from using the SWIFT system, which is projected to have a severe detrimental impact on Russia's economy, foreign trade, and numerous financial operations.

Table 1 displays summary statistics (Panel A) and the dynamics of correlations between Bitcoin, Islamic stock returns, and commodities (Panel B). Panel A shows that the Bitcoin market has the highest mean return, followed by Wheat. The MSCI Russia Islamic and MSCI Ukraine Islamic markets have negative and lower returns, indicating that the outbreak of COVID-19 and the Russia-Ukraine War have had a detrimental impact. According to the standard deviation, the returns of Bitcoin, Russia, and Ukraine Islamic stocks are very volatile when compared to other markets. Kurtosis data show that all return series deviate from normality and have a leptokurtic distribution. The Jarque-Bera test statistics, which are significant at the 1% level for all series, further confirm this deviation from normality, which implies that these markets have severe price movements and accordingly a higher risk for investors.

The correlation matrix in panel B reveals weak relationships between Bitcoin, WTI crude, Gold, Brent, Wheat, Palladium, and Islamic stock markets in the United States, Ukraine, and Russia over the examined time. Lower market integration may be ascribed to several economic and political crises, such as COVID-19 and the Russia-Ukraine Crisis. These findings show that a portfolio containing Bitcoin, WTI crude, Gold, Brent, Wheat, and Palladium could provide considerable diversification benefits. The Russo-Ukrainian conflict has triggered a global upheaval following the health crisis. New research has highlighted adverse effects on financial markets, commodity exchanges, and energy price dynamic (Wasiuzzaman, et al. (2023).



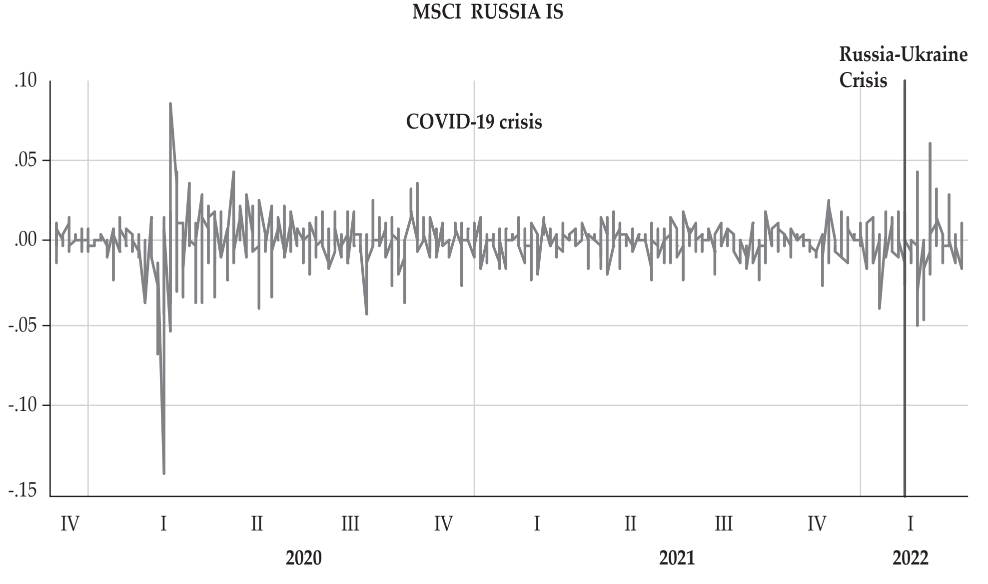
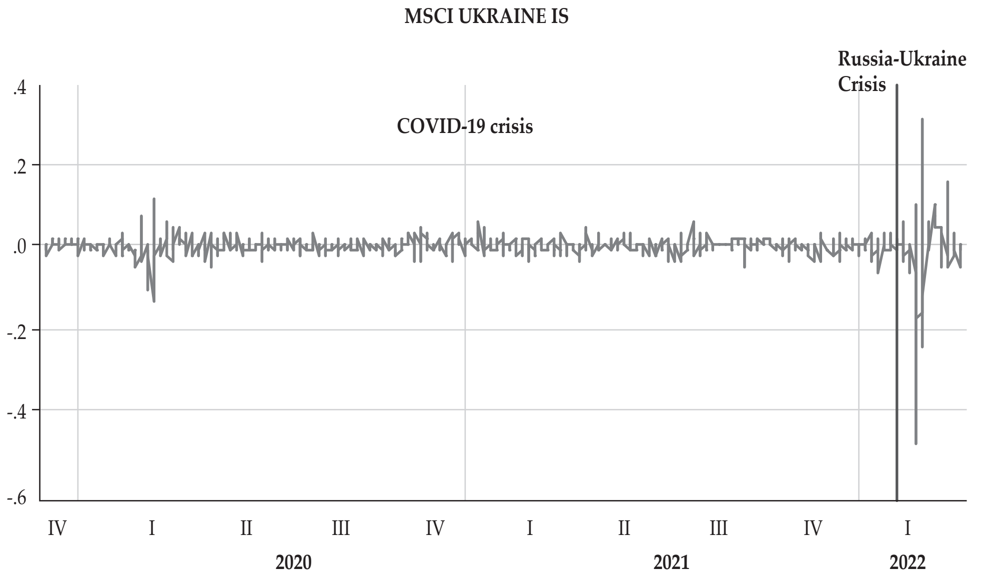


Figure 1.
The Daily Price Movement of Bitcoin, Islamic Financial Indices and Major Commodities Returns



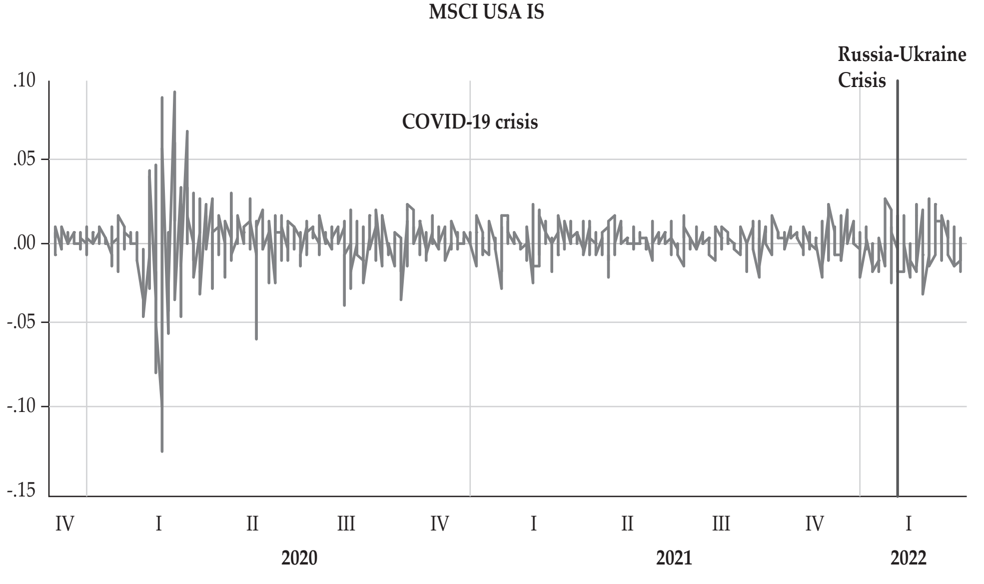
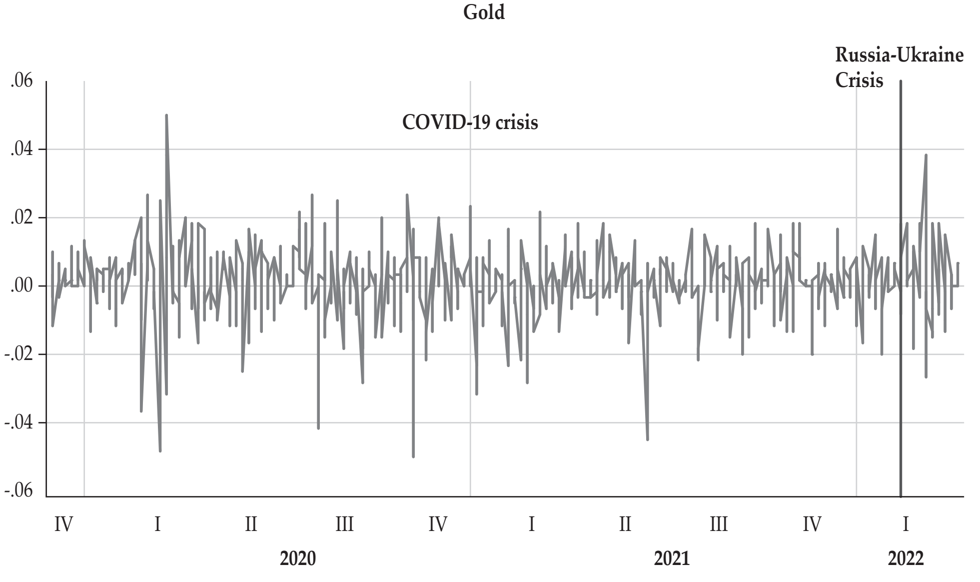


Figure 1.
The Daily Price Movement of Bitcoin, Islamic Financial Indices and Major Commodities Returns (Continued)



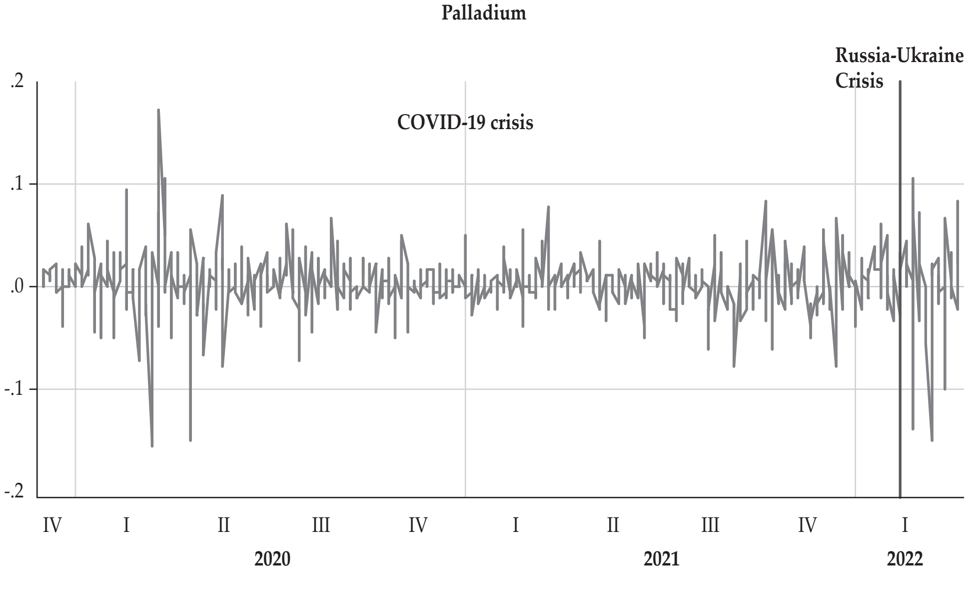
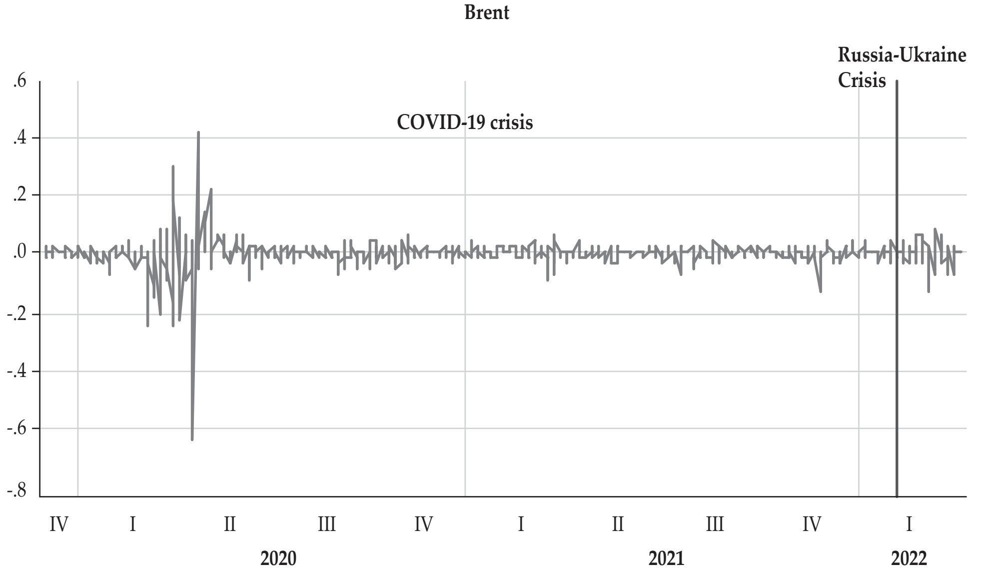


Figure 1.
The Daily Price Movement of Bitcoin, Islamic Financial Indices and Major Commodities Returns (Continued)



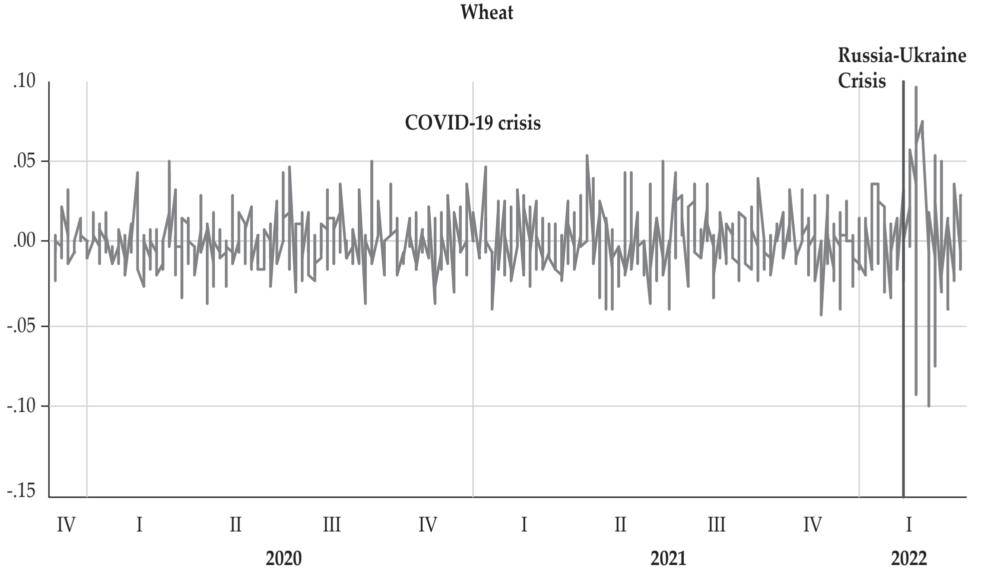


Figure 1.
The Daily Price Movement of Bitcoin, Islamic Financial Indices and Major Commodities Returns (Continued)

Table 1.
Descriptive Statistics and Correlation Matrix

	BITCOIN	MSCI RUSSIA IS	MSCI UKRAINE IS	MSCI USA IS	WTI	GOLD	PALLADIUM	WHEAT
Panel A: Summary statistics								
Mean	0.002642	-0.021777	-0.000793	0.000557	0.002042	0.000470	0.000501	0.001105
Maximum	0.191527	0.233379	0.304915	0.089831	0.300229	0.049651	0.169615	0.096065
Minimum	-0.464730	-12.36317	-0.486098	-0.129220	-0.282206	-0.050677	-0.156768	-0.100149
Std. Dev.	0.046733	0.499269	0.035628	0.015736	0.043740	0.010276	0.029623	0.019950
Skewness	-1.631181	-24.58038	-3.774615	-1.041052	0.602512	-0.626118	-0.693065	0.164609
Kurtosis	19.89035	608.0670	72.01859	18.06507	19.88730	7.196065	10.59667	6.307256
Jarque-Bera	7595.454	9458754.	123727.6	5936.484	7333.028	492.1598	1530.522	283.5224
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Panel B: Correlation Matrix								
	MSCI_ RUSSIA_ ISLAMIC	**MSCI_ UKRAINE_ ISLAMIC**	**MSCI_USA_ ISLAMIC**	**BITCOIN**	**BRENT**	**GOLD**	**PALLADIUM**	**WHEAT**
MSCI_RUSSIA IS	1.000000							
MSCI_UKRAINE ISL	-0.013333	1.000000						
MSCI_USA_ISL	-0.025499	0.137995	1.000000					
BITCOIN	-0.029621	0.092715	0.175696	1.000000				
BRENT	0.111273	0.053171	0.263626	0.062391	1.000000			
GOLD	0.075738	0.010567	0.003471	0.079558	0.067844	1.000000		
PALLADIUM	0.016721	-0.014952	0.163270	0.062918	0.193162	0.280079	1.000000	
WHEAT	0.073734	-0.068461	0.016425	0.034245	0.078177	0.070043	0.095322	1.000000

2.2. Econometric Methodology

This study employs innovative methodologies to assess the potential for diversification using Bitcoin, commodities, and Islamic stock markets from the USA, Ukraine, and Russia.

In the first stage, we examine the dynamic connectivity and spillovers between Bitcoin, commodities, and Islamic stock indices using Barunik & Krehlik, (2018) (BK-18) approach. This enables us to monitor the system-wide interconnectedness of these assets across market conditions and enhancing portfolio hedging strategies across diverse risk profiles and temporal frequencie under COVID-19. In the second stage, we perform the Narayan and Popp (2010) examination incorporating dual structural breakpoints to identify breakpoints for assessing the integration order of variables.

In the third stage, we compute the ideal weights, hedge ratios, and hedge efficiency of each Bitcoin and commodity pair against Islamic stock markets to see if they can serve as a perfect hedge amidst the COVID-19 epidemic and the geopolitical tensions between Russia and Ukraine. This methodology has significant implications for portfolio design as it helps investors optimize their asset allocation and manage systemic financial risks.

2.2.1. Quantifying Interconnectedness via Time Frequency Spillover Method

Using the BK (2018) technique, this study delves into interconnectedness within the frequency domain. The method enhances the Diebold & Yilmaz (2012), method by leveraging a spectral representation approach for variance decomposition grounded on the analysis of shock frequency responses. Based on the spectral representation of variance decompositions, the study examines spillover effects among markets across disparate frequency domains, encompassing both short-term and long-term perspectives.The frequency response function is expressed as follows:

$$\Psi(e^{-i\omega}) = \sum_{h=0}^{\infty} e^{-ih\omega}\,\Psi_h \tag{1}$$

Function (1) can be derived from the Fourier transform of the coefficients Ψ_h, where ω represents the frequency and $i = \sqrt{-1}$.

The power spectrum $S_x(\omega)$, which illustrates the distribution of of x_t across the frequency components ω, serves as a pivotal tool for grasping frequency dynamics. It can be derived as follows:

$$S_x(\omega) = \sum_{h=-\infty}^{\infty} E(x_t x'_{t-h})\, e^{-ih\omega} = \left(\left(\Psi(e^{-i\omega}\right)\Sigma\Psi'\left(e^{+i\omega}\right)\right) \tag{2}$$

The generalized variance decomposition across frequencies ω is outlined as:

$$\left(\theta(\text{ɯ})\right)_{jk} = \frac{\sigma_{kk}^{-1}\sum_{h=0}^{\infty}\left(\left(\Psi\left(e^{-ih\text{ɯ}}\right)\Sigma\right)_{jk}{}^{2}\right.}{\sum_{h=0}^{\infty}\left(\left(\Psi\left(e^{-ih\text{ɯ}}\right)\Sigma\Psi\left(e^{+ih\text{ɯ}}\right)\right)_{jj}\right.} \tag{3}$$

Where $(\theta(\text{ɯ}))_{jk}$ illustrates the spectral portion and interconnection of thej-th variable at a specific frequency ɯ due to the shoks to the k-th variable.

The generalized variance decomposition at various time scales d = (m,n) is formulated as:

$$(\theta_d)_{jk} = \frac{1}{2\pi}\int_{m}^{n} \Gamma_{\mathrm{j}}(\omega)(\theta(\omega))_{\mathrm{jk}}\,\mathrm{d}\omega \tag{4}$$

Where $\Gamma_j(\omega)$ quantifies the weighting of the j th variable at the given frequency and is computed as follows:

$$\Gamma_j(\omega) = \frac{(\psi(\mathrm{e}^{-\mathrm{i}\omega})\Sigma\psi'(\mathrm{e}^{+i\omega}))_{jj}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}\psi(\mathrm{e}^{-\mathrm{i}\lambda})\sum\psi'(\mathrm{e}^{+i\lambda})_{jj}\,\mathrm{d}\lambda} \tag{5}$$

The standardized representation of the variance decomposition within the frequency band d can be described as:

$$\left(\tilde{\theta}_d\right)_{jk} = \frac{(\theta_d)_{jk}}{\Sigma_j(\theta_\infty)_{jk}} \tag{6}$$

Where $(\theta_\infty)_{jk}$, depicts the aggregate contribution across all frequencies.
The comprehensive within connectedness across the frequency band d an be articulated as follows:

$$C_d^w = \left(1 - \frac{Tr\{\tilde{\theta}_d\}}{\Sigma\tilde{\theta}_d}\right)*100 \tag{7}$$

Where the expression $Tr\{\tilde{\theta}_d\}$ involves the trace operator, which calculates the sum of the diagonal elements of the matrix $\tilde{\theta}_d$, while $\sum\tilde{\theta}_d$ represents the total sum of all elements in the matrix

In conclusion, the frequency-connectedness within the frequency band d,denoted as C_d^F can be formulated as:

$$C_d^F = C_d^w \frac{\sum\tilde{\theta}_d}{\sum\tilde{\theta}_\infty} \tag{8}$$

On the other hand, C_d^F dissects the overall connectivity into discrete components that collectively sum up to the original connectedness metric, as illustrated by Barunik & Krehlik (2018). The frequency bands we employ, which align with existing literature, are (π+0:00001,π/4; π/16; π/32; π/64; 0) (Barunik & Krehlik, 2018; Mensi, Al Rababa'a, et al., 2022; Mensi, Shafiullah, et al., 2021; Tiwari et al., 2022; Trichilli et al., 2020).

2.2.2. Strategies for Portfolio Management and Hedging

2.2.2.1. Implementation of the Narayan and Popp (2010) Unit Root Test Incorporating Dual Structural Breaks

Before estimating DCC-GARCH model, we assess the integration order of variables using the Narayan and Popp unit root test. The Narayan and Popp (2010) test methodology builds upon the Augmented Dickey-Fuller (ADF) test approach. The primary rationale for employing the NP test is the incorporation of structural breaks in the test. Owing to its remarkable capacity to precisely detect structural breaks, the NP test is considered superior to other traditional unit root tests.

The NP test, in both level and difference forms, exhibits the capability to identify two structural breaks within the data series. Recognizing structural breaks holds significance because neglecting them can lead to biased and unreliable outcomes (Narayan and Popp, 2010).

In the NP framework, we define r_t as a series comprised of two elements : a deterministic component (d_t) and a stochastic component (μ_t). Specifically, r_t is expressed as $r_t = d_t + \mu_t$.The stochastic component μ_t follows an autoregressive AR(1) process ($\mu_t = {}^{\beta}\mu_{t-1} + {}^{\varepsilon}t$) where ${}^{\varepsilon}t$ is assumed to follow an ARMA (p,q) process (${}^{\varepsilon}t = {}_{\varphi}{}^{*}(L)vt$ with vt being normally distributed with mean zero and variance $v_t \sim (0, \sigma_\gamma^{\ 2})$.

The NP test relies on two key assumptions regarding the deterministic elements. The initial assumption accommodates two breaks in the intercept of the data series, which we refer to as Model 1 or M1. The second assumption allows for two breaks in both the level and the slope of the data series' trend, denoted as Model 2 or M2. As a result, these two model specifications vary in their definition of the deterministic component.

Alternatively, these two models are formulated as:

$$d_t^{M1} = \gamma_1 + \gamma_2 t + \varphi^*(L)(\varphi_1 DU'_{1,t} + \varphi_2 DU'_{2,t}) \tag{9}$$

$$d_t^{M2} = \gamma_1 + \gamma_2 t + \varphi^*(L)(\varphi_1 DU'_{1,t} + \varphi_2 DU'_{2,t} + \vartheta_1 DT'_{1,t} + \vartheta_2 DT'_{2,t}) \tag{10}$$

Where $DU'_{i,t} = 1(t > T'_{i,t})$; $DT'_{i,t} = 1(t > T'_{i,t})$; i=1,2. Also, $T'_{i,t}$, i=1,2 represents the actual dates of breaks. The parameters φ_t and ϑ_1, i =1,2 signify the extent of level and slope breaks, respectively. In their study, Narayan and Popp (2010) demonstrate that incorporating the polynomial lag operator ($\varphi^*(L)$) permits breaks to evolve gradually over time.

The NP test framework suggests that when there's a shift in the long-term trend of a series, like oil prices, it doesn't immediately cause a big change. Instead, the impact of this shift unfolds slowly over time, similar to how the series responds to regular fluctuations in its behavior.

We can use the innovative outlier (IO) framework to test for a unit root in a time series. This involves looking at the deterministic (dt) and stochastic (μt) components of the series. We estimate certain test regressions, which represent a simplified version of the underlying model, to carry out this unit root test.

$$r_t^{M1} = \rho r_{t-1} + \gamma_1^* + \gamma_2^* t + \theta_1 D(T_B^*)_{1,t} + \theta_2 D(T_B^*)_{2,t} + \gamma_1 DU'_{1,t-1} + \gamma_2 DU'_{2,t-1} + \sum_{j=1}^{k} \alpha_j \Delta r_{t-j} + v_t \quad (11)$$

$$r_t^{M2} = \rho r_{t-1} + \gamma_1^{**} + \gamma_2^* t + \theta_1 D(T_B^*)_{1,t} + \theta_2 D(T_B^*)_{2,t} + * \gamma_1^* DU'_{1,t-1} + \gamma_2^* DU'_{2,t-1} + \vartheta_1^* DT'_{1,t-1} + \vartheta_2^* DT'_{2,t-1} + \sum_{j=1}^{k} \alpha_j \Delta r_{t-j} + v_t \quad (12)$$

where $D(T_B^*)_{i,t} = 1\left(t = T'_{B,i} + 1\right); i = 1,2$. In this case, we want to test whether a unit root exists. This means we're testing whether the parameter ρ =1 (null hypothesis) or is less than 1 (alternative hypothesis). To do this, NP suggests using t-statistics calculated from the estimated values of $\hat{\rho}$ from Equations (11) and (12). We select break dates using a sequential procedure outlined by the NP test, and we use critical values provided in the Narayan and Popp (2010) paper to test the unit root hypothesis.

2.2.2.2. DCC-GARCH Model

Engle (2002) introduces the Dynamic Conditional Correlation GARCH (DCC-GARCH) model to capture the changing correlation over time between different time series. In our study, we employ the DCC-GARCH model to investigate the dynamic conditional correlation among Bitcoin, commodities, and Islamic stock markets in the USA, Ukraine, and Russia.

In the DCC-GARCH (1.1) model, the variance-covariance matrix H can be expressed as follows:

$$A(L)yt = \varepsilon_t \quad (13)$$

where A represents the matrix, L represents the lag operator, ε_t represents the vector of innovations which follows a standard normal distribution with $\varepsilon_t|\Omega_{t-1} \sim N(0, H_t)$ and t=1,.....T. The conditional variance-covariance matrix of the vector ε_t is written as follow:

$$H_t = D_t R_t D_t \quad (14)$$

$$\text{and } h_{i,t} = \omega_i + \sum_{p=1}^{P_i} \alpha_{ip} \varepsilon_{it-p}^2 + \sum_{q=1}^{Q_i} \beta_{iq} h_{it-q} \text{ with } i=1,2 \tag{15}$$

where $D_t = diag\sqrt{h_i}$ is the matrix containing the time-varying standard deviations obtained from estimating the GARCH model, and $R_t = \rho_{ijt}$ represents the matrix of conditional correlations with i,j=1,2.

The DCC framwork can be presented as follows:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{16}$$

$$\text{with } Q_t = (1 - \sum_{k=1}^{K} \alpha_k - \sum_{l=1}^{L} b_l)\bar{Q} + \sum_{k=1}^{K} \alpha_k (\varepsilon_{t-k} \varepsilon_{t-k}) + \sum_{l=1}^{L} b_l Q_{t-1} \tag{17}$$

where $\bar{Q}$ denotes the unconditional variance-covariance matrix, Q_t^* denotes the diagonal matrix comprising the square root of the diagonal elements of Q_t. The time-varying correlations are carried as follow:

$$\rho_{ij} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}} \text{ with } i,j=1,2 \tag{18}$$

2.3. Time Varying Optimal Weight, Hedge Ratio and Hedging Effectiveness

We employ dynamically the estimated conditional variances and covariances derived from the DCC GARCH model in a dynamic fashion to ascertain the optimal hedge ratio for crafting portfolios.

We employ the approach proposed by Kroner & Ng (1998) to calculate the optimal allocation weights for Bitcoin, commodities, and Islamic stock markets in the USA, Ukraine, and Russia. The optimal weight between two markets is expressed as follows:

$$W_{12,t} = \frac{h_{22,t} - h_{12,t}}{h_{11,t} - 2h_{12,t} + h_{22,t}} \tag{19}$$

The conditional variances of market 1 and market 2 are denoted us $h_{11,t}$ and $h_{22,t}$, respectively. $h_{12,t}$ represents the covariance between market 1 and market 2. The variances and covariances utilized in this section are generated using the BEKK-GARCH-Diagonal model.

The portfolio optimization process should justify the imposition of the following constraint:

$$\boldsymbol{W_{12,t}} = \begin{cases} \boldsymbol{0}, & \boldsymbol{if} \quad \boldsymbol{W_{12,t} < 0} \\ \boldsymbol{W_{12,t}}, & \boldsymbol{if} \quad \boldsymbol{0 \le W_{12,t} \le 1} \\ \boldsymbol{1}, & \boldsymbol{if} \quad \boldsymbol{W_{12,t} > 1} \end{cases} \tag{20}$$

This constraint is implemented to restrict the impact of short selling, which is seldom employed in practical scenarios. We adopt the methodology proposed by Kroner and Sultan (1993) to compute the beta hedge ratio for minimizing risk, as expressed below

$$\boldsymbol{\beta}_{12,t} = \frac{\boldsymbol{h}_{12,t}}{\boldsymbol{h}_{22,t}} \tag{21}$$

Finally, we measure the effectiveness of hedging (HE) to assess the extent to which each portfolio comprising Bitcoin, commodities, and other financial markets contributes to risk minimization. Consistent with Tuna (2019), we assess the effectiveness of the constructed portfolios by determining the hedging errors, which can be quantified as follows:

$$\boldsymbol{HE = 1 - \frac{VAR_{hedged}}{VAR_{unhedged}}} \tag{22}$$

Where The HE (Hedging Efficiency) ratio, indicative of the effectiveness of hedging, is determined by comparing the variance of the hedged portfolio (VAR_{hedged}), calculated from the returns of a weighted portfolio comprising Bitcoin, commodities, and stock markets, to the variance of the benchmark portfolio's returns ($VAR_{unhedged}$). A higher HE ratio signifies superior hedging performance.

$$\boldsymbol{VAR_{hedged} = (W_{12,t})^2 h_{11,t} + (1 - W_{12,t})^2 h_{22,t}}$$
$$\boldsymbol{+2 * W_{12,t} * (1 - W_{12,t})^2 h_{12,t}} \tag{23}$$

III. FINDINGS

3.1. Analysis in the Dynamic Connectedness

3.1.1. DY (2012) and BK Connectedness Results

Initially, we investigate the overall, directional, and net directional connectedness effects among these markets employing DY (2012)'s spillover index methodology to assess the degree of volatility interdependence between Bitcoin, commodities, and Islamic stock markets. Second, we utilise the frequency dynamics of spillovers using BK approach to examine how overall connectivity has changed over time and determine if contagion has occurred.

Tables 2 and 3 show the estimated spillover effects of Bitcoin, commodities, and Islamic stock markets using the DY (2012) and BK (2018) methodologies, respectively. Table 2 shows the temporal domain spillover analysis. Furthermore, using the methods proposed by BK (2018), we further decompose the DY (2021) spillover table depending on frequencies. Table 3 illustrates the time frames represented by "Freq S," which range from 1 to 5 days (short-term), "Freq M," and "Freq L," corresponding to 5 to 21 days (medium-term) and 21 days to infinity (long-term), respectively. The values within the i-th row and j-th column signify the intensity of the spillover effect from the i-th market to the j-th market. Additionally, “abs” abbreviates “absolute,” and “wtn” represents “within.”

The findings reveal a total connectedness of returns of 66.17%, indicating a strong interrelation among crude oil markets. Specifically, the WTI markets have the highest contribution to the system at 7.75%, followed by WHEAT (7.62%), Russia (7.08%), and Ukraine (6.52%). This outcome can be ascribed to the robust dependence and interaction among oil markets and the Islamic markets of these specific commodities and countries. The significant contribution of WTI markets can be attributed to their predominant position within the global oil market. Similarly, the noteworthy contributions of Russia and Ukraine could be attributed to their major roles as producers and exporters of commodities, particularly in the energy and agricultural sectors. The empirical results align with key findings found in prior literature (Naeem et al., 2021; Mezghani & Abbes, 2023). Furthermore, the observed results can be further clarified by taking into account the geopolitical factors in these regions, such as trade agreements, disruptions in supply chains, and political stability. These factors significantly contribute to the observed interconnections within these markets.

The research emphasizes the critical importance of the long-term investment horizon in monitoring spillovers among markets and optimizing asset allocations to manage risks effectively. This is supported by the fact that the overall spillover from the long-term frequency exhibits the highest overall spillover among the three frequencies examined (66.46%), followed by the medium-term (53.62%) and short-term (46.54%) frequencies. This suggests that the interconnections between these markets are stronger in the long-term, underscoring the importance of considering the investment horizon factor in risk management strategies. Moreover, understanding these long-term dynamics allows investors to make informed decisions that align with their financial objectives and contribute to more robust and resilient portfolios. Our results illustrate the viability of commodities as hedging or safe-haven assets for Islamic equities, especially over extended periods.

Therefore, the cumulative spillovers presented in Table 2 show that Ukraine is the highest net transmitter of spillovers into other markets (3.54%), followed by the USA (3.32%) and Bitcoin (1.43%). As per the research by Huang et al. (2021), Bitcoin could function as a safe haven in Europe, the UK, and the US amid the virus pandemic, suggesting that investors in these areas may find it beneficial to incorporate Bitcoin into their portfolio hedging strategies.

Yet, WTI emerges as the primary recipient of net spillovers (-4.05%), followed by Wheat (-3.75%), Palladium (-3.71%), and Gold (-0.001%). Similar results are reported for short-, medium-, and long-term spillovers, with Ukraine being the net transmitter and Wheat, Palladium, and Gold being the net receivers. These dynamics can be explained by the unique characteristics and roles of each asset class within the global financial landscape. These results are consistent with those of Wen & Wang (2021) and Okorie & Lin (2020), who find significant bidirectional spillover transmission between WTI and stock markets. This result is consistent with that of Mensi et al. (2021), who show using a Markov switching vector autoregressive model that the US, Chinese, and commodity markets are significantly impacted by shocks, and that the effects change with changes in regime.

Table2.
DY (2012) Spillover Results

	MSCI USA IS	MSCI RUSSIA IS	MSCI UKRAINE IS	Brent	Palladium	WHEAT	Gold	Bitcoin	FROM
MSCI USA IS	44.62	1.16	0.15	2.04	0.59	0.62	2.75	23.94	5.03
MSCI RUSSIA IS	1.71	22.14	26.83	19.47	1.70	9.44	3.90	1.40	7.08
MSCI UKRAINE IS	1.13	21.64	28.27	18.78	2.91	8.15	5.08	1.22	6.52
Brent	12.37	6.55	13.90	34.02	0.39	8.29	1.75	3.63	6.00
Palladium	5.74	0.43	1.49	7.50	43.32	1.30	11.71	1.64	5.15
WHEAT	2.03	16.90	26.12	23.08	0.50	16.18	4.30	1.45	7.62
Gold	1.63	4.57	13.15	6.79	6.83	3.16	57.07	0.02	3.90
Bitcoin	9.62	2.65	3.31	0.81	1.04	0.76	0.89	56.17	3.98
TO	8.35	7.08	10.07	10.62	1.44	3.86	3.90	5.42	**66.17**
Net	3.3205	-0.0024	3.5469	4.6268	-3.7127	-3.7568	-0.0019	1.4354	

Notes: The market i's overall connection from the entire system is shown in the column labeled "FROM." The column ''TO'' displays the overall connection that the market i has sent to the entire system. The ''NET'' row displays how connected to the internet each market is.

Table 3.
BK (2018) Return Spillover Results

Freq S: The Spillover Table for Band: 3.14 to 0.63. Roughly Corresponds to 1 Days to 5 Days.										
	MSCI USA IS	**MSCI RUSSIA IS**	**MSCI UKRAINE IS**	**Brent**	**Palladium**	**WHEAT**	**Gold**	**Bitcoin**	**FROM_ ABS**	**FROM_ WTH**
MSCI USA IS	0.25	0.00	0.01	0.02	0.04	0.01	0.00	0.01	0.02	3.12
MSCI RUSSIA IS	0.00	0.00	0.01	0.19	0.00	0.05	0.03	0.00	0.03	4.97
MSCI UKRAINE IS	0.00	0.01	0.01	0.14	0.00	0.03	0.02	0.00	0.02	3.49
Brent	0.01	0.09	0.11	0.06	0.03	0.00	0.00	0.02	0.03	4.11
Palladium	0.05	0.08	0.08	0.03	0.99	0.06	0.10	0.00	0.05	6.85
WHEAT	0.03	0.09	0.12	0.05	0.01	0.09	0.01	0.01	0.03	4.73
Gold	0.00	0.06	0.05	0.01	0.07	0.00	0.69	0.00	0.03	4.12
Bitcoin	0.00	0.02	0.02	0.02	0.00	0.00	0.00	0.23	0.01	1.74
TO_ABS	0.02	0.05	0.05	0.06	0.02	0.02	0.02	0.01	0.31	
TO_WTH	3.28	6.72	7.96	9.45	3.08	2.42	2.65	1.69		**46.54**
Net	0	0.02	0.03	0.03	-0.03	-0.01	-0.01	0		
Freq M: The Spillover Table for Band: 0.63 to 0.15. Roughly Corresponds to 5 Days to 21 Days.										
	MSCI USA IS	**MSCI RUSSIA IS**	**MSCI UKRAINE IS**	**Brent**	**Palladium**	**WHEAT**	**Gold**	**Bitcoin**	**FROM_ ABS**	**FROM_ WTH**
MSCI USA IS	0.25	0.00	0.00	0.02	0.05	0.01	0.01	0.03	0.02	1.91
MSCI RUSSIA IS	0.01	0.01	0.04	0.34	0.01	0.08	0.05	0.00	0.06	5.11
MSCI UKRAINE IS	0.00	0.02	0.04	0.23	0.00	0.02	0.04	0.01	0.04	3.41
Brent	0.03	0.21	0.27	0.13	0.06	0.01	0.02	0.03	0.07	5.51
Palladium	0.15	0.07	0.04	0.09	2.16	0.18	0.32	0.01	0.10	8.24
WHEAT	0.07	0.30	0.37	0.04	0.02	0.23	0.05	0.02	0.08	6.81
Gold	0.01	0.15	0.12	0.02	0.13	0.01	1.34	0.00	0.06	5.33
Bitcoin	0.00	0.04	0.07	0.05	0.00	0.01	0.01	0.41	0.03	2.49
TO_ABS	0.05	0.10	0.12	0.12	0.04	0.03	0.05	0.02	0.65	
TO_WTH	4.22	8.19	9.63	9.84	3.27	2.68	4.25	1.38		**53.62**
Net	0.03	0.04	0.08	0.05	-0.06	-0.05	-0.01	-0.01		

Table 3.
BK (2018) Return Spillover Results (Continued)

Freq L: The Spillover Table for Band: 0.15 to 0.01. Roughly Corresponds to More than 21 Days.										
	MSCI USA IS	**MSCI RUSSIA IS**	**MSCI UKRAINE IS**	**Brent**	**Palladium**	**WHEAT**	**Gold**	**Bitcoin**	**FROM_ ABS**	**FROM_ WTH**
MSCI USA IS	44.11	1.15	0.13	1.99	0.49	0.61	2.74	23.90	4.99	5.09
MSCI RUSSIA IS	1.69	22.12	26.78	18.94	1.69	9.31	3.81	1.39	6.98	7.12
MSCI UKRAINE IS	1.13	21.61	28.22	18.41	2.91	8.10	5.02	1.20	6.46	6.58
Brent	12.33	6.26	13.51	33.83	0.30	8.28	1.73	3.58	5.90	6.02
Palladium	5.53	0.28	1.36	7.38	40.16	1.06	11.28	1.62	5.01	5.10
WHEAT	1.93	16.52	25.63	22.99	0.48	15.86	4.24	1.42	7.51	7.65
Gold	1.62	4.36	12.98	6.77	6.62	3.15	55.04	0.02	3.81	3.88
Bitcoin	9.62	2.59	3.22	0.73	1.04	0.75	0.87	55.52	3.94	4.02
TO_ABS	8.28	6.93	9.90	10.44	1.38	3.81	3.83	5.39	1.21	
TO_WTH	8.44	7.06	10.09	10.64	1.41	3.89	3.91	5.50		**66.46**
Net	3.29	-0.05	3.44	4.54	-3.63	-3.7	0.02	1.45		

Notes: The market i's overall connection from the entire system is shown in the column labeled "FROM." The column ''TO'' displays the overall connection that the market i has sent to the entire system. The row ''NET'' displays how connected to the internet each market is.

This finding is in line with that of Khalfaoui et al., (2023); Soni & Nandan, (2022); Trichilli & Boujelbéne (2023); Wen & Wang, (2021); Wu et al., (2023) and Yang et al., (2022) who find that cryptocurrency markets, notably Bitcoin, exhibit strong hedging and safe haven characteristics. Consequently, investors making strategic investment decisions across various time frequencies will find it especially helpful to identify the dynamic connectivity between major financial markets, various commodity markets, and Islamic stocks over a variety of time horizons (Naeem et al., 2021; Mezghani, T. et al., 2021).

3.1.2. Frequency Connectedness of the Islamic Stock Markets, Bitcoin and Commodities

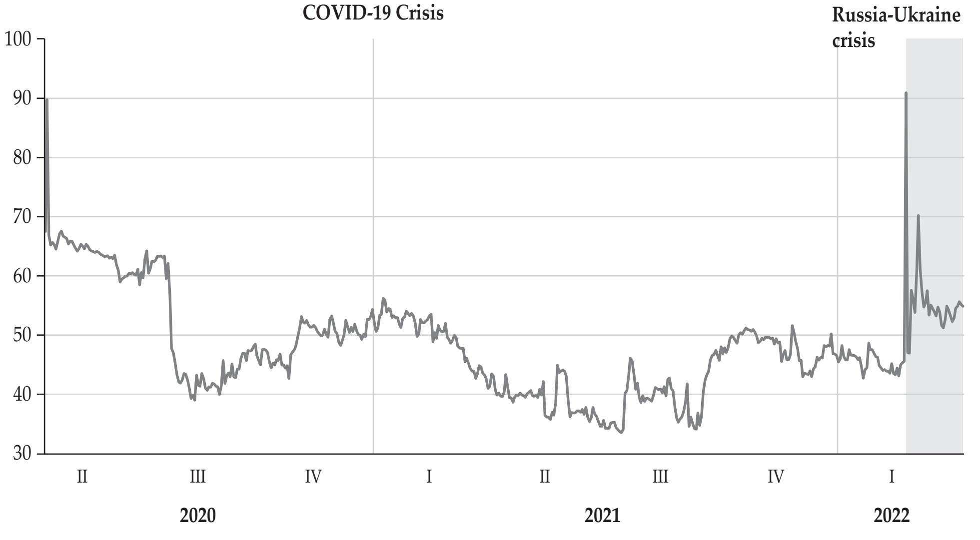
The time-frequency connectivity between commodities, Bitcoin, and Islamic stock markets is shown in Figure 2. Panel B displays the dynamic frequency connectivity in the short (a), medium (b), and long terms (c), whereas Panel A displays the DY total spillover.

We can see that spillovers vary depending on economic stressors and are responsive to crises. Significant spikes may be seen in Panel A, suggesting moments of stress and instability in the economy.

We can see from Panel B that during the sample period, long-term spillovers outweigh short-term spillovers. This is explained by the fact that information travels more quickly across intermediate and long time horizons than it does over shorter ones. This result is due to the inherent nature of financial markets, where short-term price movements can be influenced by noise and speculative trading, leading to greater volatility and less reliable signals. In contrast, intermediate and long-term spillovers may reflect more fundamental factors and underlying trends, which take time to fully materialize and impact asset prices. As a result, information with a longer time horizon is frequently given more weight by investors and market players because they believe it to be more solid and trustworthy when making judgments.

Additionally, the research delves into optimizing investment portfolio diversification and underscores the significance of adhering to Islamic principles in this process. Incorporating Islamic guidelines into diversification strategies can improve their efficacy and appropriateness for investors.

Panel A. DY *total spillover*



Panel B. Dynamic frequency connectedness

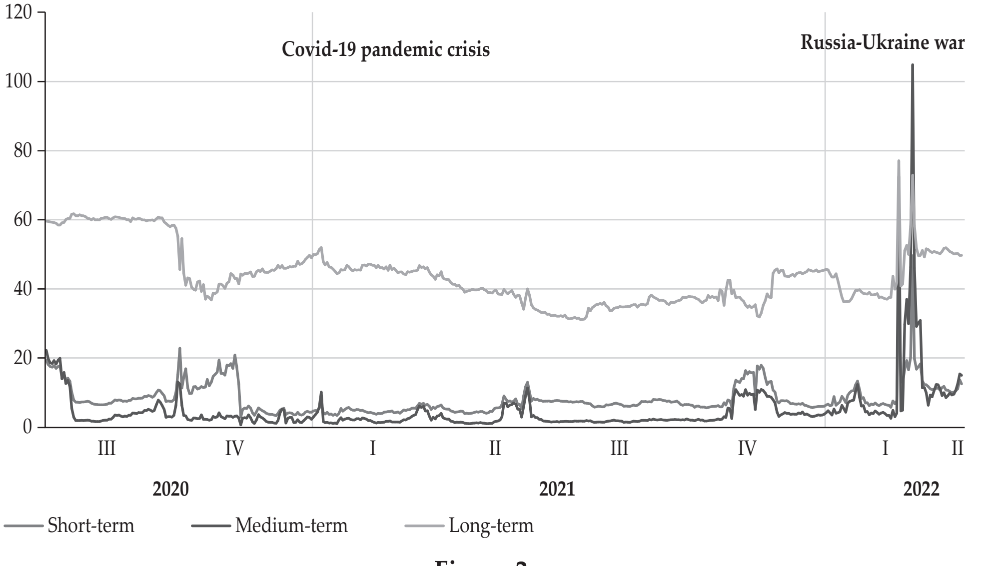


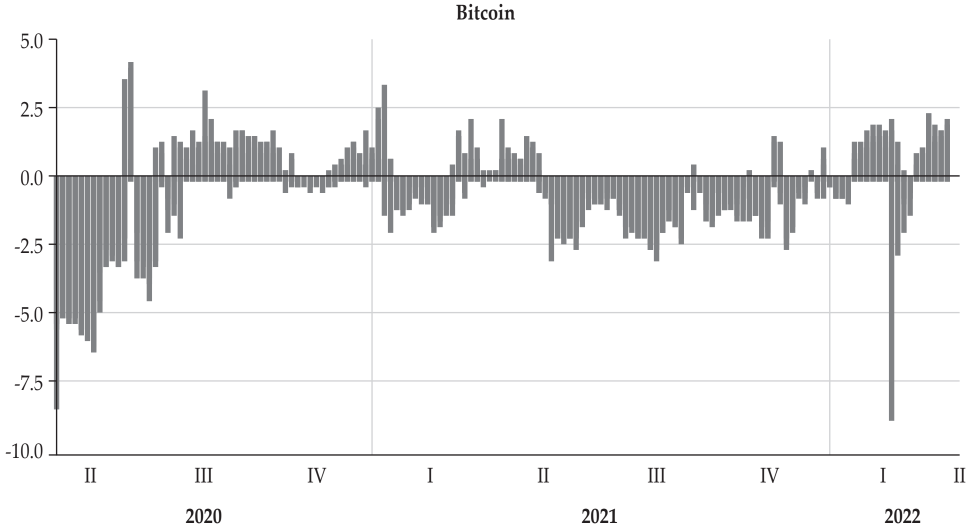
Figure 2.
Dynamic Frequency Connectedness of the Islamic Stock Markets, Bitcoin and Commodities

3.1.3. Net Connectedness of the Islamic stock markets, Bitcoin and Commodities

Figure 3 displays the dynamic net directional returns spillovers between Islamic stock markets, Bitcoin, and commodities, which help us determine the main recipients and transmitters of shocks throughout the sample period. Panel A presents the dynamic net volatility spillover, while Panel B presents the dynamic net frequency connectedness.

Accordingly, our empirical results have significant long-term implications. In doing so, they validate previous study findings (Balcilar et al., 2017; Baur and Hoang, 2021). They also highlight the diversity and safe-haven qualities of major markets in contrast to Bitcoin markets, and they provide an extensive review of the links between Bitcoin and large assets. Our findings, however, differ from those of Shehzad et al. (2021), who claim that, over the COVID-19 era, gold investments have frequently turned out to be more advantageous than Bitcoin investments.

Panel A. *Dynamic net volatility spillover*



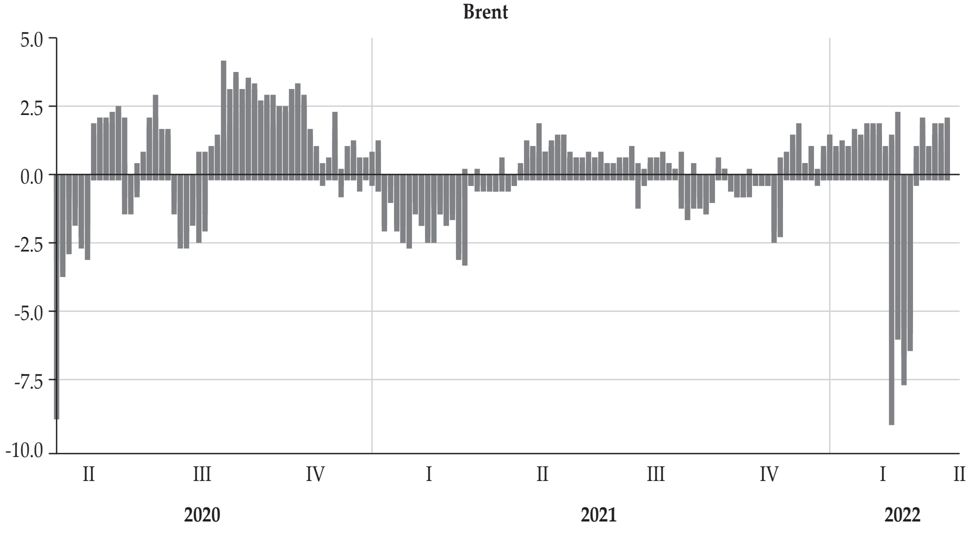
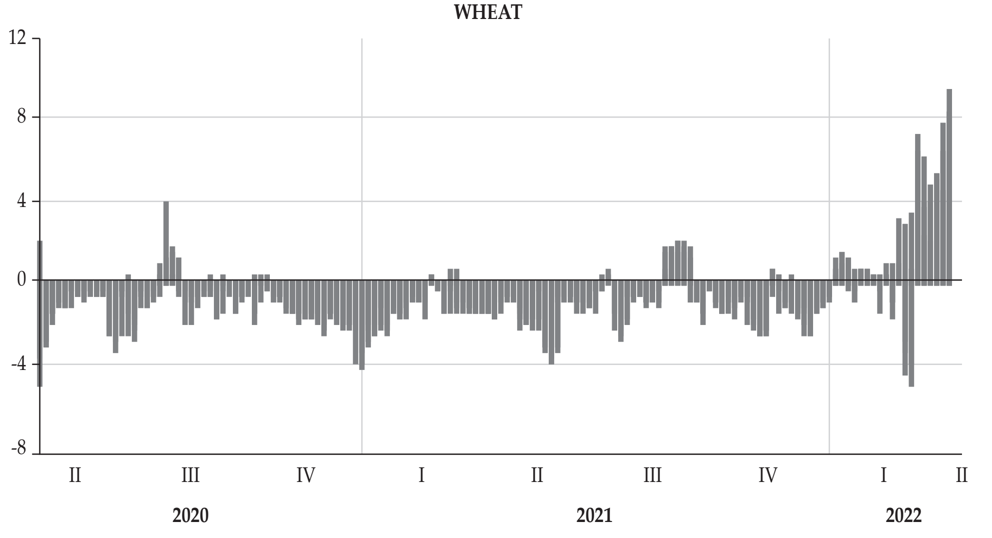


Figure 3.
Net Connectedness of the Financial Markets, Bitcoin and Commodities



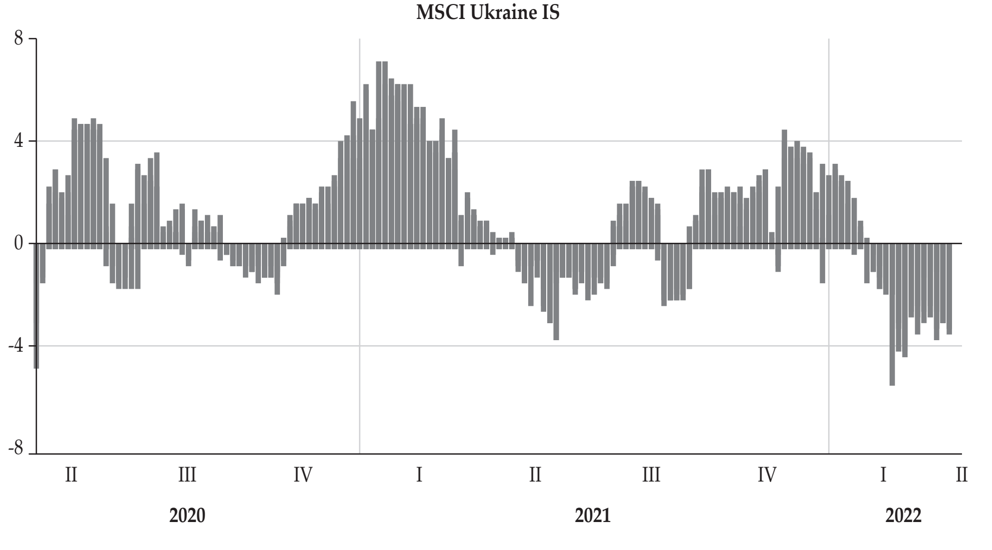
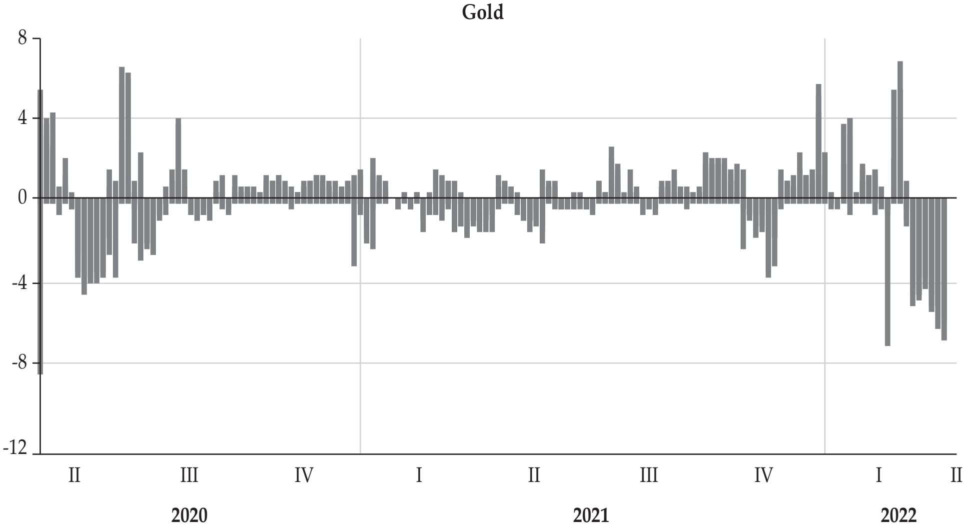


Figure 3.
Net Connectedness of the Financial Markets, Bitcoin and Commodities (Continued)



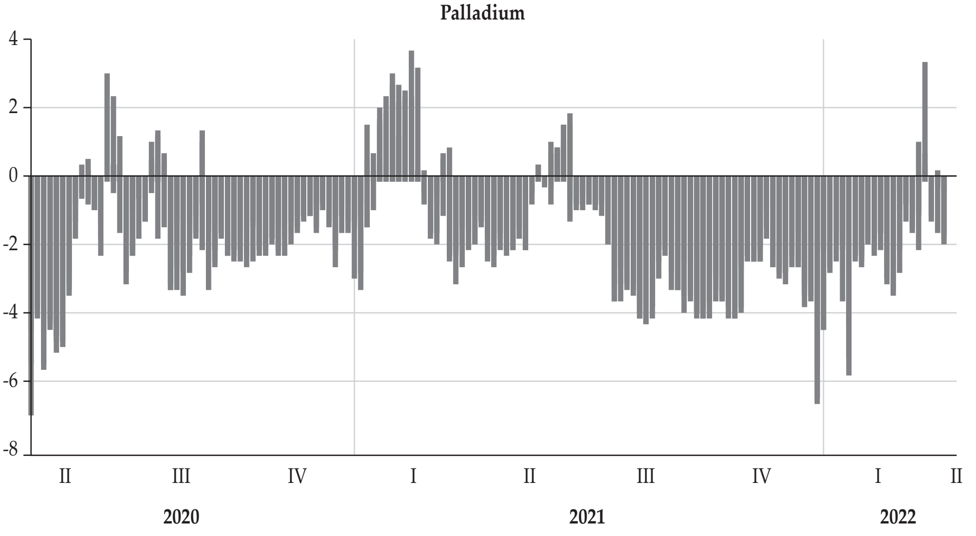
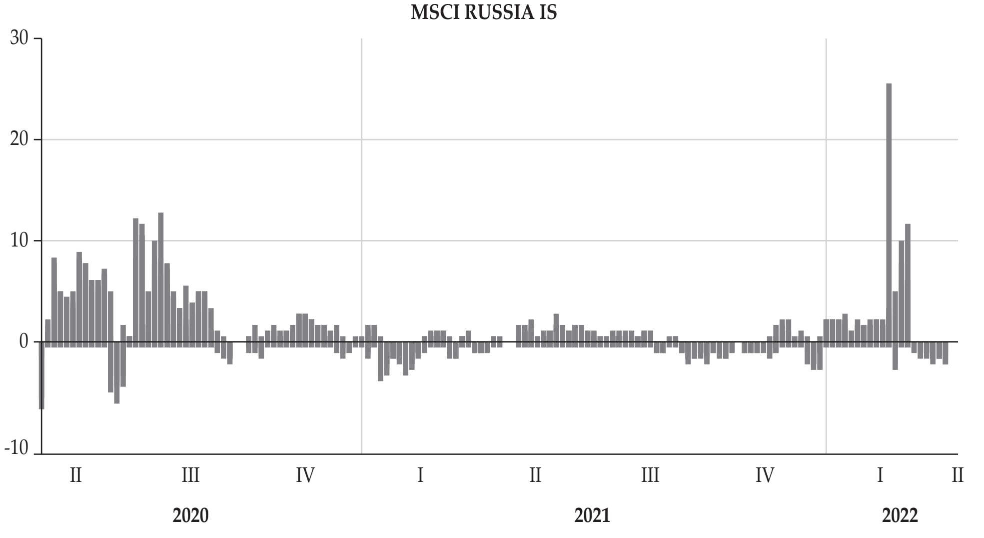


Figure 3.
Net Connectedness of the Financial Markets, Bitcoin and Commodities (Continued)



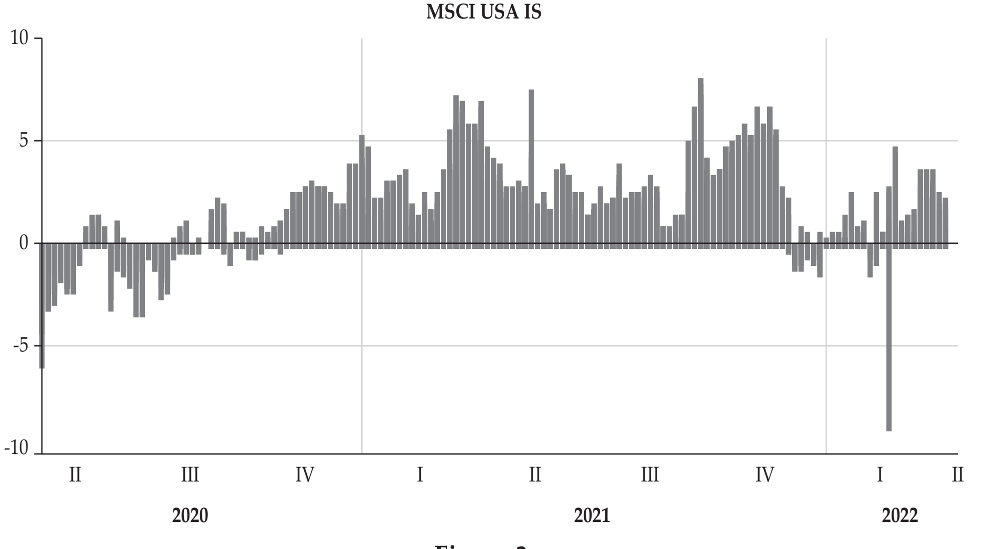
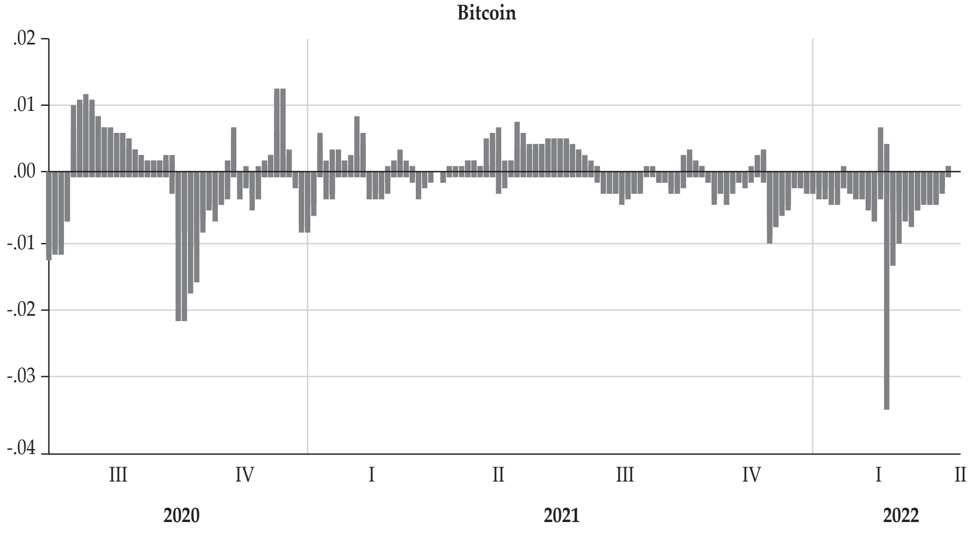


Figure 3.
Net Connectedness of the Financial Markets, Bitcoin and Commodities (Continued)

Panel B. Dynamic net frequency connectedness

(a) Short-term



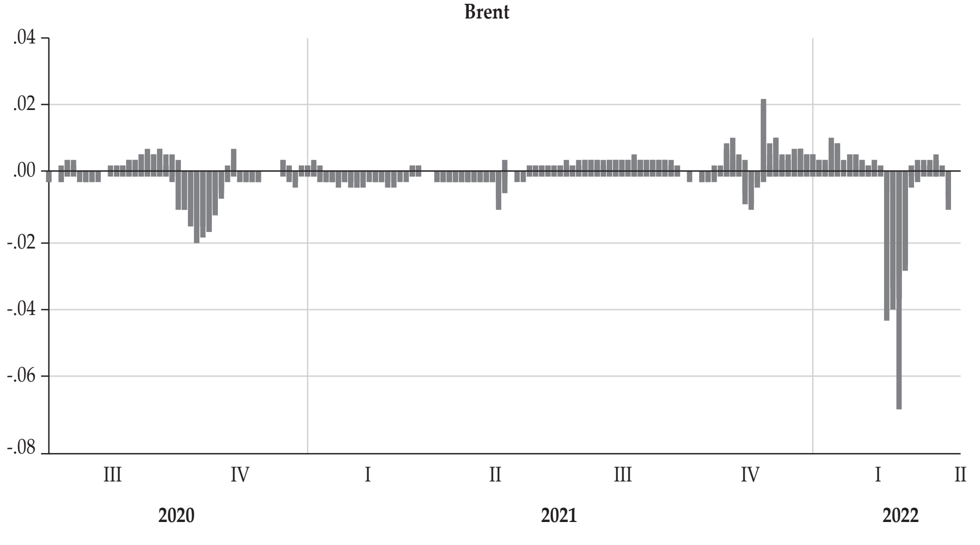
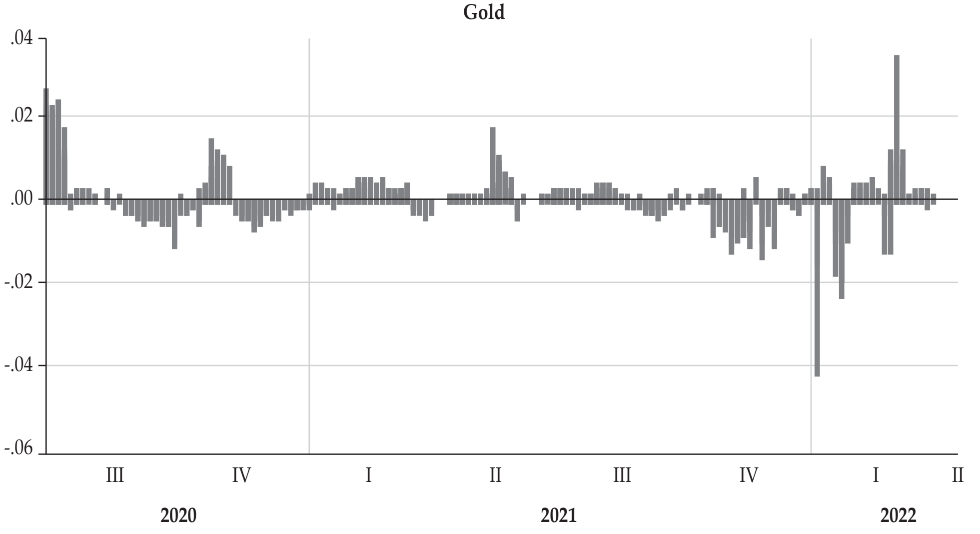


Figure 3.
Net Connectedness of the Financial Markets, Bitcoin and Commodities (Continued)



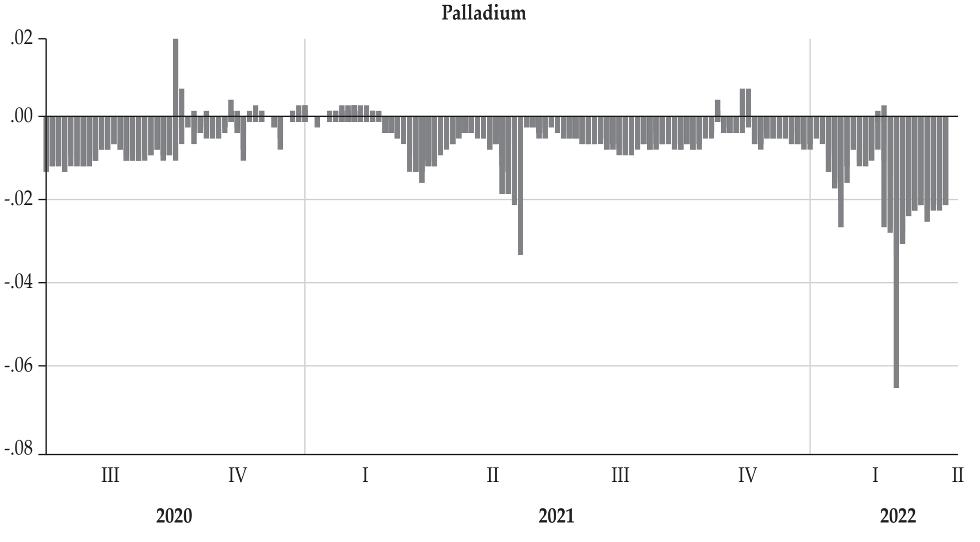
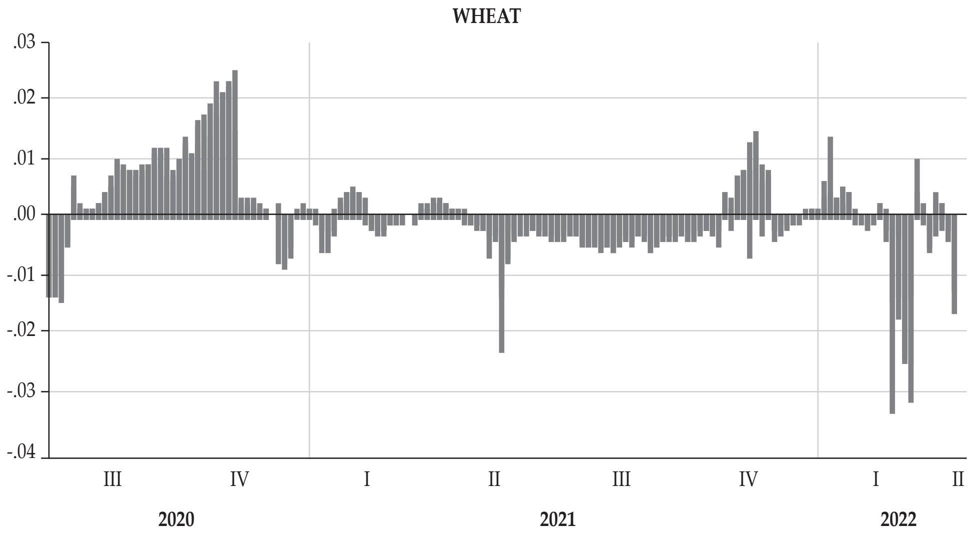


Figure 3.
Net Connectedness of the Financial Markets, Bitcoin and Commodities (Continued)



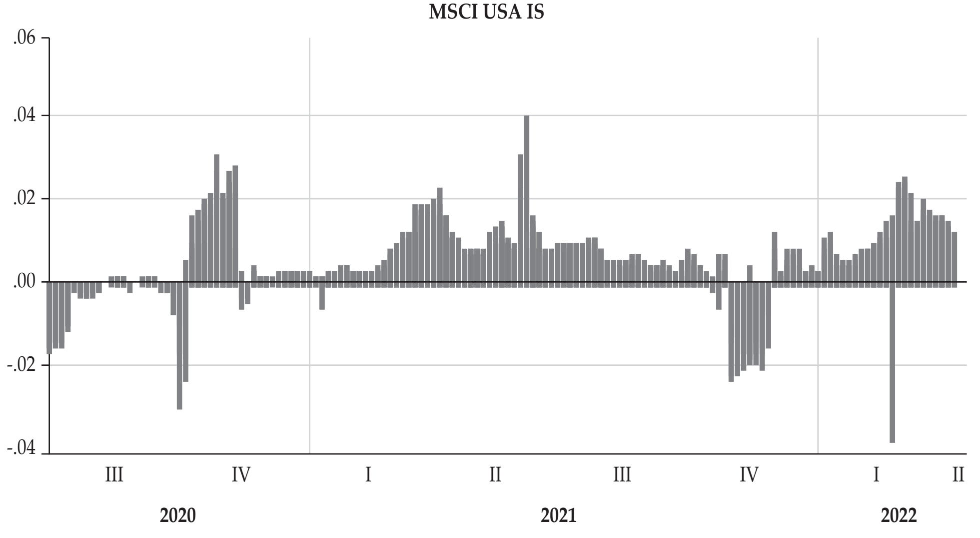
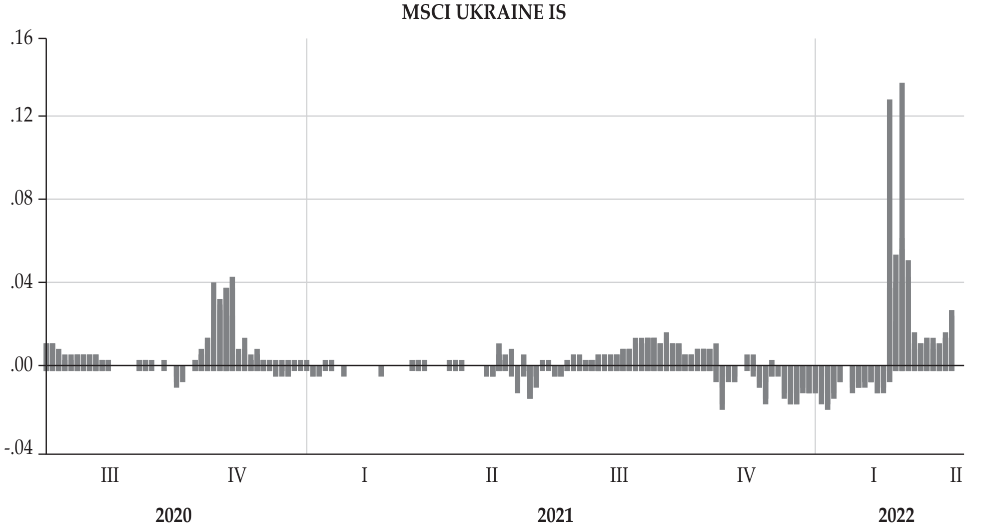


Figure 3.
Net Connectedness of the Financial Markets, Bitcoin and Commodities (Continued)



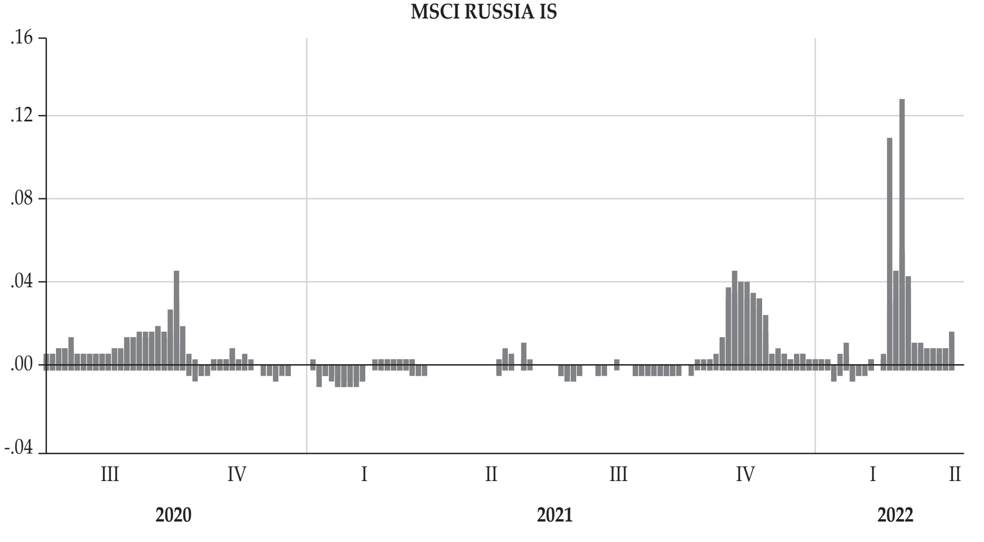
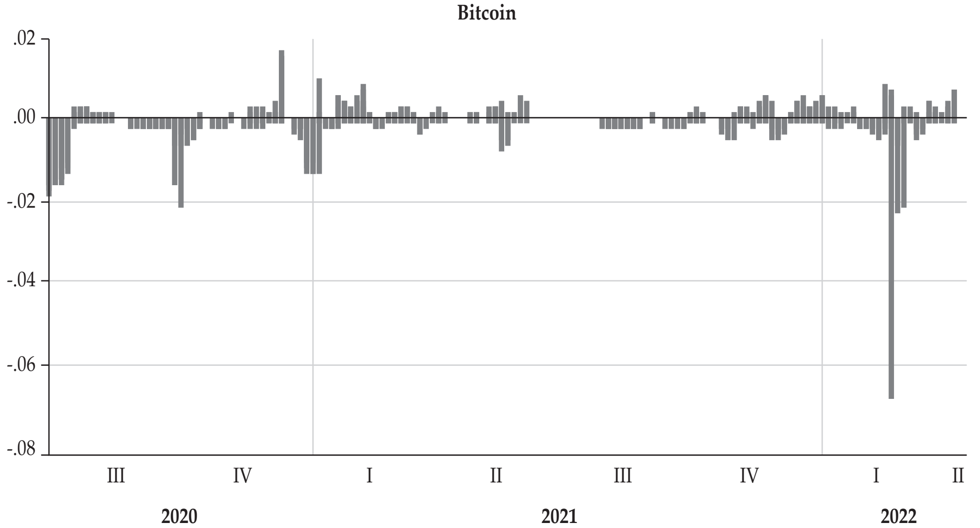


Figure 3.
Net Connectedness of the Financial Markets, Bitcoin and Commodities (Continued)

(b) Medium-term



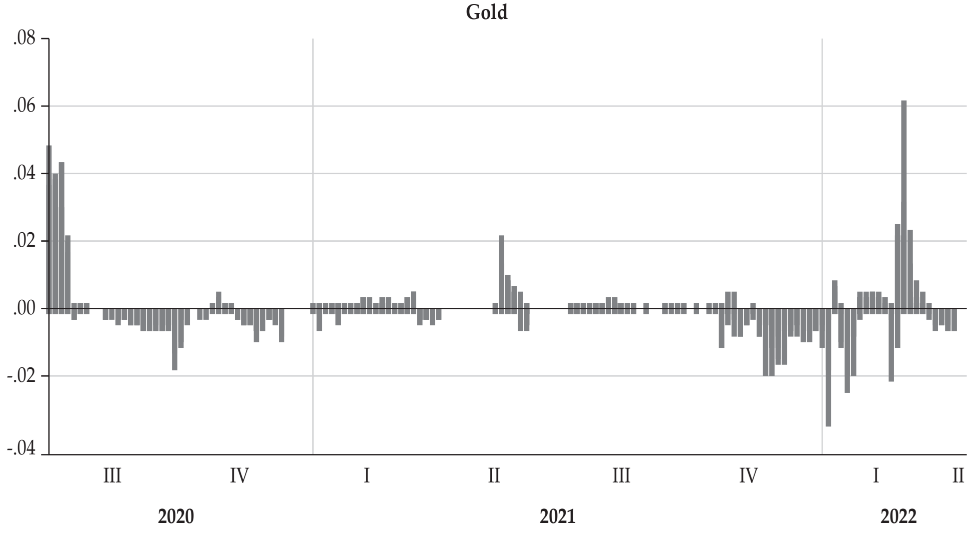


Figure 3.
Net Connectedness of the Financial Markets, Bitcoin and Commodities (Continued)

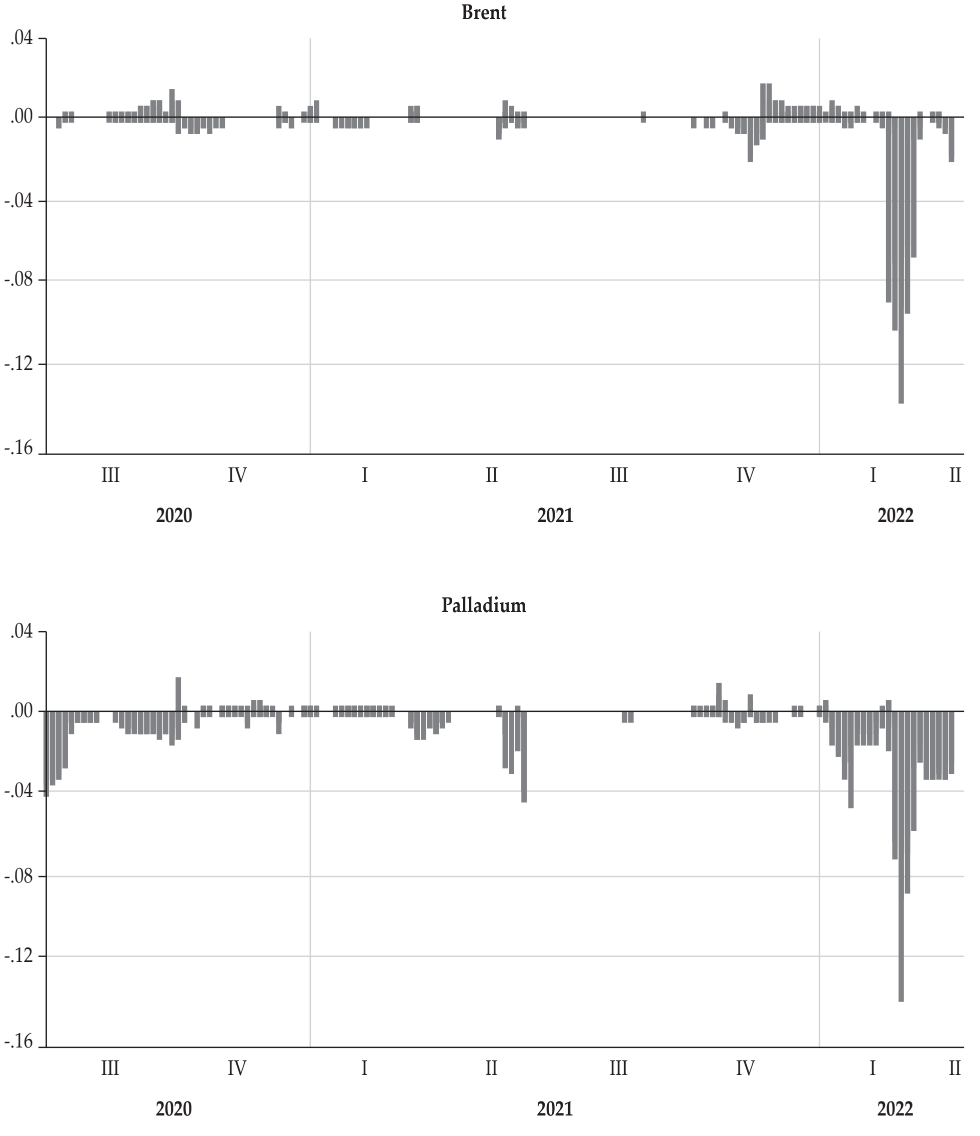
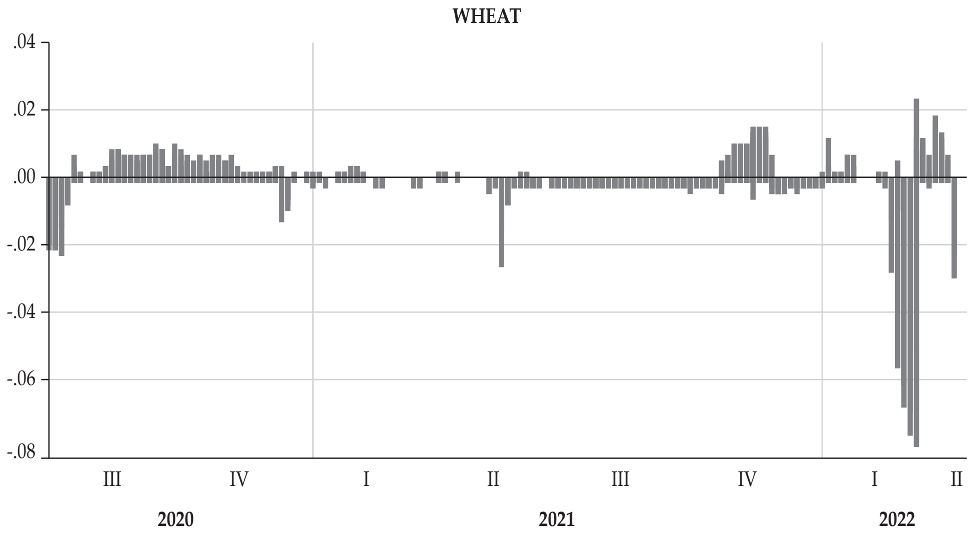


Figure 3.
Net Connectedness of the Financial Markets, Bitcoin and Commodities (Continued)



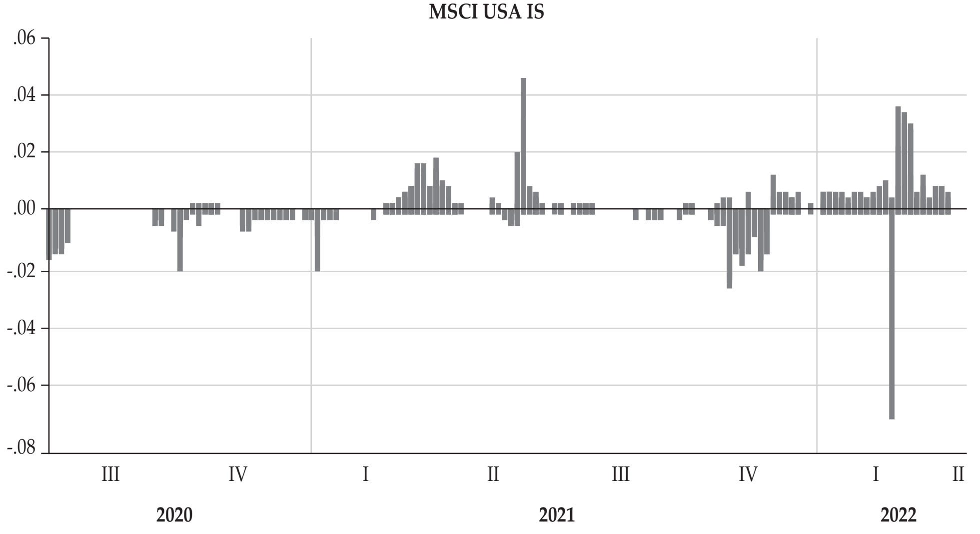
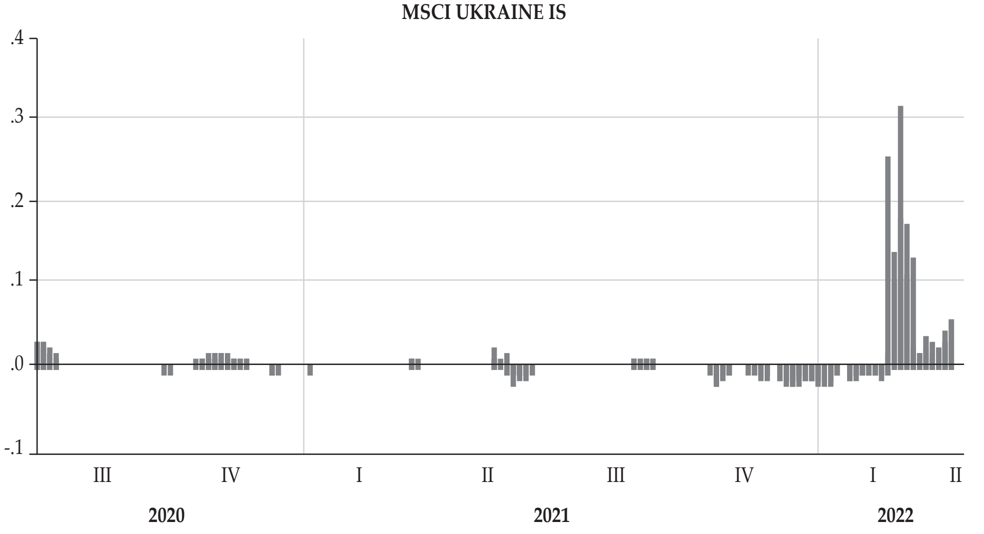


Figure 3.
Net Connectedness of the Financial Markets, Bitcoin and Commodities (Continued)



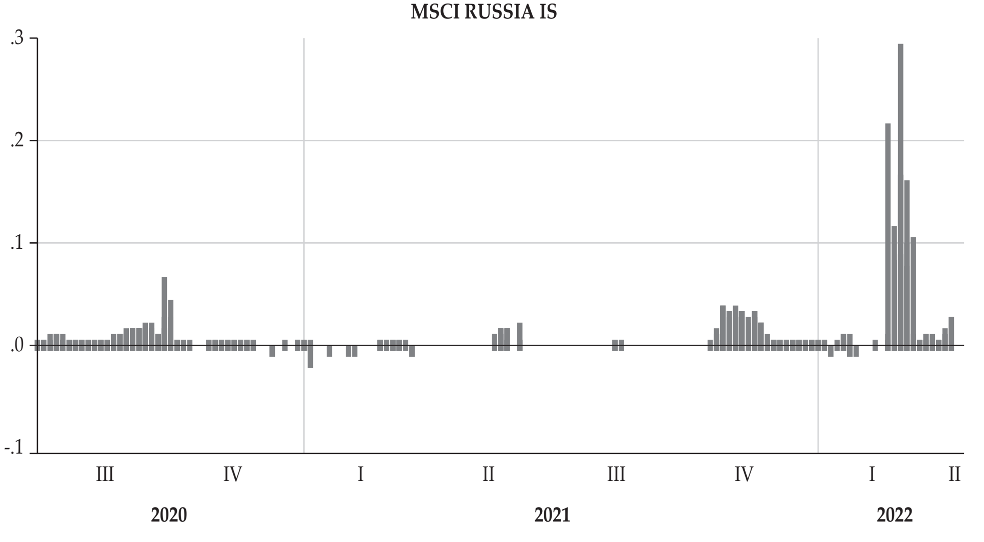
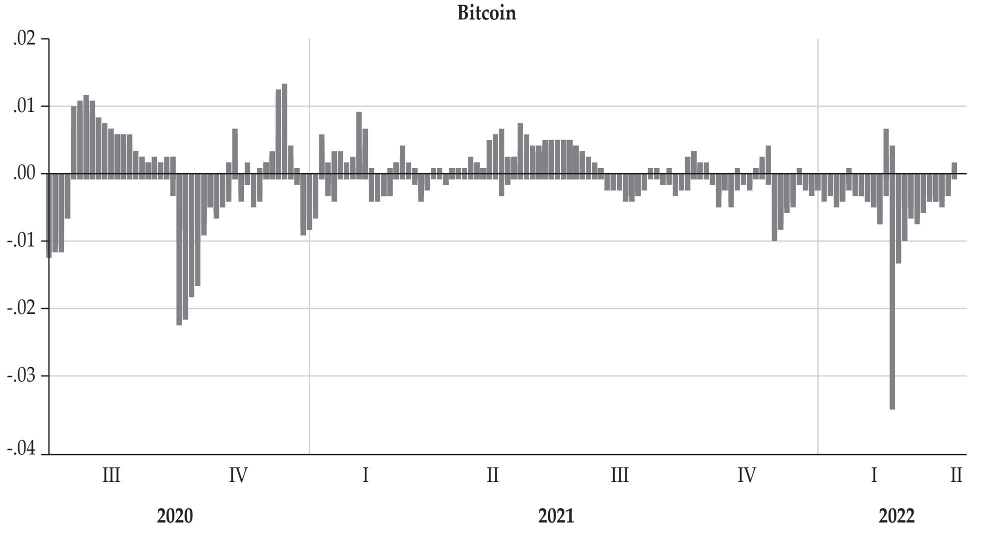


Figure 3.
Net Connectedness of the Financial Markets, Bitcoin and Commodities (Continued)

(c) Long-term



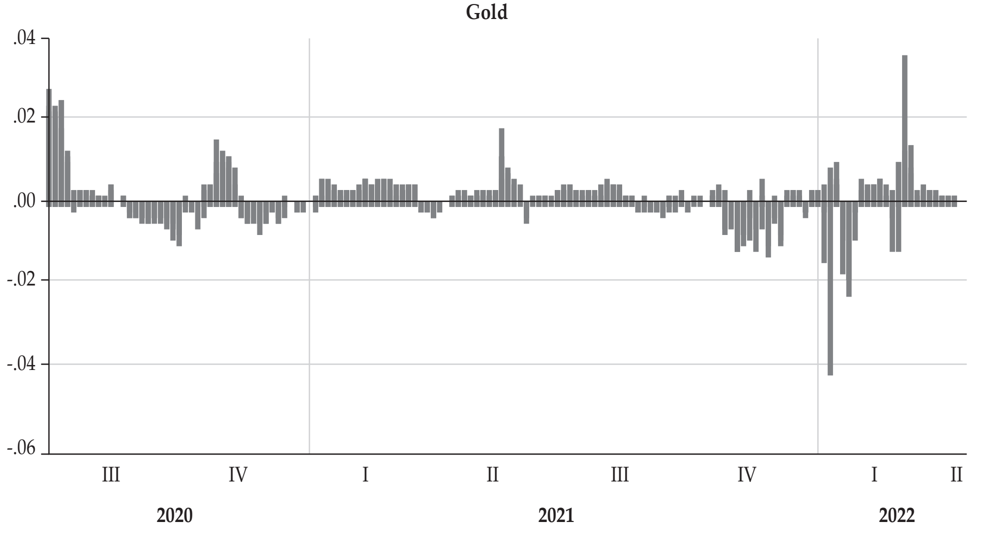
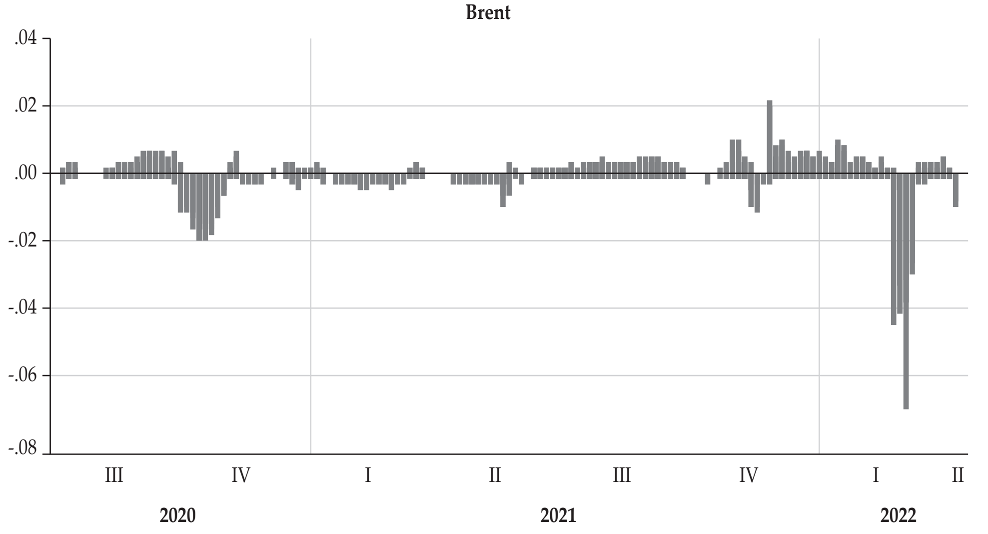


Figure 3.
Net Connectedness of the Financial Markets, Bitcoin and Commodities (Continued)



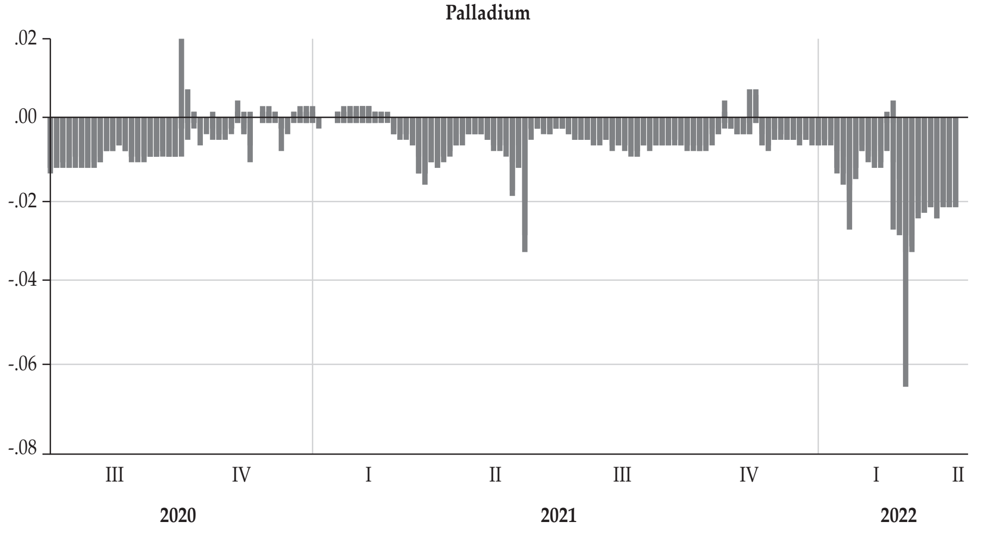
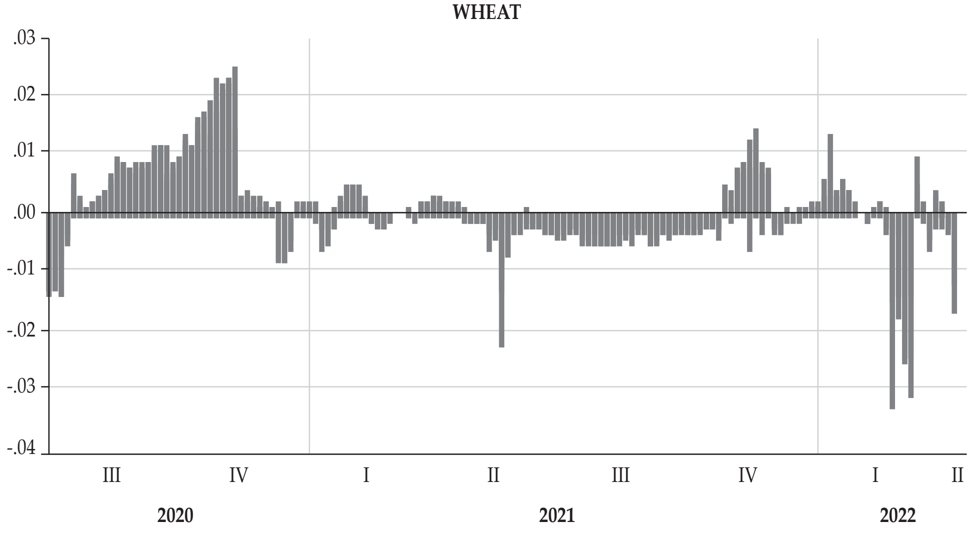


Figure 3.
Net Connectedness of the Financial Markets, Bitcoin and Commodities (Continued)



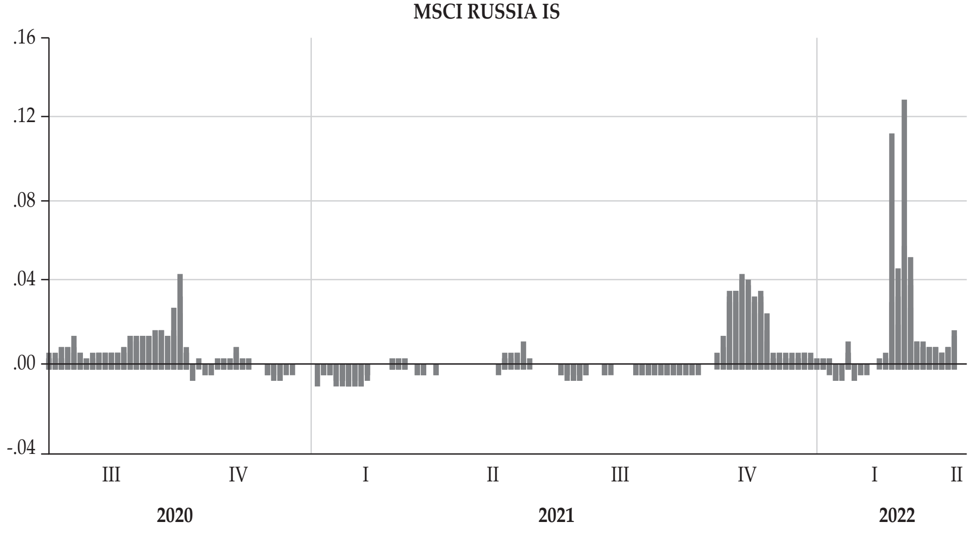


Figure 3.
Net Connectedness of the Financial Markets, Bitcoin and Commodities (Continued)

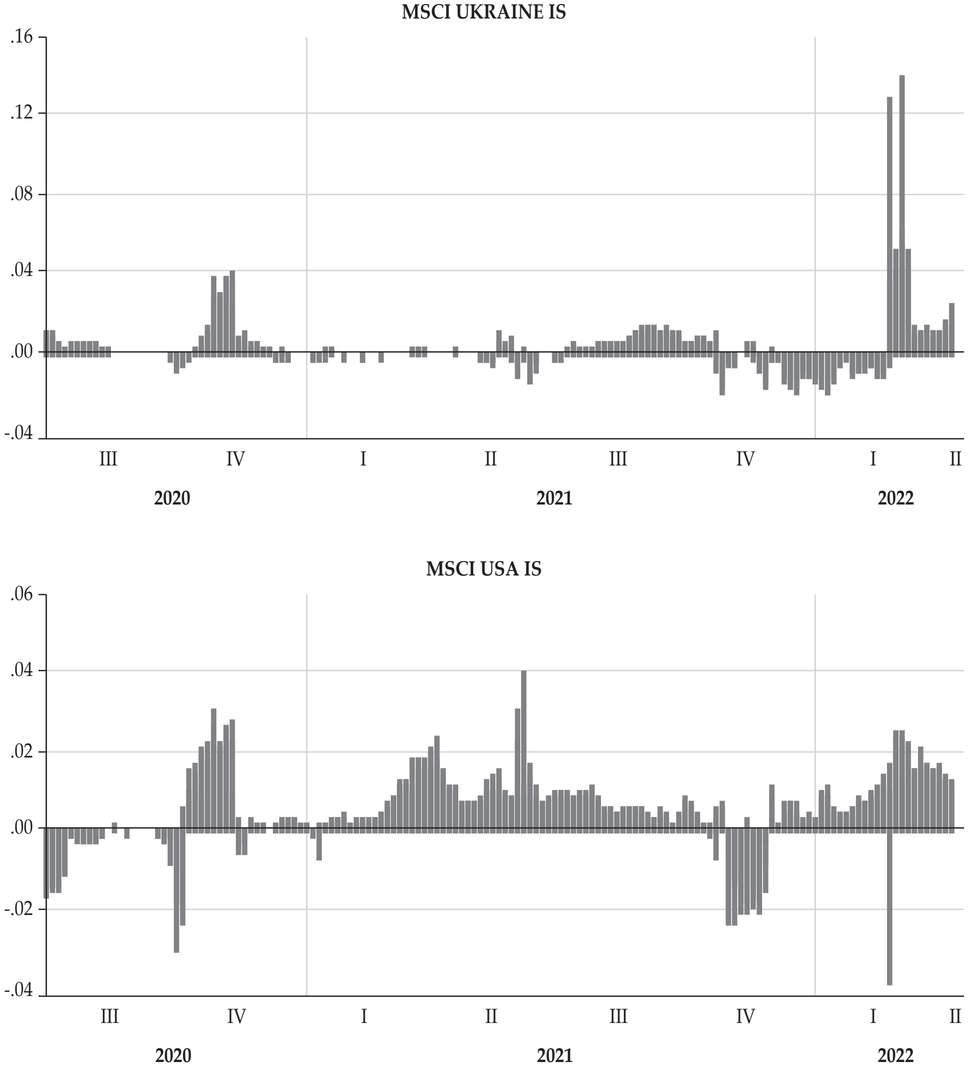


Figure 3.
Net Connectedness of the Financial Markets, Bitcoin and Commodities (Continued)

3.2. Portfolio Designs and Hedging Strategy Analysis

3.2.1. Unit root test with two structural breaks conducted by Narayan and Popp (2010)

Table 4 summarizes the results of Narayan and Popp's (2010) unit root test with structural fractures. Both Model 1 (M1) (two breaks in intercept) and Model 2 (M2) (two breaks in intercept and slope) show that Bitcoin, commodities, and Islamic stock markets have two significant break points.

The significance of examining the interplay between Bitcoin, commodities, and Islamic stock markets in this time frame is underscored by the notable influence these events have had on global financial markets (Xiao et al. 2021; Kumar et al. 2022).

Table 4.
Narayan and Popp (2010) Unit Root Tests with Two Break Dates

	Two breaks in level and slope			
Variable	**Test statistic**	**Break dates**	**φ**	**k**
BITCOIN	-3.26551	2020M04; 2022M03	-0.27865	2
MSCI RUSSIA IS	-2.32541	2020M05; 2022M04	-0.36551	2
MSCI UKRAINE IS	-3.99854	2020M03; 2022M03	-0.44125	2
MSCI USA IS	-3.00581	2020M03; 2022M05	-1.36458	2
WTI	-2.23698	2020M04; 2022M03	-0.55689	2
GOLD	-1.36542	2020M05; 2022M04	-0.96352	2
PALLADIUM	-3.26974	2020M04; 2022M04	-0.22251	2
WHEAT	-1.66652	2020M05; 2022M104	-0.62387	2
Δ BITCOIN	-5.21555**	2020M03; 2022M03	-0.22569	5
Δ MSCI RUSSIA IS	-4.68378***	2020M03; 2022M05	-0.95487	5
Δ MSCI UKRAINE IS	-6.56810**	2020M04; 2022M03	-1.23554	5
Δ MSCI USA IS	-6.34478**	2020M03; 2022M03	-1.32658	5
Δ WTI	-4.66925***	2020M05; 2022M05	-1.56987	5
Δ GOLD	-5.31269**	2020M04; 2022M03	-3.53184	5
Δ PALLADIUM	-4.11245**	2020M04; 2022M04	-2.88797	5
Δ WHEAT	-6.66698***	2020M03; 2022M04	-1.14777	5

Notes: Δ represents the first difference operator, where φ denotes the autoregressive coefficient, and k stands for the optimal lag order. The critical values at the 1%, 5%, and 10% significance levels are -5.138, -4.741, and -4.430, respectively, sourced from Narayan and Popp (2010). The symbols *** and ** signify the rejection of the null hypothesis of a unit root at the 1% and 5% significance levels, respectively.

3.2.2. Time-Varying Hedge Ratio

In this section, we analyze the results of hedge ratios. Figure 4 illustrates the time-varying hedge ratios for all examined pairs. Table 5 presents the summary statistics of hedge ratios.

These results imply that investors in Islamic finance who seek to manage their risk exposure in gold-related assets may benefit from considering both MSCI USA ISL_ Gold and Bitcoin _Gold as potential hedges, depending on their individual Shariah compliance and the specific hedge ratio they are targeting.

During the COVID-19 period, our findings demonstrate that Bitcoin presents a superior diversification opportunity for mitigating risks associated with major Islamic equity markets. This observation underscores Bitcoin's capacity for effective risk reduction in investment during times of crisis. During the COVID-19 pandemic, research by Wang et al. (2021), Rubbaniy et al. (2021), and Kumar (2020) shows the advantages of diversification with Bitcoin.

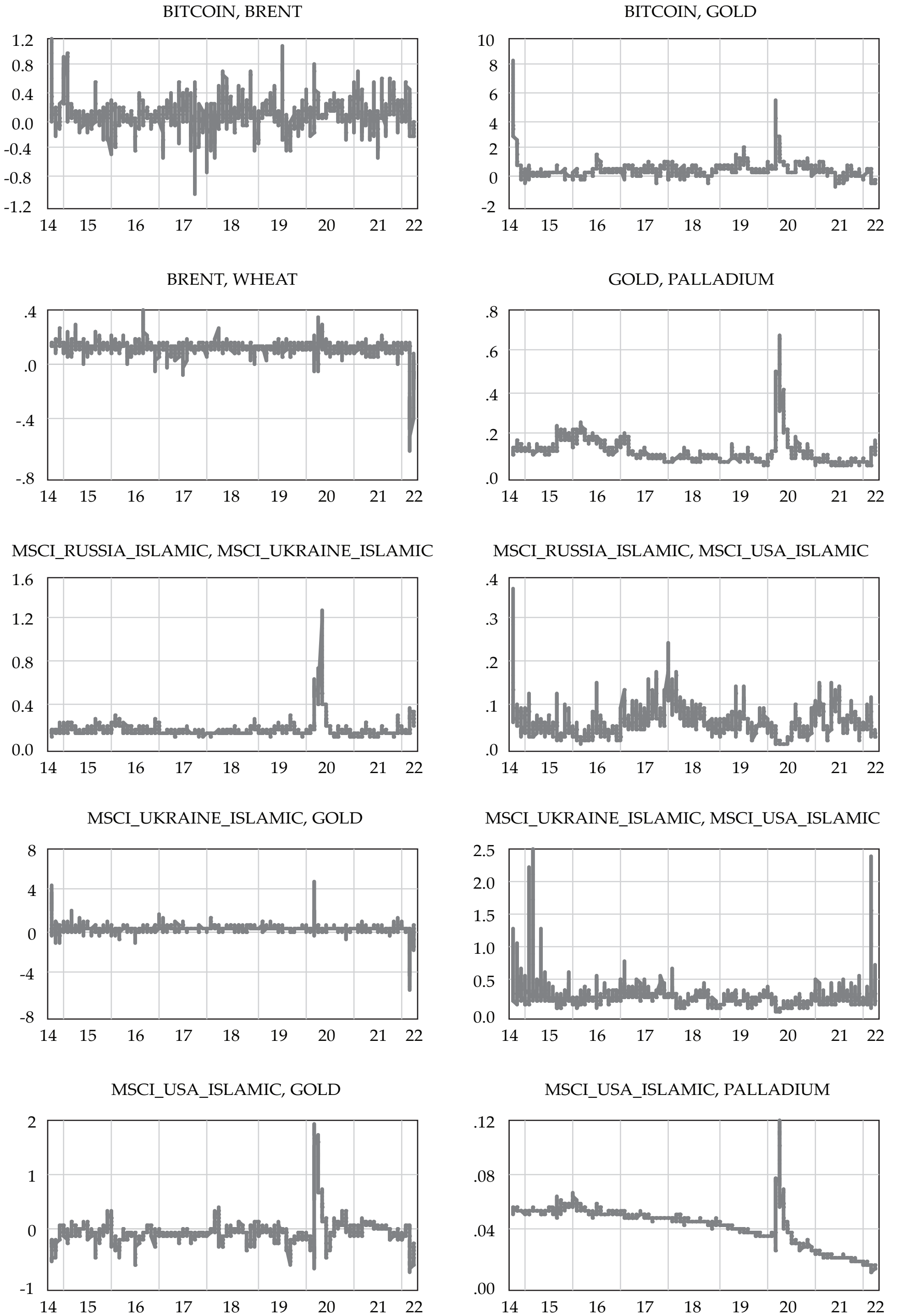


Figure 4.
Time-varying Hedge Ratios

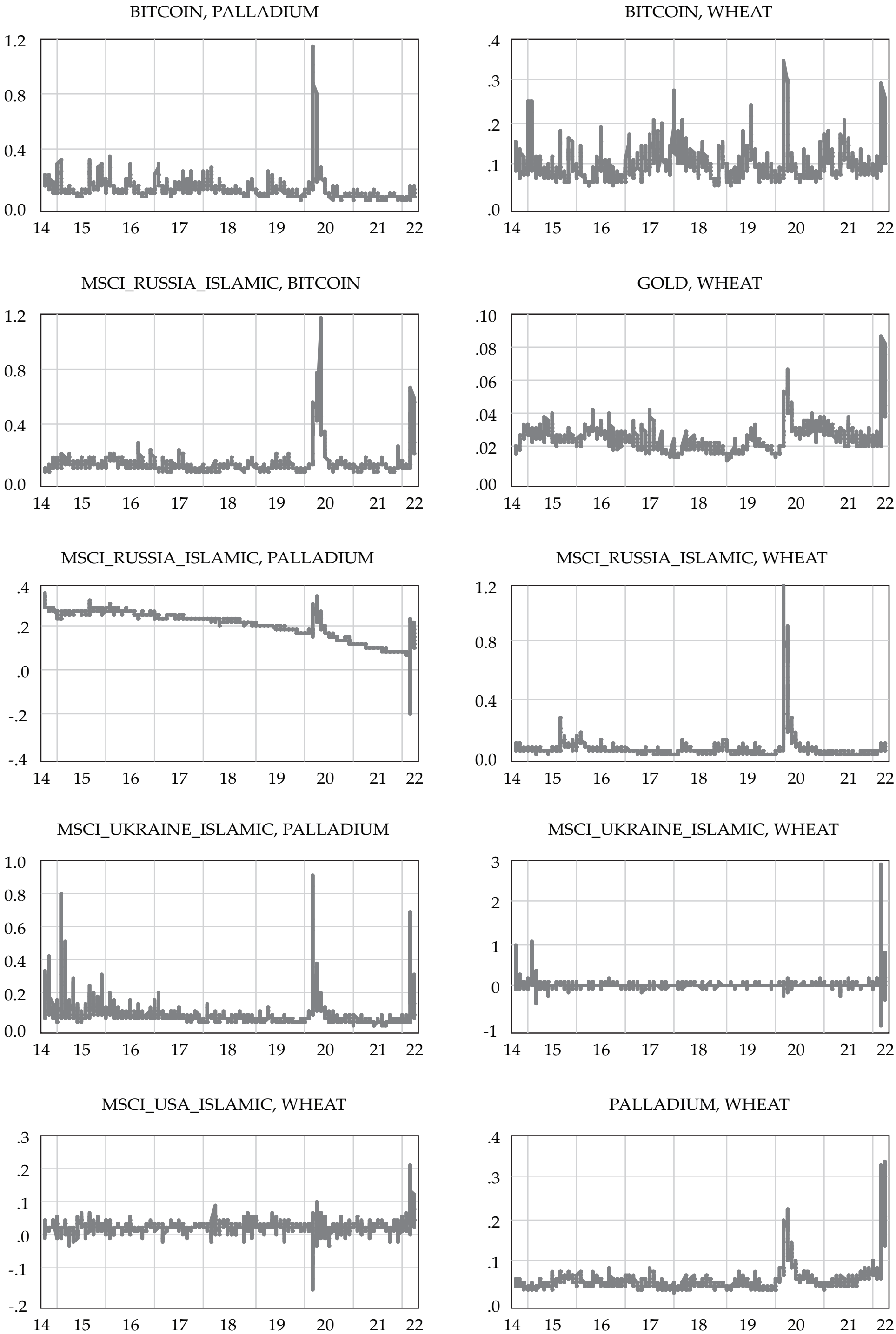


Figure 4.
***Time-varying Hedge Ratios* (Continued)**

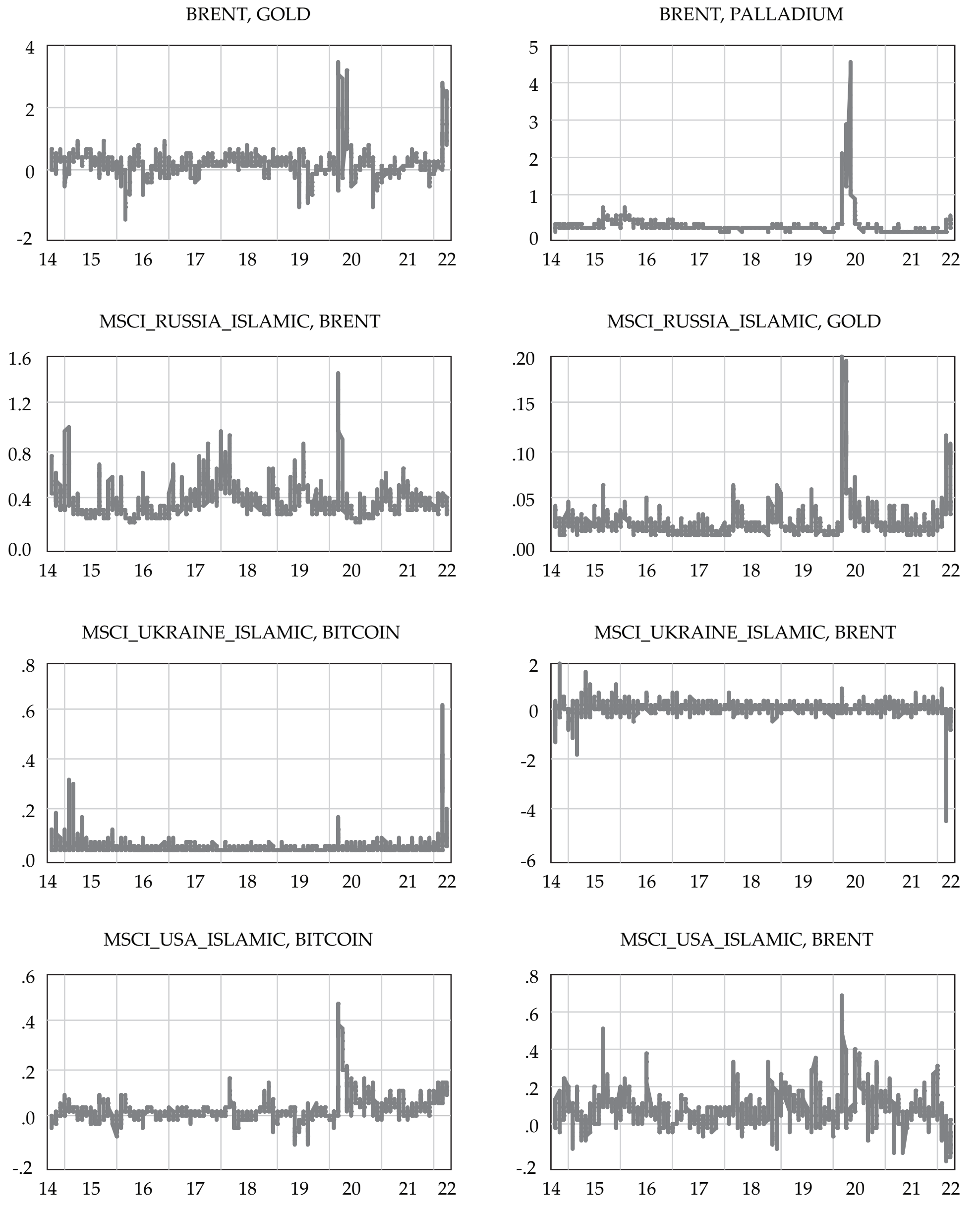


Figure 4.
***Time-varying Hedge Ratios* (Continued)**

Table 5.
Descriptive Statistics of Time Varying Hedge Ratio

	Mean	Median	Maximum	Minimum	Std. Dev.
BITCOIN_BRENT	0.082290	0.074802	1.149597	-1.062905	0.211305
BITCOIN_GOLD	0.429008	0.320730	8.287726	-0.716261	0.704886
BITCOIN_PALLADIUM	0.118353	0.102975	1.131302	0.038865	0.078344
BITCOIN_WHEAT	0.096937	0.087883	0.346407	0.049011	0.036497
BRENT_GOLD	0.215869	0.208484	3.384852	-1.514866	0.418888
BRENT_PALLADIUM	0.237365	0.172275	4.562042	0.048181	0.339382
BRENT_WHEAT	0.114322	0.119147	0.387069	-0.629701	0.053930
GOLD_PALLADIUM	0.111082	0.094572	0.676785	0.037587	0.065121
GOLD_WHEAT	0.025189	0.024291	0.086340	0.012911	0.007809
MSCI RUSSIA ISL_BITCOIN	0.127206	0.106168	1.165625	0.052568	0.098082
MSCI RUSSIA ISL_BRENT	0.368713	0.336733	1.434829	0.199677	0.130129
MSCI RUSSIA ISL_GOLD	0.024628	0.019881	0.195837	0.009623	0.017914
MSCI RUSSIA ISL_MSCI UKRAINE ISL	0.156925	0.136193	1.283862	0.088829	0.094124
MSCI RUSSIA ISL_MSCI USA ISL	0.055723	0.049478	0.370088	0.000353	0.032993
MSCI RUSSIA ISL_PALLADIUM	0.208611	0.231527	0.354100	-0.211702	0.067609
MSCI RUSSIA ISL_WHEAT	0.052727	0.037027	1.185104	0.008850	0.077086
MSCI UKRAINE ISL_BITCOIN	0.037941	0.031349	0.618900	0.019478	0.030334
MSCI UKRAINE ISL_BRENT	0.084420	0.090690	1.853252	-4.586250	0.285878
MSCI UKRAINE ISL_GOLD	0.145237	0.153876	4.770890	-5.639229	0.411255
MSCI UKRAINE ISL_MSCI USA ISL	0.243555	0.217219	2.467732	0.034036	0.171007
MSCI UKRAINE ISL_PALLADIUM	0.072155	0.055801	0.902227	0.018161	0.067953
MSCI UKRAINE ISL_WHEAT	0.020235	0.011976	2.837319	-0.968376	0.129170
MSCI USA ISL_BITCOIN	0.025571	0.014138	0.464116	-0.115448	0.054303
MSCI USA ISL_BRENT	0.087834	0.074304	0.670373	-0.183245	0.091027
MSCI USA ISL_GOLD	-0.053314	-0.063587	1.882511	-0.790328	0.226286
MSCI USA ISL_PALLADIUM	0.042260	0.046583	0.118931	0.008568	0.013864
MSCI USA ISL_WHEAT	0.023776	0.024051	0.207623	-0.163679	0.017827
PALLADIUM_WHEAT	0.053406	0.046315	0.339020	0.025811	0.031810

3.3 Time Varying Optimal Weight Ratios

Figure 5 depicts the time-varying optimal weights. Table 6 provides the summary statistics of the optimal weight ratios for each variable pair across the sample period.

The findings suggest that the optimal weights vary over time across the sample period, indicating the need for active portfolio management when investing in cryptocurrency, commodity, and Islamic stock markets. Moreover, the optimal weight for the MSCI UKRAINE ISL_PALLADIUM portfolio was found to be 0.46, suggesting that in a USD 1 portfolio comprising MSCI UKRAINE ISL stocks and PALLADIUM, USD 0.54 should be invested in MSCI UKRAINE ISL stocks and USD 0.46 in PALLADIUM to achieve diversification benefits. This finding can be explained by the low correlation between the returns of MSCI UKRAINE ISL_ PALLADIUM portfolio components, which provides diversification benefits to investors.

Financial analysts can ultimately rely on these results to help investors achieve optimal risk reduction during the COVID-19 crisis by building a well-diversified portfolio.

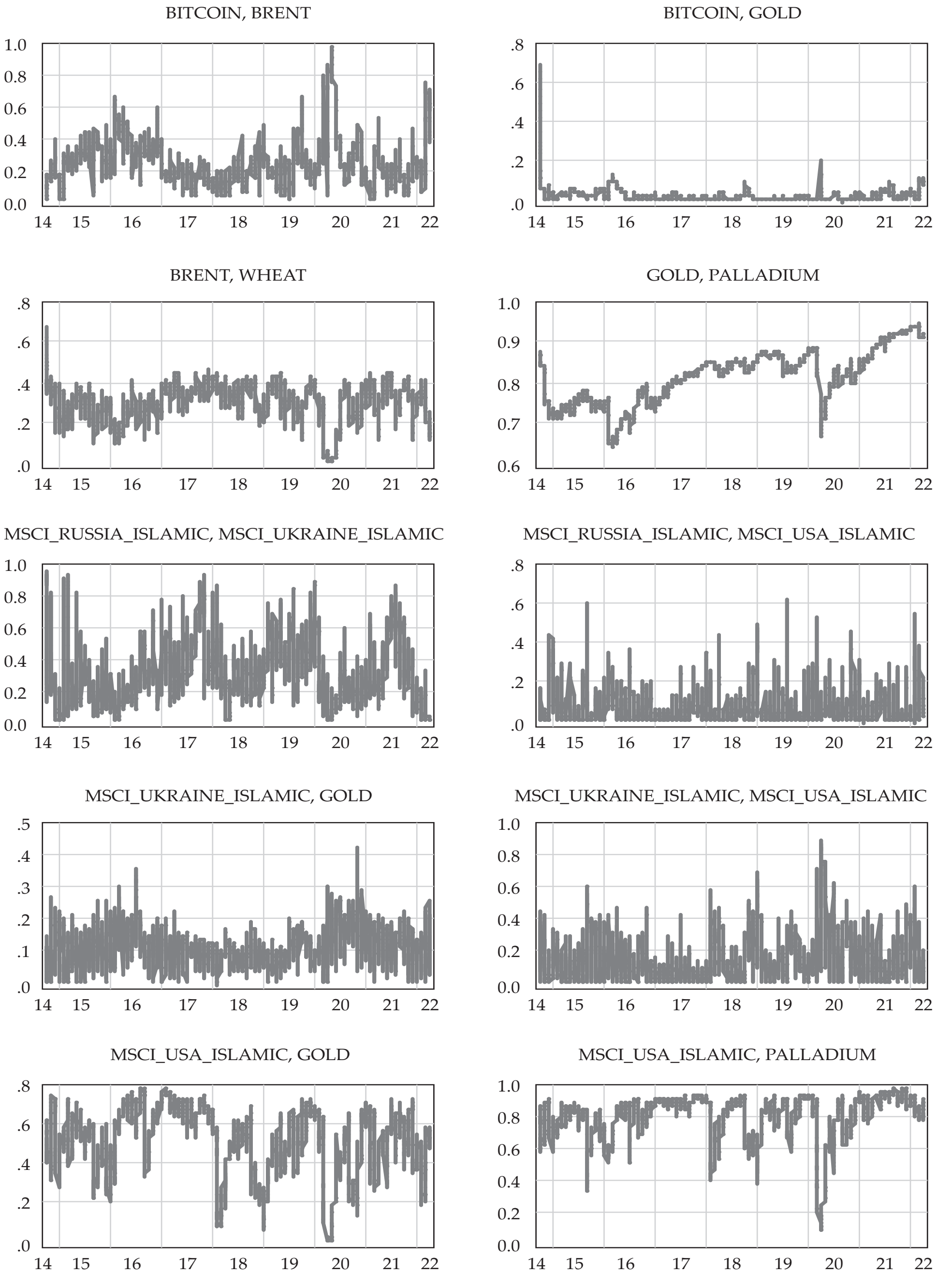


Figure 5.
Time Varying Optimal Weight Ratios

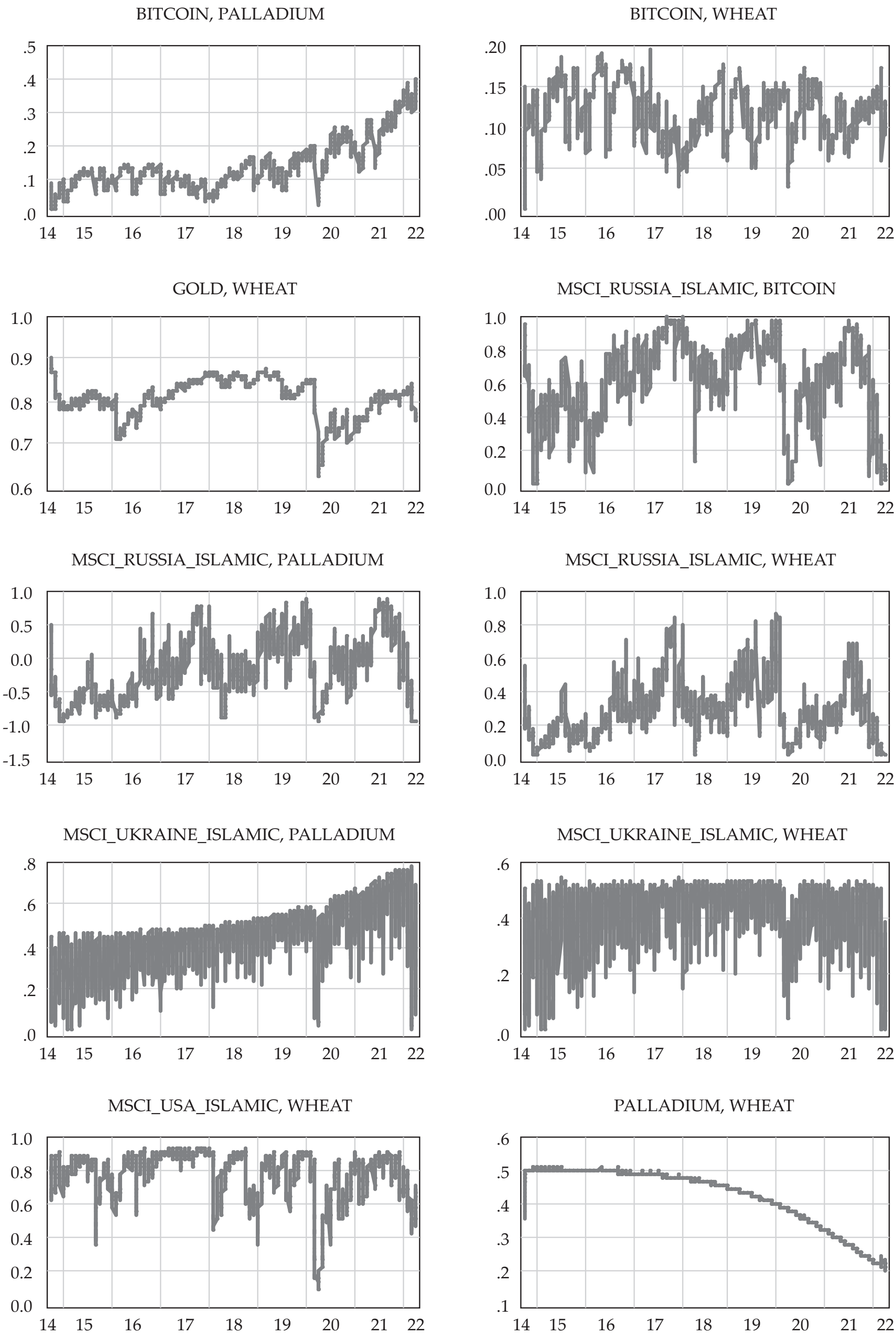


Figure 5.
Time Varying Optimal Weight Ratios (Continued)

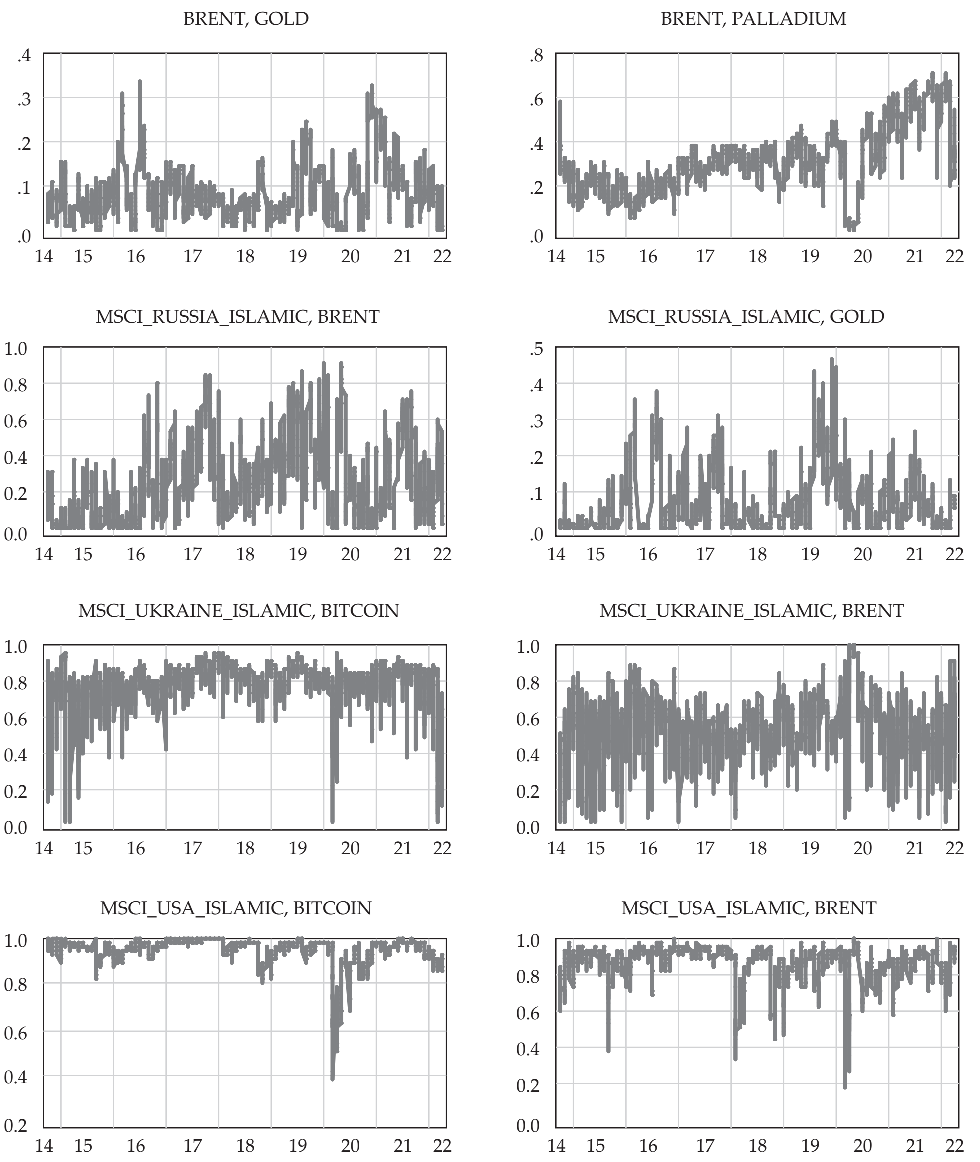


Figure 5.
Time Varying Optimal Weight Ratios (Continued)

Table 6.
Descriptive Statistics of Time Varying Optimal Weight Ratio

	Mean	Median	Maximum	Minimum	Std. Dev.
BITCOIN_BRENT	0.253875	0.229674	1.069178	-0.012044	0.143217
BITCOIN_GOLD	0.024885	0.024946	0.097120	-0.093923	0.022147
BITCOIN_PALLADIUM	0.160715	0.147332	0.420754	-0.090444	0.079514
BITCOIN_WHEAT	0.133671	0.135027	0.206592	-0.139088	0.037335
BRENT_GOLD	0.092800	0.090246	0.247452	-0.068183	0.045969
BRENT_PALLADIUM	0.384323	0.375865	0.866261	0.003747	0.152900
BRENT_WHEAT	0.338715	0.355402	0.795720	0.003210	0.104442
GOLD_PALLADIUM	0.918762	0.928710	1.139819	0.742774	0.055421
GOLD_WHEAT	0.823438	0.827551	1.155250	0.623834	0.048416
MSCI RUSSIA ISL_BITCOIN	0.649972	0.689194	1.084092	-0.065569	0.242766
MSCI RUSSIA ISL_BRENT	0.381637	0.345366	1.323301	-0.391967	0.297920
MSCI RUSSIA ISL_GOLD	0.074476	0.054348	0.523913	-0.057430	0.078518
MSCI RUSSIA ISL_MSCI UKRAINE ISL	0.339061	0.303784	0.983596	-0.002427	0.205615
MSCI RUSSIA ISL_MSCI USA ISL	0.007329	-0.002313	0.560325	-0.467005	0.102024
MSCI RUSSIA ISL_PALLADIUM	0.324659	0.282998	1.073995	7.62E-06	0.227555
MSCI RUSSIA ISL_WHEAT	0.291350	0.260197	0.895678	-0.009783	0.182493
MSCI UKRAINE ISL_BITCOIN	0.809958	0.839715	1.243289	-0.010528	0.131012
MSCI UKRAINE ISL_BRENT	0.583977	0.586542	1.966285	-0.046455	0.170774
MSCI UKRAINE ISL_GOLD	0.131297	0.130272	0.308329	-0.058512	0.054676
MSCI UKRAINE ISL_MSCI USA ISL	0.158492	0.124392	1.069909	-0.439589	0.143642
MSCI UKRAINE ISL_PALLADIUM	0.468750	0.483286	0.787584	0.004400	0.143887
MSCI UKRAINE ISL_WHEAT	0.418697	0.454500	0.542653	-0.017912	0.110194
MSCI USA ISL_BITCOIN	0.966562	0.977247	1.230212	0.576967	0.047567
MSCI USA ISL_BRENT	0.942851	0.958524	1.290087	0.378579	0.098422
MSCI USA ISL_GOLD	0.478508	0.512155	0.743710	-0.039275	0.157731
MSCI USA ISL_PALLADIUM	0.827642	0.878629	0.980974	0.076651	0.147102
MSCI USA ISL_WHEAT	0.785385	0.839724	0.952340	0.065710	0.152699
PALLADIUM_WHEAT	0.446714	0.490919	0.578297	0.212033	0.093476

3.4 Time varying Hedging Effectiveness

Now, let's delve into the outcomes of the HE ratios (Figure 7). The HE values ranged from 0.02 for BITCOIN-GOLD to 0.94 for MSCI USA ISL-BITCOIN. Therefore, the most effective (least effective) hedging strategy for mitigating portfolio risk involves the MSCI USA ISL-BITCOIN pair, while the least effective hedging strategy involves the BITCOIN-GOLD pair (Table 7).

This suggests that the MSCI USA ISL-BITCOIN pair serves as the optimal hedging strategy, offering the most efficient protection against portfolio risk. Conversely, the BITCOIN-GOLD pair represents the least effective hedging strategy, providing minimal protection against portfolio risk.

In the context of Islamic finance, the HE ratios provide important information for investors who are seeking to manage their portfolio risk while adhering to Shariah principles (Sheikh et al., 2023).

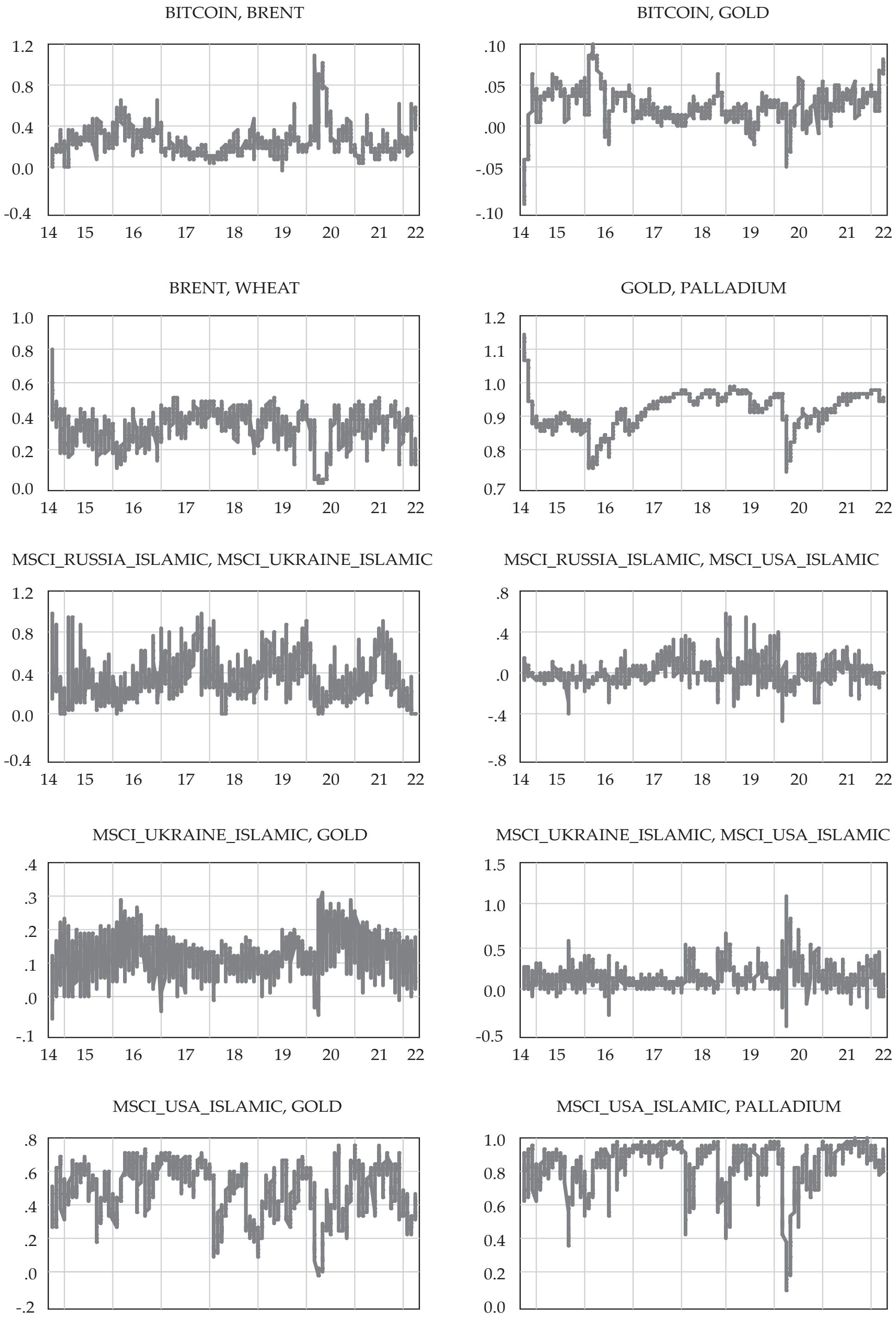


Figure 6.
Time varying Hedging Effectiveness

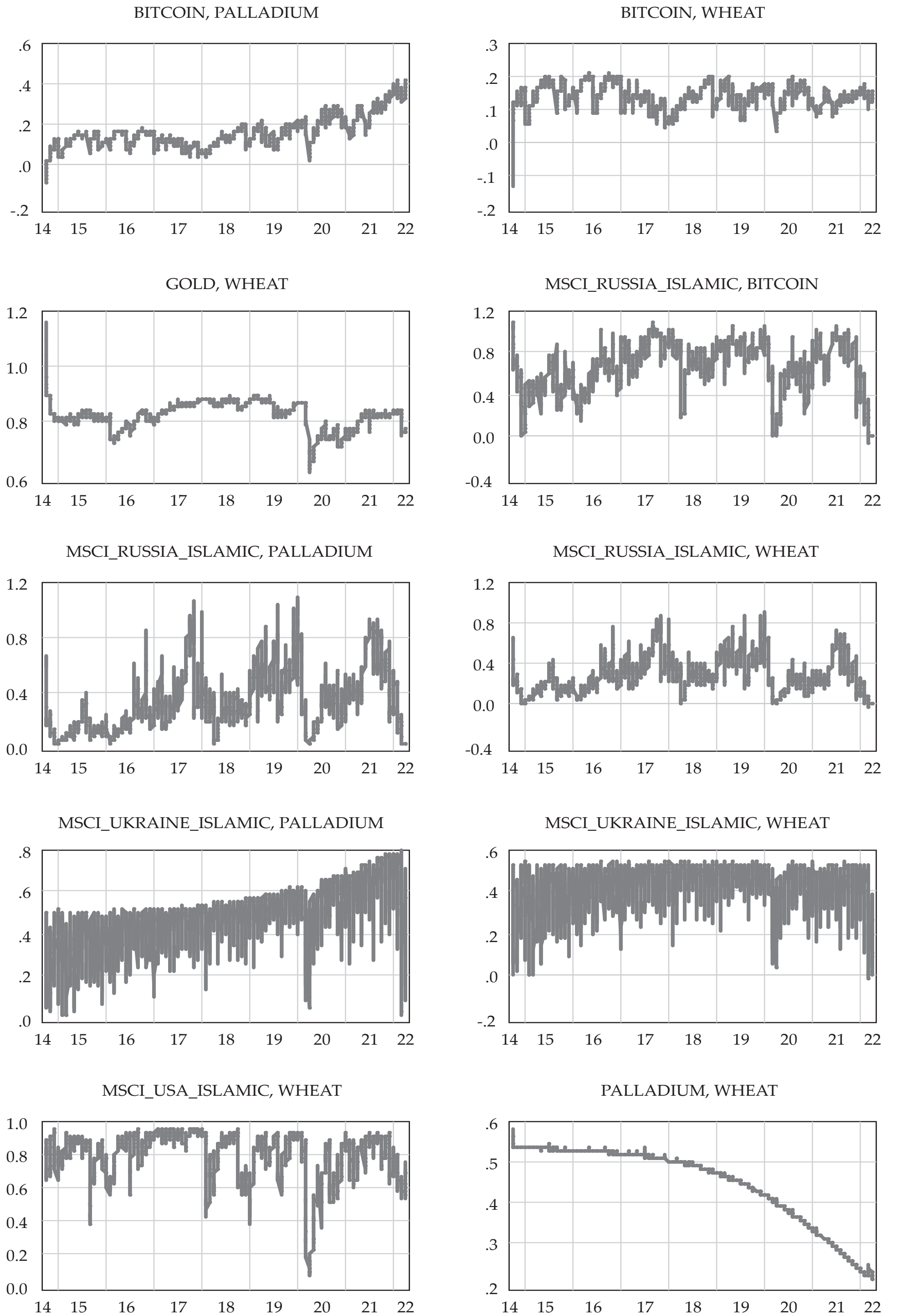


Figure 6.
Time varying Hedging Effectiveness (Continued)

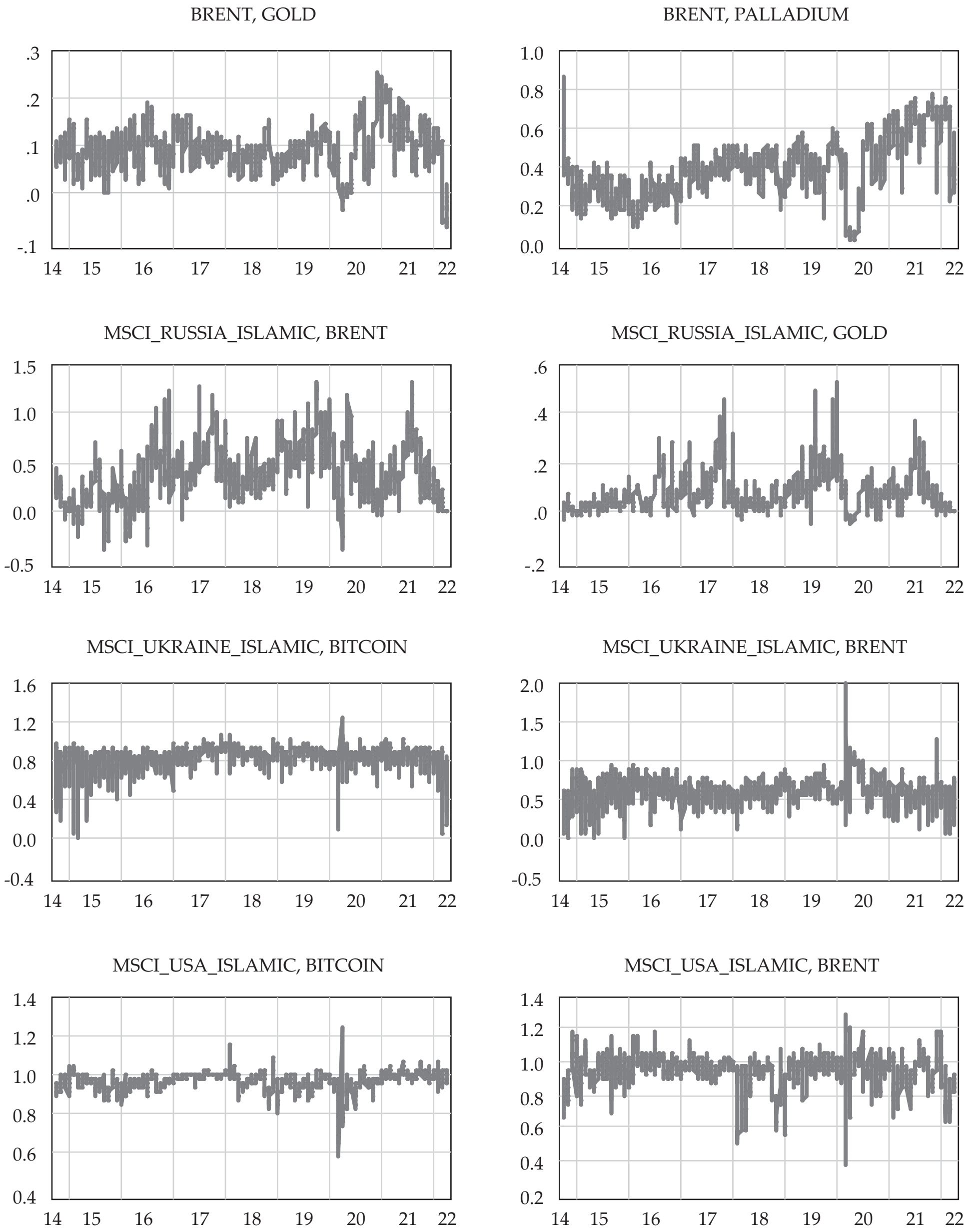


Figure 6.
Time varying Hedging Effectiveness (Continued)

Table 7.
Descriptive Statistics of Time Varying Hedging Effectiveness

	Mean	Median	Maximum	Minimum	Std. Dev.
BITCOIN_BRENT	0.238678	0.217472	0.968732	0.000176	0.144988
BITCOIN_GOLD	0.026471	0.018369	0.684482	1.64E-09	0.042807
BITCOIN_PALLADIUM	0.136441	0.117124	0.399406	9.48E-09	0.076425
BITCOIN_WHEAT	0.118410	0.119802	0.193895	9.58E-05	0.032855
BRENT_GOLD	0.084991	0.072379	0.334505	4.65E-08	0.058658
BRENT_PALLADIUM	0.319081	0.300630	0.702869	0.002118	0.144864
BRENT_WHEAT	0.299386	0.314093	0.675529	0.002353	0.091286
GOLD_PALLADIUM	0.812288	0.824835	0.939302	0.640800	0.066409
GOLD_WHEAT	0.805040	0.810114	0.898369	0.620136	0.044825
MSCI RUSSIA ISL_BITCOIN	0.608561	0.651264	0.984742	1.26E-05	0.242486
MSCI RUSSIA ISL_BRENT	0.261123	0.211032	0.907582	2.92E-07	0.219020
MSCI RUSSIA ISL_GOLD	0.074744	0.046674	0.457856	2.26E-09	0.080445
MSCI RUSSIA ISL_MSCI UKRAINE ISL	0.294686	0.254610	0.953575	6.39E-06	0.197716
MSCI RUSSIA ISL_MSCI USA ISL	0.069259	0.036021	0.609982	9.02E-11	0.085386
MSCI RUSSIA ISL_PALLADIUM	0.177871	-0.202783	0.859178	-0.999975	0.471839
MSCI RUSSIA ISL_WHEAT	0.279559	0.249699	0.855974	0.000130	0.174064
MSCI UKRAINE ISL_BITCOIN	0.778584	0.810260	0.945605	0.000828	0.135272
MSCI UKRAINE ISL_BRENT	0.531110	0.538292	0.995278	8.46E-06	0.169943
MSCI UKRAINE ISL_GOLD	0.116371	0.113320	0.422207	3.20E-10	0.056396
MSCI UKRAINE ISL_MSCI USA ISL	0.155915	0.115145	0.883972	6.98E-07	0.139708
MSCI UKRAINE ISL_PALLADIUM	0.441534	0.448975	0.770200	0.003971	0.141423
MSCI UKRAINE ISL_WHEAT	0.414082	0.450961	0.540806	1.05E-06	0.109345
MSCI USA ISL_BITCOIN	0.941953	0.962581	0.994236	0.382790	0.066746
MSCI USA ISL_BRENT	0.857014	0.889428	0.991500	0.186174	0.097633
MSCI USA ISL_GOLD	0.510813	0.541568	0.777784	2.19E-07	0.167374
MSCI USA ISL_PALLADIUM	0.793431	0.842176	0.964808	0.070780	0.143769
MSCI USA ISL_WHEAT	0.766553	0.819090	0.928531	0.066934	0.149334
PALLADIUM_WHEAT	0.419308	0.460886	0.507291	0.199544	0.087484

IV. CONCLUSION AND RECOMMENDATIONS

To assess the possibility for commodity diversification with financial assets, we examine the dynamic connectivity between financial and commodity markets over time and throughout various time frames. The commodities, energy, and agricultural markets are represented by precious metals (gold), WTI crude, corn, and soybeans, respectively, while the financial sector is represented by the S&P-500 index. According to the entire spillover index, connectivity accounts for 35.81% of the return spillover across commodities and financial assets. The remaining 64.19% comes from one's own shocks.

We find that during the Russian-Ukrainian crisis, Bitcoin's NET connection remains negative for a brief or extended amount of time, making it a prominent beneficiary of global risk contagion, based on the results of the frequency decomposition. However, due to the rapid increase in NET connectivity in these nations, the USA, Russia, and Ukraine have emerged as the main sources of risk contagion in Islamic markets for both the short term and the long term. The recent crisis spillover patterns are in line with the Bitcoin market's net return spillovers staying above zero for a sizable chunk of the sample period. This shows that, for the vast majority of the sample period, the Bitcoin market not only transmitts return shocks to the oil and gold markets but also receives return spillovers from Islamic stocks.

Our findings show that the BITCOIN (MSCI USA ISL) GOLD at 0.429 (-0.035) has the highest (lowest) hedging ratio values. This discovery indicates that a short position (long position) in the gold market could be employed to hedge a long position of $1 in the bitcoin market for 0.429 (0.035) cents. Importantly, according to this result, BITCOIN (MSCI USA ISL) appears to be the most expensive (least costly) hedge for the gold market.

These findings suggest that, depending on their individual Shariah compliance and the precise hedge ratio they are aiming for, Islamic finance investors who want to manage their risk exposure in gold-related assets may benefit from considering both MSCI USA ISL_ Gold and Bitcoin _Gold as potential hedges.

When investing in the cryptocurrency, commodities, and Islamic stock markets, active portfolio management is required, based on the findings from the time-varying optimal hedging ratio, indicating that the optimal weights fluctuate throughout the sample period. Additionally, the optimal weight for the MSCI UKRAINE ISL_PALLADIUM portfolio is discovered to be 0.46, indicating that in a USD 1 portfolio consisting of MSCI UKRAINE ISL stocks and PALLADIUM, USD 0.54 should be invested in MSCI UKRAINE ISL stocks and USD 0.46 in PALLADIUM to reap the benefits of diversity. The low correlation between the returns of the MSCI UKRAINE ISL_PALLADIUM portfolio's components, which benefits investors by ensuring diversity, can be used to explain this finding. Investors can lower portfolio risk without sacrificing returns by holding both MSCI UKRAINE ISL equities and PALLADIUM. According to the time-varying optimal weights, the correlation between the two assets shifts with time, necessitating active portfolio management to preserve the ideal allocation.

The conclusions drawn from this research are expected to have substantial implications for portfolio managers and investors, both adhering to Shariah principles and conventional, as they will facilitate a better understanding of the advantages of portfolio diversification across various stock holding durations or investment horizons. The study offers a more thorough understanding of the dynamic interconnections and hedging opportunities that exist in the markets for commodities, Islamic stocks, and cryptocurrencies, which is likely to aid portfolio managers in resource allocation and portfolio optimization.

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