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Time-varying market efficiency of safe-haven assets

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ABSTRACT

This study investigates the hedge and safe-haven possibilities with bitcoin, gold and crude oil in different equity markets in the presence of time-varying market inefficiency. Our results indicate that periods of market inefficiency for the Bitcoin, gold and crude oil price positively influence their function as a hedge asset for the equity markets of Japan, China, the US, Europe and emerging countries. In addition to contributing to the discussion on the factors which affect the functioning of safe-haven assets, the empirical findings of this study further highlight the importance of market efficiency as a market microstructure feature. These results have important implications for investors seeking to manage risk through diversification across different asset classes.

1. Introduction

In this paper, we investigate the safe-haven and hedge properties of Bitcoin, gold, and crude oil during periods of time-varying market efficiency, focusing on their ability to hedge performance in equity markets across Japan, China, the US, Europe, and emerging countries. Our hypothesis is that the level of market inefficiency in these safe-haven assets significantly influences their effectiveness as hedging instruments for equity markets. We employ a regression analysis that accounts for time-varying market inefficiency to provide insights into their hedging abilities under various economic conditions. By analyzing these popular assets, we contribute to the discussion on factors affecting the functioning of safe-haven assets and highlight the importance of market efficiency as a market microstructure feature, with implications for investors seeking risk management through diversification across different asset classes.

The ability of one asset to reduce and even minimize the loss of an investment portfolio is a persistent and recurring debate in the financial literature, particularly in periods following global financial distress. Baur and McDermott (2010) define a safe-haven asset as an investment that is expected to retain or increase its value during times of market turbulence and economic uncertainty. The safe-haven property for an asset is the most sought-after property among the three risk-reducing properties, as it exhibits a value-preserving function when it is most needed. While hedge assets and diversifiers offer negative or low correlation, respectively, during "normal times", the safe-haven asset acts as a hedge asset when the financial market is in turmoil and investments are prone to capital depreciation. Despite ongoing research, there is still no widespread agreement on the degree of reliability and consistency with which safe-haven assets perform, nor is there a consensus on the factors that may cause variations in their performance over

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time. To address this, we analyze how market efficiency evolves over time, and how this is related to the safe-haven properties of common SHA's.

Although various types of "flight to safety" assets have been suggested, see e.g Hartmann et al. (2004) and Ranaldo and Söderlind (2010), the last few decades have seen much attention given to commodities (especially oil and gold) and, in recent years, cryptocurrency (especially Bitcoin), see, for example, Kumar and Padakandla (2022) and Wen et al. (2022). The inverse relationship between these commodities and other asset markets has been the basis for including gold and oil as safe assets in financial portfolios (Jensen et al., 2000). Before the financial market crash of 2008, there was an exponential increase in the purchase of commodity futures by hedge funds and institutional investors looking to diversify their investment risk (Masters, 2008). In our study, we examine the pricing efficiency of gold, Bitcoin, and oil, focusing on how efficiency evolves over time in general, and during times of crisis in particular.

The activities of index speculators have been widely criticized for contributing to the phenomenon known as the "financialization of commodity markets". A study by Silvennoinen and Thorp (2013) suggests that this trend has increased speculation and volatility in the commodity market, and raises questions about the reliability of gold and oil as safe-haven assets for investors during times of market turbulence. For instance, while both Baur and Lucey (2010) and Kumar and Padakandla (2022) find that gold in fact acts as a strong safe-haven asset for stocks and bond markets of developed countries during extreme shocks, albeit for a limited duration, Drake (2022) finds that gold does not act as a safe-haven unless the real-interest rate is negative. Moreover, Bekiros et al. (2017) find that gold is a diversifier but not a hedge or safe-haven asset for equity markets in BRIC countries, whereas Bouri et al. (2020b) find that it performs well as a safe-haven asset for developed and emerging equity indices. Although Wen et al. (2022) find empirical evidence of strong hedging abilities with gold during the pandemic, Akhtaruzzaman et al. (2021) and Drake (2022) find that the pandemic impacts gold's safe-haven abilities. Furthermore, Silvennoinen and Thorp (2013), Junttila et al. (2018), Martínez-Cañete et al. (2022) find evidence of an increasing correlation between the oil and equity market, while Batten et al. (2021), Belhassine and Karamti (2021) find evidence of oil's hedge abilities in the equity market during the pandemic. In our paper, we aim to shed light on the lack of consensus regarding the safe-haven property of gold by examining various factors that may influence its risk-reducing abilities.

Bitcoin has been classified as a safe-haven asset and earned the nickname "digital gold" since its establishment in 2010 (Popper, 2015). In fact, Bouri et al. (2020b) find that bitcoin outperforms gold and commodities in terms of risk-hedging in the equity market. However, even bitcoin's designation as a safe-haven asset has not been without controversy. For instance, while Bouri et al. (2020a,b), Dyhrberg (2016), Belhassine and Karamti (2021) argue for the validity of bitcoin as a safe-haven asset for the traditional asset markets, Cheema et al. (2020), Long et al. (2021), Choi and Shin (2022), Kumar and Padakandla (2022), Wen et al. (2022) argue the contrary. Long et al. (2021) find that bitcoin cannot act as a safe-haven in the presence of uncertainty-based shocks. Choi and Shin (2022) suggests that bitcoin can only function as a hedge against inflation but not as a safe- haven during periods of turmoil in the global equity market. Kumar and Padakandla (2022), Wen et al. (2022) observe that the hedging abilities of bitcoin are time-varying and noticeably lacking during the pandemic.

Several external factors have been proposed as affecting safe-haven abilities over time. For example, proponents of commodity market financialization suggest that the volatility in the equity market can explain changes in the relationship between commodities and equity stocks, which has motivated the use of the stock market volatility index (VIX) in the existing literature (Silvennoinen and Thorp, 2013; Batten et al., 2021; Long et al., 2021). The impact of macroeconomic factors, such as changes in interest rates and monetary policy, has also been examined by other studies. For instance, Drake (2022), Martínez-Cañete et al. (2022) find that changes in interest rates explain the changing relationship between safe-haven assets and the equity market. We apply a similar methodology as Drake (2022), including dummy variables for periods of particular interest.

According to Mikhaylov et al. (2022), the interdependence of oil prices and exchange rate movements of oil-exporting countries is crucial in analyzing the risk-based oil market spillovers during periods of crises. Akhtaruzzaman et al. (2021) find that gold's relationship with other asset markets becomes positive, and it loses its SHA abilities after introducing the Covid-19 economic relief packages. Furthermore, Moiseev et al. (2023) analyze shock effects on a particular segment of the market, e-commerce, and find that the impact of Covid-19 restrictions on revenues was dependent on the market capitalization of the firm. This study departs from the existing literature by looking at the impact of internal factors, such as the microstructure features of the safe-haven asset market. We further examine the role efficient price discovery plays in the hedging abilities of these assets.

Examining the influence of a safe-haven asset's market microstructure is not entirely novel. In a critique of the growing attention bitcoin has received, Smales (2019) suggests that several aspects of the cryptocurrency market, such as limited liquidity and the price formation process, may make for an unreliable safe-haven asset. While previous studies suggest that commodities and cryptocurrencies retain their value during market turbulence due to the supply restrictions associated with these markets, our study hypothesizes that inefficiency in the pricing discovery of these assets also plays a role in their hedging abilities during market downturns.

Market efficiency is an essential market attribute as it determines how closely the market price of an asset reflects its fundamental or intrinsic value. While the definition of an efficient market, as a market in which the price reflects all available information about the asset, is still widely used, there have been several advancements in the study of market efficiency since the seminal work of Fama (1970). One example is the adaptive market hypothesis (AMH) proposed by Lo (2004), which suggests that the efficiency level within a market is time-variant and depends on the conditions, events, and participants within a market. Following the proposition of Lo, several measures of time-varying market efficiency have been developed and applied to various classes of asset markets with empirical findings which confirm the AMH (see e.g. Noda, 2016; Tran and Leirvik, 2019). In this paper, we study how efficiency varies over time.

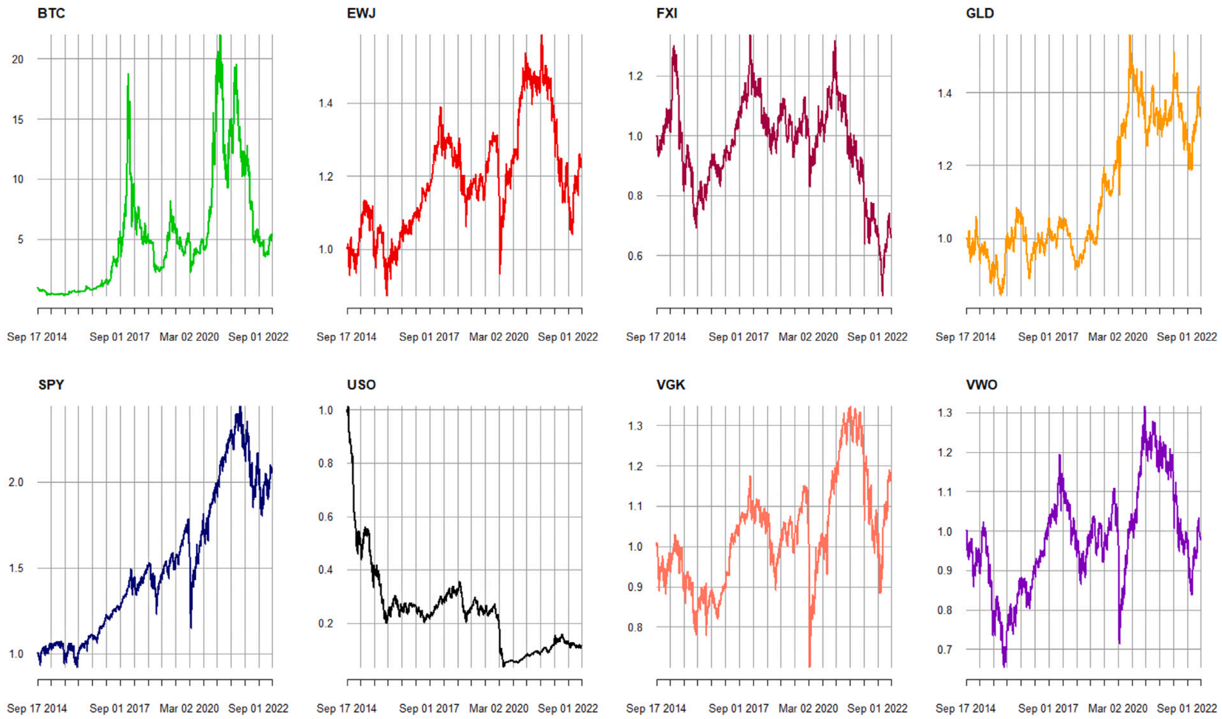


Fig. 1. Performance of each market based on 1 USD invested on September 17, 2014.

Several studies have investigated the efficiency levels of safe-haven assets, but none have explored if this efficiency influences their hedging abilities. For example, Wang et al. (2011) claims that gold market efficiency has improved since 2001, while Al-Yahyaee et al. (2018) finds that stock and currency markets are more efficient than gold or bitcoin markets. Although Tran and Leirvik (2020) reports increasing bitcoin efficiency over time, Manahov and Urquhart (2021) concludes the market is inefficient using high-frequency data. Zhang (2013) observes improved WTI crude oil market efficiency since 2005, but Okoroafor and Leirvik (2022) finds WTI becoming less efficient than Brent over time. Furthermore, Mikhaylov et al. (2023) highlights crucial factors for well-functioning liquid financial markets, emphasizing competitive bank lending and equal, transparent access to information.

Given the evidence of intermittent efficiency in these markets, this study contributes to the literature by investigating the influence of market inefficiency on the risk-hedging abilities of safe-haven assets during periods of market turbulence. We apply the definitions of safe-haven and hedge assets developed in Baur and Lucey (2010) and the measures of time-varying market efficiency by Tran and Leirvik (2019) and Noda (2016). The results indicate market inefficiency influences the relationship between these safe-haven assets and the equity markets studied as increasing (decreasing) market inefficiency improves (inhibits) the hedging abilities of these assets in the equity market.

2. Data

We apply daily prices for Bitcoin and Exchange Traded Funds (ETFs) tracking gold, crude oil, and the equity markets in the US, China, Europe, Japan, and emerging economies. Representing gold in this study is the SPDR gold Exchange Traded fund (*gld*), the largest with respect to assets under management physically backed gold ETF in the world. For the equity markets, we apply the iShares MSCI Japan (*ewj*), iShares China Large-Cap ETF (*fxi*), SPDR S&P500 (*spy*), Vanguard FTSE Europe (*vgk*) and Vanguard FTSE Emerging markets (*vwo*) as proxies for the stock indices of these equity markets. The United States Oil Fund (*uso*), an exchange-traded fund whose benchmark is the near-month West Texas Intermediate (WTI) crude oil futures contract, represents the oil prices. We include the Chicago Board Options Exchange's CBOE Volatility Index (*vix*) and the SP 500 VIX Mid-Term Futures Index (*vixm*) as a control for the market's expectation of stock volatility over the next 30 days and five months, respectively. We have observations from December 1st 2007, through February 17 2023, but for Bitcoin (*btc*), the starting date is September 18, 2014. All variables have been transformed by taking the logarithmic price difference. From the observations, we compute the time-varying market inefficiency for the safe-haven assets gold, oil, and bitcoin. Fig. 1 presents the log-returns of the variables used in our analysis. We observe a sharp decline in the crude oil ETF (*uso*) resulting from the oil price supply glut of 2014, which adversely affected the market.

The level of market inefficiency within the market is measured using the Adjusted Market Inefficiency Magnitude (AMIM) model derived in Tran and Leirvik (2019).

$$\begin{aligned} r_t &= \alpha + \beta_1 r_{t-1} + \cdots + \beta_q r_{t-q} + \varepsilon_t \\ MIM_t &= \frac{\sum_{j=1}^{q} \mid \hat{\beta}_{j,t}^{standard} \mid}{1 + \sum_{j=1}^{q} \mid \hat{\beta}_{j,t}^{standard} \mid} \\ AMIM_t &= \frac{MIM_t - R_{CI}}{1 - R_{CI}} \end{aligned} \tag{1}$$

where r_t is the return of the asset, MIM_t is the Market Inefficiency Magnitude (MIM) at time t, R_{CI} is the range of confidence intervals for the MIM and $\hat{\beta}_{j,t}^{standard}$ are the standardized beta coefficient from an auto-regressive model with q number of lags AR(q) as in the Equation for r_t. The AMIM model is chosen in this study due to its ability to capture the time-varying level of market inefficiency in an asset's price. The asset is significantly efficient when $AMIM \leq 0$ and is significantly inefficient otherwise, which makes comparison over time and across assets simple. A thorough derivation of $AMIM_t$ and its range of confidence intervals (R_{CI}) is provided in Tran and Leirvik (2019).

In Table 1, we have presented summary statistics for all variables for the entire period (Panel A), for periods without any substantial crisis in the global financial markets (Panel B), periods during the ongoing war in Ukraine (Panel C), the global Covid-19 pandemic period (Panel D), and the Global Financial Crisis (Panel E). The average return on BTC is relatively higher than any of the other assets studied except in the period since the onset of the war in Ukraine. However, Bitcoin also consistently has the highest level of risk in every period examined. Crude oil offers the only positive average return among the assets studied during the financial distress caused by the war in Ukraine. On the other hand, while not offering the highest average returns, Gold has the lowest variance of all other assets in both crises and non-crises periods. GLD had the highest return and lowest standard deviation of all other investment assets during the GFC period. During the Covid period, it had the third highest mean return and lowest standard deviation of all other assets studied. The statistics for the gold market in every sub-sample are consistent with its reputation as a safe-haven asset. As identified in Smales (2019), Bitcoin's high volatility during the crises and non-crises period casts doubt on whether its inclusion in a portfolio may offer an investor any peace of mind.

Table 2 presents summary statistics for the market efficiency, as measured by AMIM. From Panel A in Table 2, we see that for the entire period, AMIM is generally negative in the Gold and Oil market, indicating that prices are, on average, efficiently priced in these markets. The efficiency level in the gold market significantly deteriorated during the GFC and the pandemic, while in the oil market, market inefficiency is observed during every crisis period. In contrast, the inefficient Bitcoin market became the most efficient during the Covid pandemic and the ongoing war. This increase in Bitcoin's efficiency is likely a result of increased liquidity within the cryptocurrency market as investors move their investments from other assets when there is financial distress in the global market.

Methodology

Our analysis begins by investigating if gold, bitcoin and crude oil function as safe-haven assets, hedge assets or diversifiers in the stock market. The definition of the terms safe-haven, hedge and diversified, and the regression models are based on Baur and Lucey (2010). In the baseline model, we investigate the relationship between the safe-haven assets (Bitcoin, Gold, and Oil) and the stock market, considering periods of substantial financial stress in the stock market.

$$\begin{aligned} r_{i,t} &= \alpha + \beta r_{m,t} + \varepsilon_t \\ \beta &= \beta_1 + \beta_2 D_{m,q_{0.01}} + \beta_3 D_{m,q_{0.05}} + \beta_4 D_{m,q_{0.10}} \end{aligned} \tag{2}$$

Where: i = safe-haven assets (*btc, gld and uso*), m = regional stock assets (*ewj, fxi, spy, vgk, vwo*), and the dummy variables ($D_{m,q_{0.01}}, D_{m,q_{0.05}}$ and $D_{m,q_{0.10}}$) take the value of 1 when the stock market return is below the 1%, 5% and 10% lower percentile respectively. In Eq. (2), $\beta = \beta_1, \beta_2, \beta_3, \beta_4$ is a vector which tests the relationship between the SHA and the stock asset when stock returns fall below the specified threshold. The significance of the parameters β_2, β_3 and β_4 indicate a non-linear relationship between the safe-haven asset and the stock market. The safe-haven asset is a strong safe-haven asset if the values of $\beta_1, \beta_2, \beta_3$ and β_4 are negative and statistically significant, and a weak safe-haven asset if they are negative but not statistically significant. The SHA function as a strong (weak) hedge if the value of β_1 is negative (zero) and if the sum of β_2, β_3 and β_4 does not exceed the value of β_1.

$$\begin{aligned} r_{i,t} &= \alpha + \beta r_{m,t} + \zeta_1 vix_{m,t} + \zeta_2 vixm_{m,t} + \varepsilon_t \\ \beta &= \beta_1 + \beta_2 D_{m,q_{0.01}} + \beta_3 D_{m,q_{0.05}} + \beta_4 D_{m,q_{0.10}} \end{aligned} \tag{3}$$

In Eq. (3), $vix_{m,t}$ and $vixm_{m,t}$ are interactive dummy variables which take the value of the stock return when stock market volatility increases and the value zero otherwise. When the value of the coefficient for $vix_{m,t}$ and $vixm_{m,t}$ is positive, it indicates that an increase in market volatility in the short and medium term inhibits the hedge abilities of these assets in the equity market.

$$\begin{aligned} r_{i,t} &= \alpha + \beta r_{m,t} + \zeta_1 vix_{m,t} + \zeta_2 vixm_{m,t} + \zeta_3 ME_{i,m,t} + \varepsilon_t \\ \beta &= \beta_1 + \beta_2 D_{m,q_{0.01}} + \beta_3 D_{m,q_{0.05}} + \beta_4 D_{m,q_{0.10}} \end{aligned} \tag{4}$$

Table 1
Descriptive statistics for the market historical return in the safe-haven and the regional equity markets. The mean is the sample average; sd is the standard deviation; and max(min) is the maximum (minimum) values obtained in this sample. The ADF is the Augmented Dickey–Fuller test for stationarity.

Descriptive statistics of market return								
	Panel A: Full sample (2014–2023)							
	btc	ewj	fxi	gld	spy	uso	vgk	vwo
mean	47.3533	3.8880	−1.2525	4.4742	10.2690	−16.9991	4.0259	1.8986
sd	72.479	17.333	27.459	14.289	18.506	42.077	20.062	20.892
max	22.512	6.714	19.261	4.787	8.673	15.415	8.670	7.494
min	−46.473	−10.319	−10.860	−5.519	−11.589	−29.189	−12.532	−12.885
skew	−0.6900	−0.6021	0.4422	−0.1329	−0.7916	−1.5451	−1.4201	−0.8426
kurtosis	8.8017	7.3798	9.9002	3.0736	13.2566	17.3544	16.1033	9.0683
ADF	−11.578***	−13.232***	−12.929***	−12.288***	−12.827***	−12.707***	−13.477***	−12.913***
	Panel B: Non-crises sample (2014–2019)							
	btc	ewj	fxi	gld	spy	uso	vgk	vwo
mean	0.2070	0.0241	0.0167	0.0147	0.0436	−0.0755	0.0150	0.0121
sd	4.5438	0.9599	1.4293	0.8164	0.8482	2.1909	0.9925	1.1489
max	22.5119	4.8417	6.8199	4.7874	4.9290	11.4670	4.0762	3.9495
min	−23.8740	−4.8493	−7.4438	−3.5328	−4.3019	−8.6816	−11.9779	−5.8303
	Panel C: Russo-Ukraine (2022–2023)							
	btc	ewj	fxi	gld	spy	uso	vgk	vwo
mean	−0.1953	−0.0391	−0.0770	−0.0135	−0.0192	0.0138	−0.0092	−0.0638
sd	4.0654	1.2371	2.7070	0.9749	1.5088	2.7482	1.6168	1.3900
max	10.4854	5.4356	19.2612	3.0235	5.3497	7.6115	5.6726	7.4942
min	−25.7227	−3.5775	−10.5268	−3.0162	−4.4456	−12.3962	−4.3199	−3.9689
	Panel D: Covid pandemic (2020)							
	btc	ewj	fxi	gld	spy	uso	vgk	vwo
mean	0.5511	0.0566	0.0338	0.0876	0.0665	−0.4478	0.0234	0.0558
sd	4.8356	1.6160	2.0151	1.2302	2.1196	4.6327	2.1777	2.0825
max	16.7104	6.7139	9.0783	4.7390	8.6731	15.4151	8.6697	6.7700
min	−46.4730	−10.3193	−10.8599	−5.5190	−11.5886	−29.1891	−12.5316	−12.8847
	Panel E: Global Financial Crisis (2007–2009)							
	btc	ewj	fxi	gld	spy	uso	vgk	vwo
mean		−0.0653	−0.2539	0.0443	−0.0491	−0.0894	−0.0682	−0.1630
sd		2.2820	6.4490	1.7070	2.1620	3.0710	2.5370	4.4880
max		15.8560	18.4570	10.6970	13.5580	9.1690	13.2700	18.4670
min		−10.9900	−114.2500	−7.7210	−10.3640	−11.3000	−11.9420	−68.4350

***Indicates a stationary time series at the 1% significance level.

Table 2
Descriptive statistics for the time-varying inefficiency level in the safe-haven and the regional equity markets. The full sample is from 2014 to February 2023, the non-crises sample is from 2014–2019, the Russo-Ukraine war is from February 2022–17 February 2023, the Covid-19 sample covers 2020, and the Global Financial Crisis (GFC) sample is from Dec 2007–June 2009. AMIM values $AMIM \leq 0$ indicate efficiency within the market, while values greater than zero indicate inefficiency.

Descriptive statistics of AMIM (market inefficiency)	Full sample			Non-crises			Russo-Ukraine war			Covid pandemic			GFC sample	
	btc	gld	uso	btc	gld	uso	btc	gld	uso	btc	gld	uso	gld	USO
mean	0.006	−0.006	−0.005	0.014	−0.011	−0.011	−0.014	−0.008	0.023	−0.011	0.011	0.018	0.043	0.010
sd	0.077	0.075	0.071	0.081	0.085	0.065	0.049	0.039	0.064	0.106	0.065	0.093	0.089	0.051
max	0.4586	0.2918	0.3366	0.4586	0.2918	0.3366	0.082	0.119	0.264	0.1856	0.2748	0.3151	0.387	0.241
min	−0.3082	−0.4253	−0.3739	−0.308	−0.425	−0.374	−0.288	−0.280	−0.154	−0.2288	−0.2207	−0.2288	−0.084	−0.229

In Eq. (4), $ME_{i,m,t}$ is an interactive dummy variable which takes the value of the stock return when the safe-haven asset is inefficient and the value 0 otherwise. When market inefficiency is measured using the AMIM measure, then

$$ME_{i,m,t} = \begin{cases} r_{m,t} & \text{if AMIM} > 0 \\ 0 & \text{if AMIM} \leq 0 \end{cases}$$

Table 3
Correlation between the return of each safe-haven and the regional stock market. The full sample is from September 2014 to February 2023, the non-crises sample is from September 2014–December 2019, the Russo-Ukraine war is from February 2022–February 2023, the Covid-19 sample covers the year 2020, and the Global Financial Crisis (GFC) sample is from Dec 2007–June 2009.

Pearson correlation between the safe haven assets and the regional stock market.

	Full sample					Non-crises				
	ewj	fxi	spy	vgk	vwo	ewj	fxi	spy	vgk	vwo
btc	0.1708***	0.1370***	0.2187***	0.2168***	0.1850***	−0.0111	0.0079	0.0175	0.0250	0.0172
gld	0.0477**	0.0523 **	0.0287	0.1007***	0.1202***	−0.1194***	−0.0824***	−0.1621***	−0.0584	0.0113
uso	0.2522***	0.2363***	0.3350***	0.3482***	0.3585***	0.2761***	0.2856***	0.3391***	0.3655***	0.3842***

	Russo-Ukraine war					Covid pandemic				
	ewj	fxi	spy	vgk	vwo	ewj	fxi	spy	vgk	vwo
btc	0.5176***	0.4021***	0.5594***	0.5286***	0.5249***	0.4536***	0.3381***	0.4479***	0.4802***	0.4347***
gld	0.3353***	0.2205***	0.2229***	0.3245***	0.3228***	0.1621***	0.1626***	0.1605***	0.1840***	0.1858***
uso	0.1587**	0.0779	0.1329**	0.1145*	0.1294*	0.2730***	0.3438***	0.4344***	0.4433***	0.4460***

	Global Financial Crisis				
	ewj	fxi	spy	vgk	vwo
btc					
gld	0.0961**	0.0011	0.0305	0.1549***	0.0829*
uso	0.3989***	0.2504***	0.461***	0.5199***	0.3631***

***Indicate significance at the 1% significance level.
**Indicate significance at the 5% significance level.
*Indicate significance at the 10% significance level.

Table 4
Summary statics of the 30-day rolling correlation between each Safe-haven asset and the regional Equity Markets from 18/09/2014 to 17/02/2023.

Summary statics of the 30-day rolling correlation

	Panel A: Bitcoin (btc)					Panel B: Gold (gld)					Panel C: Crude oil (uso)				
	ewj	fxi	spy	vgk	vwo	ewj	fxi	spy	vgk	vwo	ewj	fxi	spy	vgk	vwo
mean	0.0980	0.0853	0.1373	0.1426	0.1260	0.0430	0.0301	−0.0285	0.1139	0.1256	0.2499	0.2430	0.3062	0.3262	0.3269
sd	0.2983	0.2602	0.2843	0.2725	0.2850	0.3174	0.2846	0.3184	0.3243	0.2945	0.2232	0.2379	0.2266	0.2311	0.2274
max	0.7920	0.7085	0.7940	0.8070	0.7836	0.8037	0.7484	0.6982	0.8273	0.8226	0.7502	0.7229	0.8565	0.8479	0.8478
min	−0.6204	−0.5469	−0.6485	−0.6011	−0.6131	−0.7632	−0.7015	−0.7431	−0.7242	−0.6688	−0.6345	−0.4975	−0.5184	−0.6238	−0.5423

The coefficient on $ME_{i,m,t}$ determines if inefficiency in the SHA market affects its ability to hedge equity market portfolios. If the coefficient is significant and positive, this indicates that the driver of the safe-haven-to-market relationship is the inefficiency in the safe-haven asset's price.

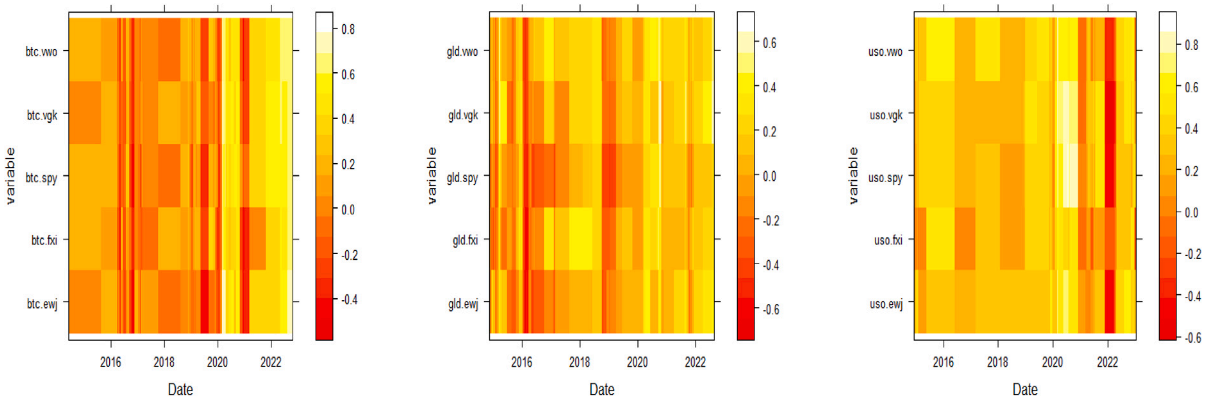
3. Empirical results and discussion

3.1. Correlation between the SHAs and the equity market

The results from the Pearson correlation test are presented in Tables 3. The Pearson correlation estimates indicate that the BTC market return is positively correlated with the return of the regional equity markets during the crisis periods. Gold is negatively correlated with the equity market during non-crises periods but becomes positively correlated with these markets during every crisis. Crude oil positively correlates with every equity market in this study in both crisis and non-crisis periods. When the correlation size is examined, bitcoin has the strongest correlation with the equity market during the Covid pandemic and the war in Ukraine, while crude oil has the strongest correlation with the equity market during the GFC (see Fig. 2).

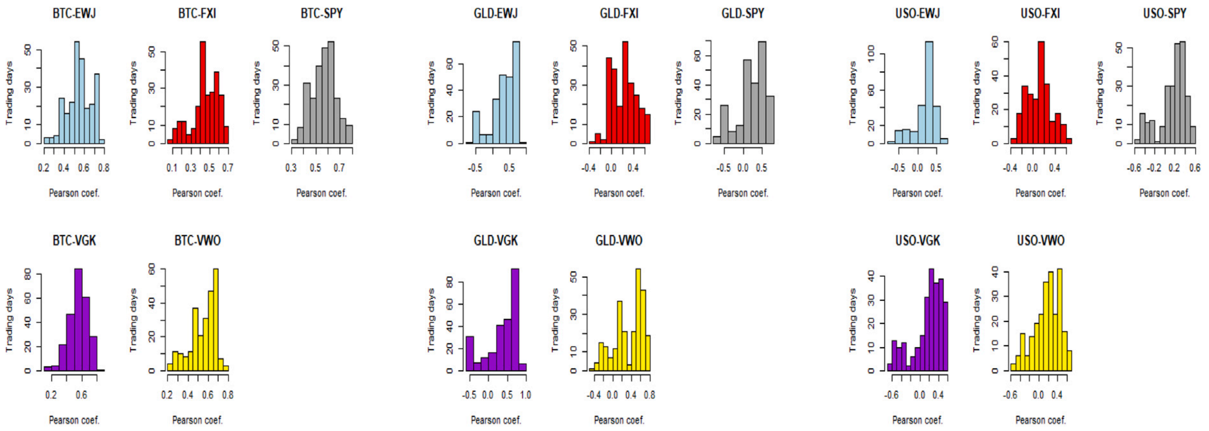
The 30-day rolling correlation is used to investigate the correlation between the return of the safe-haven assets and equity assets over time. The results are summarized in Table 4 and support those obtained above in that the correlation between the safe-haven assets and the equity market is primarily positive.

The histograms in Figs. 3–5 present the correlation distribution between the safe-haven and regional equity markets during the war in Ukraine, the Covid pandemic and the global financial crisis. The correlation distribution of the correlation coefficient during these periods is a U-shaped bi-modal distribution with one cluster of negative correlations and one cluster with positive correlations. This indicates two local extremes during this period, representing a maximum number of trading days with negative and positive correlations. It also suggests that the market is split into two regimes during this period, trading days with higher and lower levels of market inefficiency. A test of the difference between the mean levels of market inefficiency in these two groups using the Welch t-test indicates that the average level of market inefficiency is statistically different. The trading days with higher (lower) inefficiency levels have a local maximum centred around a negative (positive) correlation coefficient. This suggests that the relationship between safe-haven assets and the equity market is state-dependent on the inefficiency of the safe-haven market.



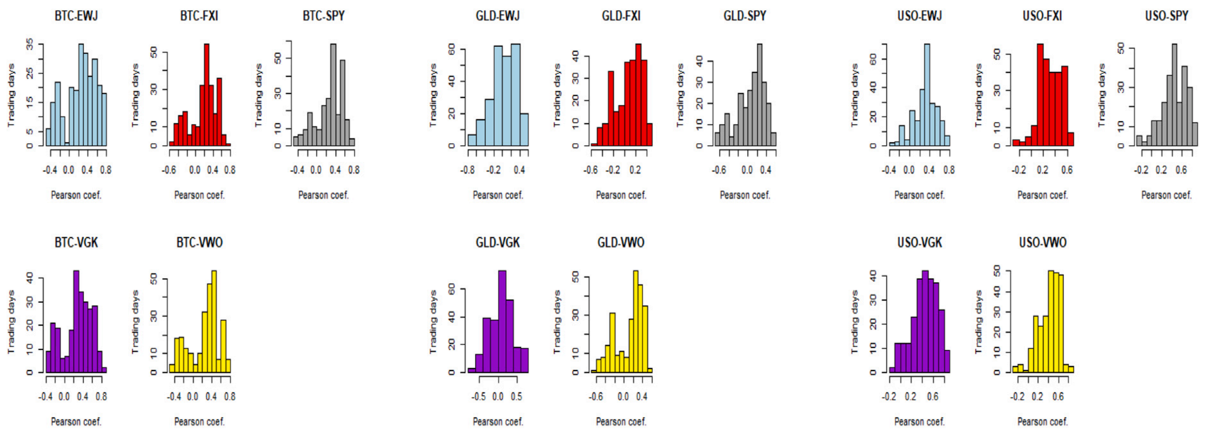
(a) BTC (b) GLD (c) USO

Fig. 2. Heatmap of the 30-day moving correlation between the safe-haven assets and the regional equity markets in Japan (EWJ), China (FXI), the US (SPY), Europe (VGK) and emerging countries (VWO) during periods of inefficiency in the SHA market.



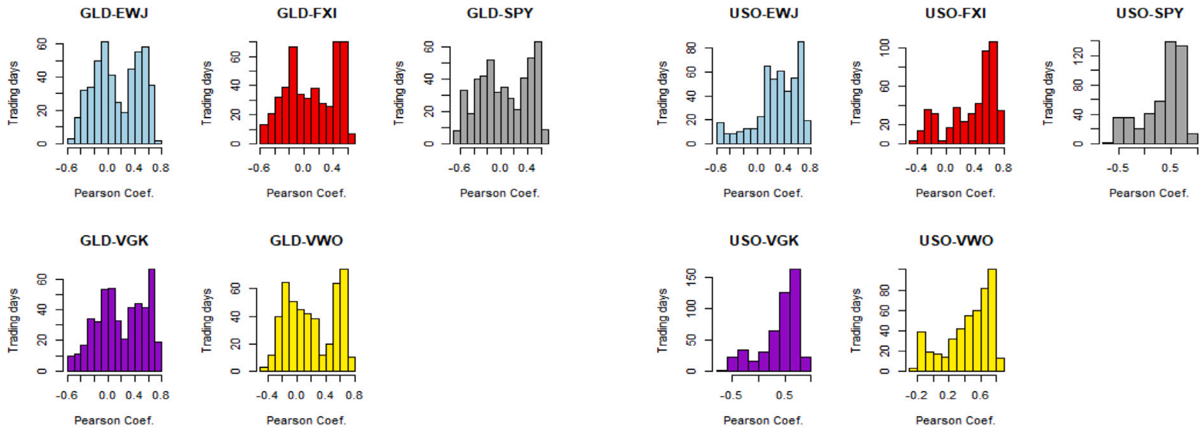
(a) BTC (b) GLD (c) USO

Fig. 3. Distribution of the 30-day rolling correlation between the safe-haven assets and the regional equity markets in Japan (EWJ), China (FXI), the US (SPY), Europe (VGK) and emerging countries (VWO) during the war in Ukraine.



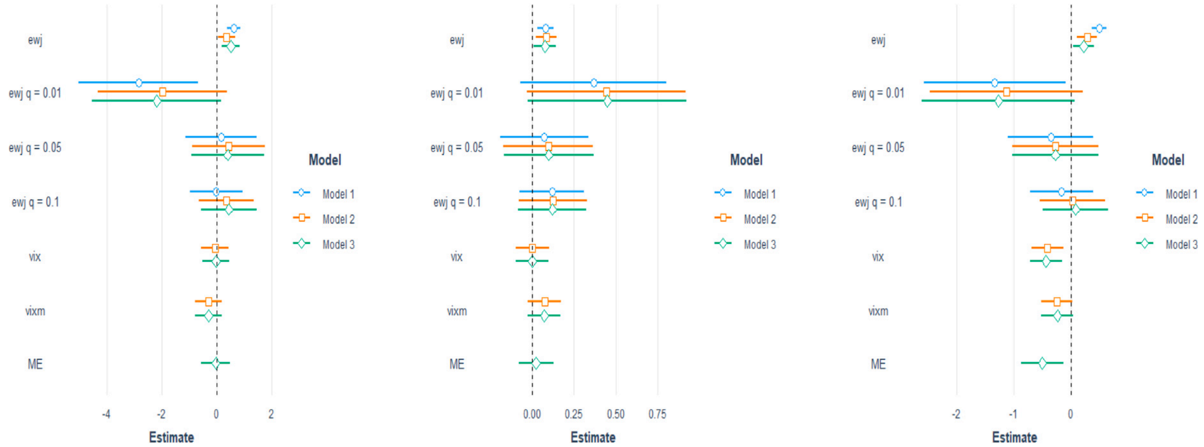
(a) BTC (b) GLD (c) USO

Fig. 4. Distribution of the 30-day rolling correlation between the safe-haven assets and the regional equity markets in Japan (EWJ), China (FXI), the US (SPY), Europe (VGK) and emerging countries (VWO) during the Covid pandemic of 2020.



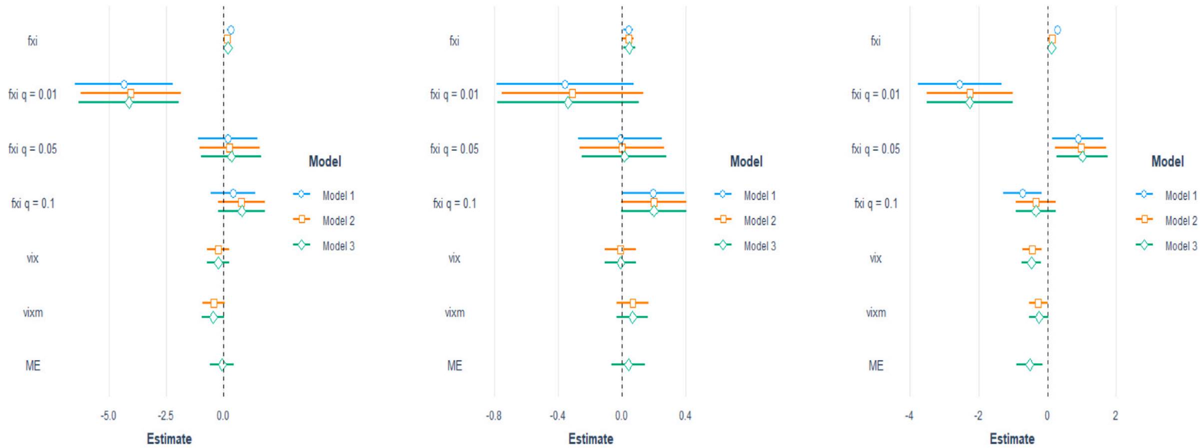
(a) GLD (b) USO

Fig. 5. Distribution of the 30-day rolling correlation between the safe-haven assets and the regional equity markets in Japan (EWJ), China (FXI), the US (SPY), Europe (VGK) and emerging countries (VWO) during the Global Financial crises of December 2007–June 2009.



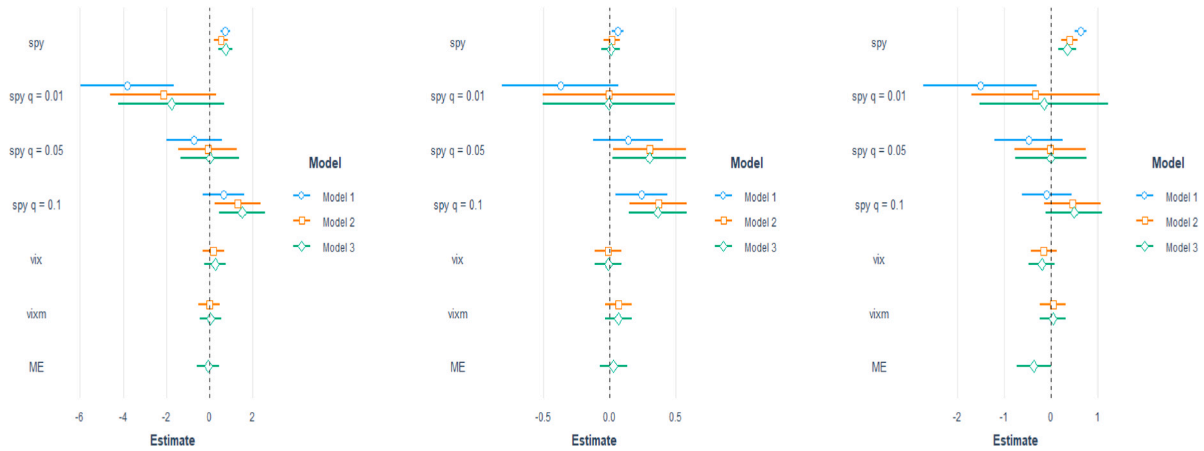
(a) BTC (b) GLD (c) USO

Fig. 6. Visual comparison of the regression coefficients for the equity market in Japan (EWJ).



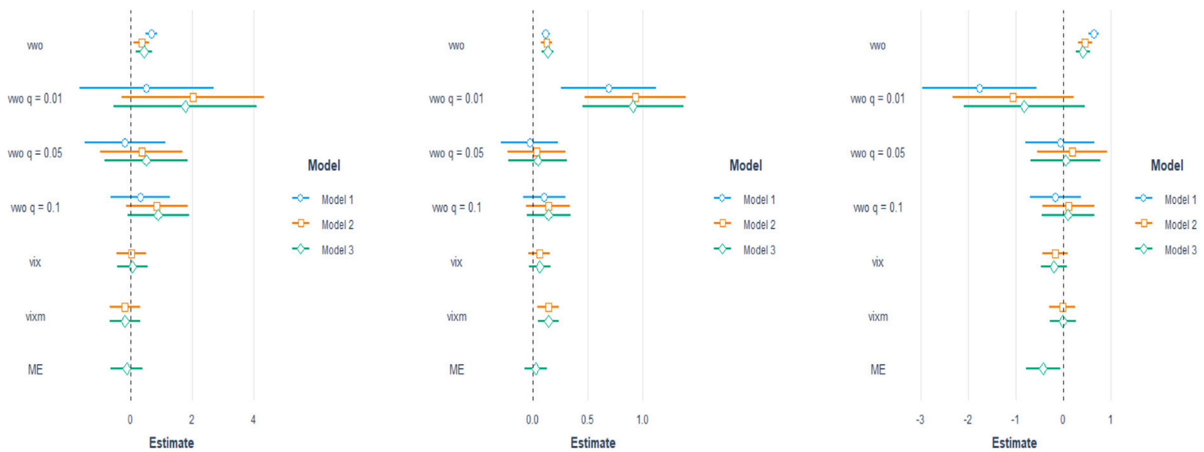
(a) BTC (b) GLD (c) USO

Fig. 7. Visual comparison of the regression coefficients for the equity market in China (FXI).



(a) BTC (b) GLD (c) USO

Fig. 8. Visual comparison of the regression coefficients for the equity market in the US (SPY).



(a) BTC (b) GLD (c) USO

Fig. 9. Visual comparison of the regression coefficients for the equity market in Europe (VWO).

3.2. Regression results

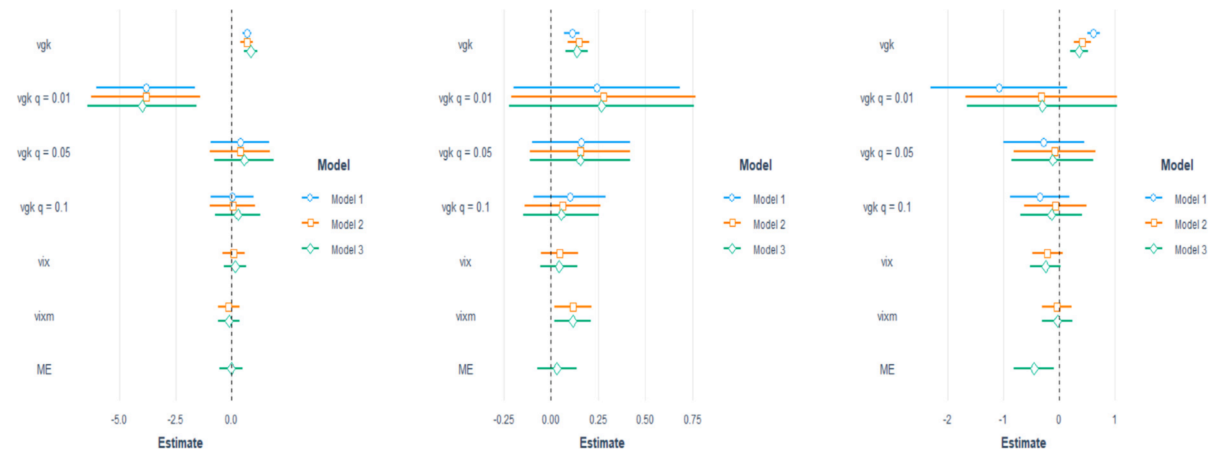
The coefficient estimates from fitting the data to the models in Eqs. (2) and (4) are presented in Tables 5–9 for each equity market studied. The bitcoin, gold and crude oil results are presented in Panel A, B and C in each regression table. Figs. 6–10 further illustrate the regression coefficients with diagrams.

3.2.1. Bitcoin

The β_1 coefficient in the Bitcoin model is consistently positive across all equity markets, indicating that Bitcoin does not serve as a hedge for any of the stocks in the sample, which is consistent with previous research by Cheema et al. (2020).

In terms of Bitcoin's safe-haven abilities, the results are mixed depending on the market conditions. When stock returns are lower than the 0.01, 0.05, and 0.1 percentiles, Bitcoin functions as a safe-haven asset in Japan, China, the US, and Europe, but not in emerging economies. However, at the 5% and 10% percentiles, Bitcoin's safe-haven abilities in the equity markets are notably lacking.

The findings suggest that the expectation of higher stock volatility in the medium term improves the hedge function of Bitcoin in the European equity market. Furthermore, the coefficient ζ_3, which measures the impact of market inefficiency on Bitcoin returns, is negative across all equity markets analyzed. This suggests that inefficiency influences the relationship between Bitcoin and the equity markets, and the otherwise positive relationship becomes negative when the Bitcoin market is inefficient.



(a) BTC (b) GLD (c) USO

Fig. 10. Visual comparison of the regression coefficients for the equity market in Emerging economies (VGK).

Table 5
Regression estimates for the regression models. BTC, GLD and USO refer to the safe-haven assets: bitcoin, gold and crude oil, respectively. The sample size of the regression is 2110, and p-values are reported in parentheses. Model 3a is based on the Adjusted Market inefficiency Measure (Tran and Leirvik, 2019), while Model 3b is based on the Time-Varying Autoregressive (TV-AR) measure of market efficiency (Noda,2016).

Estimates of the regression between the safe-haven assets and the equity market in the US (SPY)

	Panel 1: BTC				Panel 2: GLD				Panel 3: USO			
	Model 1	*Model 2*	*Model 3a*	*Model 3b*	*Model 1*	*Model 2*	*Model 3a*	*Model 3b*	*Model 1*	*Model 2*	*Model 3a*	*Model 3b*
Intercept	0.1747	0.22982	0.17597	0.15199	−0.01153	−0.004285	−0.005949	−0.019552	−0.04498	0.127583	0.181104	0.153854
	(0.102880)	(0.185760)	(0.32580)	(0.40866)	(0.5950)	(0.902869)	(0.86931)	(0.60666)	(0.4553)	(0.1907)	(0.068098)	(0.1335)
spy	0.7454	0.54261	0.75774	0.97815	0.06280	0.015531	0.008702	0.016327	0.63759	0.402040	0.351484	0.404326
	(0.0000)	(0.000647)	(0.0000)	(0.0000)	(0.0071)	(0.628719)	(0.80250)	(0.66894)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
spy q = 0.01	−3.8109	−2.13422	−1.75676	−2.04429	−0.37064	−0.005808	−0.007628	−0.010234	−1.51673	−0.331434	−0.149310	−0.324493
	(0.000564)	(0.088611)	(0.16097)	(0.10086)	(0.0975)	(0.981710)	(0.97604)	(0.96780)	(0.0147)	(0.6375)	(0.832418)	(0.6449)
spy q = 0.05	−0.7012	’-0.07244	0.02868	−0.06403	0.14064	0.303205	0.298961	0.303749	−0.47855	−0.007821	−0.004165	−0.010166
	(0.288139)	(0.916834)	(0.96695)	(0.92604)	(0.2930)	(0.030737)	(0.03386)	(0.03088)	(0.1978)	(0.9840)	(0.991456)	(0.9792)
spy q = 0.1	0.6623	1.31948	1.52830	1.48094	0.23942	0.366078	0.361188	0.365881	−0.08742	0.466024	0.498574	0.477040
	(0.175421)	(0.016249)	(0.00548)	(0.00676)	(0.0157)	(0.000982)	(0.00118)	(0.0010)	(0.7506)	(0.1304)	(0.105862)	(0.1221)
vix		0.45443	0.68409	0.50271		0.206991	0.203369	0.206923		0.380942	0.385409	0.384599
		(0.143811)	(0.03018)	(0.10392)		(0.001004)	(0.00134)	(0.00102)		(0.0291)	(0.027362)	(0.0277)
vixm		0.41149	0.27339	0.38055		−0.005841	−0.003233	−0.004195		0.328671	0.331848	0.323818
		(0.231569)	(0.42790)	(0.26572)		(0.933059)	(0.96309)	(0.95193)		(0.0888)	(0.085967)	(0.0946)
ME			−0.79790	−0.88626			0.017432	−0.004603			0.219859	−0.002466
			(0.0000)	(0.0000)			(0.64607)	(0.89334)			(0.055954)	(0.9802)
F-test	31.24	16.77	15.04	16.38	4.156	4.289	3.479	3.549	69.84	37.62	30.96	30.15
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.002346)	(0.0000)	(0.0001478)	(0.0001128)	(0.0000)	(0.0000)	(0.00009	(0.0000)

Model 1: $r_{i,t} = \alpha + \beta_1 r_{m,t} + \beta_2 r_{m,t(0.01)} + \beta_3 r_{m,t(0.05)} + \beta_4 r_{m,t(0.1)} + \varepsilon_t$
Model 2: $r_{i,t} = \alpha + \beta_1 r_{m,t} + \beta_2 r_{m,t(0.01)} + \beta_3 r_{m,t(0.05)} + \beta_4 r_{m,t(0.1)} + \zeta_1 vix_{m,t} + \zeta_2 vixm_{m,t} + \varepsilon_t$
Model 3: $r_{i,t} = \alpha + \beta_1 r_{m,t} + \beta_2 r_{m,t(0.01)} + \beta_3 r_{m,t(0.05)} + \beta_4 r_{m,t(0.1)} + \zeta_1 vix_{m,t} + \zeta_2 vixm_{m,t} + \zeta_3 ME_{i,m,t} + \varepsilon_t$

3.2.2. Gold

Gold is found to be an SHA for the equity markets in China and the US when stock returns are at the lower 1%. At the 5% percentile, gold does not offer any safe-haven benefits in any of the equity markets studied. The expectation of increased stock market volatility in the medium term positively affects the hedge function of gold in all the equity markets examined. The level of inefficiency affects the relationship between the gold and equity market in China and emerging economies, indicating that gold may only be used as a hedge in this equity market when the gold market is inefficient.

3.2.3. Crude oil

Similar to the results obtained for bitcoin and gold, crude oil is not a suitable hedge for any of the equity markets sampled. Only when stocks are at the lower ten per cent level can crude oil act as a safe-haven asset in the European equity market. At the lower 5 per cent, oil is a weak SHA for equities in Japan, the USA and Europe. When stock returns drop below the 1% level, crude oil is a safe-haven asset for all the regional equity markets sampled. Market inefficiency in crude oil pricing does not affect its relationship with the equity markets, as crude oil is still an unsuitable hedge during this period.

Table 6

Regression estimates for the regression models in Equations 1 and 2. BTC, GLD and USO refer to the safe-haven assets of bitcoin, gold and crude oil, respectively. The sample size of the regression is 2110, and p-values are reported in parentheses. Model 3a is based on the Adjusted Market inefficiency Measure (Tran and Leirvik, 2019), while Model 3b is based on the Time-Varying Autoregressive (TV-AR) measure of market efficiency (Noda,2016).

Estimates of the regression between the safe-haven assets and the equity market in Japan (EWJ)

	Panel 1: BTC				Panel 2: GLD				Panel 3: USO			
	Model 1	*Model 2*	*Model 3a*	*Model 3b*	*Model 1*	*Model 2*	*Model 3a*	*Model 3b*	*Model 1*	*Model 2*	*Model 3a*	*Model 3b*
Intercept	0.21243	0.45255	0.43952	0.4322	−0.002669	−0.033679	−0.035735	−0.047001	−0.02610	0.30575	0.35819	0.33858
	(0.04745)	(0.00466)	(0.00800)	(0.0119)	(0.901044)	(0.29320)	(0.2778)	(0.1803)	(0.6698)	(0.000781)	(0.000102)	(0.000418)
ewj	0.61963	0.35437	0.50861	0.69872	0.082338	0.087271	0.078685	0.090530	0.49300	0.27952	0.22023	0.29099
	(0.0000)	(0.02498)	(0.00219)	(0.0000)	(0.000659)	(0.00591)	(0.0208)	(0.0148)	(0.0000)	(0.001891)	(0.017916)	(0.002642)
ewj q = 0.01	−2.85889	−1.98290	−2.19196	−2.27592	0.367219	0.445531	0.448832	0.434469	−1.33423	−1.12751	−1.27155	−1.12949
	(0.00992)	(0.09902)	(0.06827)	(0.0580)	(0.098150)	(0.06453)	(0.0629)	(0.0722)	(0.0351)	(0.099142)	(0.062702)	(0.098756)
ewj q = 0.05	0.14700	0.42936	0.39396	0.44848	0.074447	0.097698	0.099773	0.090057	−0.35731	−0.27448	−0.27589	−0.27518
	(0.82487)	(0.52752)	(0.56163)	(0.5078)	(0.575941)	(0.47336)	(0.4649)	(0.5096)	(0.3466)	(0.477671)	(0.474067)	(0.476705)
ewj q = 0.1	−0.02833	0.34320	0.43488	0.37444	0.119270	0.124696	0.122701	0.125125	−0.16557	0.02767	0.07984	0.03289
	(0.9540)	(0.50535)	(0.39894)	(0.4660)	(0.225894)	(0.22745)	(0.2355)	(0.2276)	(0.5555)	(0.924790)	(0.785017)	(0.910678)
vix		0.34002	0.41116	0.32167		0.061365	0.059313	0.060037		0.31335	0.30435	0.31111
		(0.24703)	(0.16252)	(0.2718)		(0.29740)	(0.3145)	(0.3083)		(0.060797)	(0.067761)	(0.062736)
vixm		0.24581	0.15853	0.18080		−0.030858	−0.026396	−0.030388		−0.06477	−0.05714	−0.06805
		(0.40407)	(0.59193)	(0.5386)		(0.60136)	(0.6569)	(0.6071)		(0.699121)	(0.732382)	(0.684976)
ME			−0.67908	−0.75650			0.026594	−0.008555			0.40582	−0.02684
			(0.00265)	(0.0000)			(0.5234)	(0.8137)			(0.004763)	(0.811349)
F-test	17.83	9.824	8.797	9.614	3.14	2.096	1.738	1.764	38.16	22.55	19.64	18.16
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.01382)	(0.03312)	(0.06709)	(0.06219)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Model 1: $r_{i,t} = \alpha + \beta_1 r_{m,t} + \beta_2 r_{m,t(0.01)} + \beta_3 r_{m,t(0.05)} + \beta_4 r_{m,t(0.1)} + \varepsilon_t$

Model 2: $r_{i,t} = \alpha + \beta_1 r_{m,t} + \beta_2 r_{m,t(0.01)} + \beta_3 r_{m,t(0.05)} + \beta_4 r_{m,t(0.1)} + \zeta_1 vix_{m,t} + \zeta_2 vixm_{m,t} + \varepsilon_t$

Model 3: $r_{i,t} = \alpha + \beta_1 r_{m,t} + \beta_2 r_{m,t(0.01)} + \beta_3 r_{m,t(0.05)} + \beta_4 r_{m,t(0.1)} + \zeta_1 vix_{m,t} + \zeta_2 vixm_{m,t} + \zeta_3 ME_{i,m,t} + \varepsilon_t$

Table 7

Regression estimates for the regression models. BTC, GLD and USO refer to the safe-haven assets of bitcoin, gold and crude oil, respectively. The sample size of the regression is 2110, and p-values are reported in parentheses. Model 3a is based on the Adjusted Market inefficiency Measure (Tran and Leirvik, 2019), while Model 3b is based on the Time-Varying Autoregressive (TV-AR) measure of market efficiency (Noda,2016).

Estimates of the regression between the safe-haven assets and the equity market in China (FXI)

	Panel 1: BTC				Panel 2: GLD				Panel 3: USO			
	Model 1	*Model 2*	*Model 3a*	*Model 3b*	*Model 1*	*Model 2*	*Model 3a*	*Model 3b*	*Model 1*	*Model 2*	*Model 3a*	*Model 3b*
Intercept	0.19092	0.52528	0.55543	0.55443	0.003464	−0.0187692	−0.02402	−0.036001	−0.01284	0.35543	0.40093	0.398878
	(0.0726)	(0.000627)	(0.000513)	(0.000911)	(0.87037)	(0.5406)	(0.4473)	(0.2893)	(0.8323)	(0.0000)	(0.0000)	(0.0000)
fxi	0.32586	0.16856	0.20115	0.24554	0.039253	0.0389944	0.04410	0.044144	0.29375	0.12953	0.11739	0.130057
	(0.0000)	(0.061988)	(0.027977)	(0.011186)	(0.00704)	(0.0309)	(0.0182)	(0.0241)	(0.0000)	(0.011341)	(0.024953)	(0.015877)
fxi q = 0.01	−4.37041	−4.05319	−4.14382	−4.15328	−0.357501	−0.3092422	−0.33787	−0.325257	−2.54991	−2.25718	−2.26052	−2.279973
	(0.0000)	(0.000320)	(0.000235)	(0.000228)	(0.10226)	(0.1692)	(0.1348)	(0.1491)	(0.0000)	(0.000402)	(0.000385)	(0.000366)
fxi q = 0.05	0.19277	0.27388	0.35582	0.30112	−0.012311	0.0006065	0.01425	0.012571	0.88972	0.97354	1.01316	0.989033
	(0.7725)	(0.683886)	(0.597444)	(0.654237)	(0.92633)	(0.9964)	(0.9159)	(0.9258)	(0.0193)	(0.010649)	(0.007796)	(0.009567)
fxi q = 0.1	0.42990	0.79357	0.81054	0.83742	0.192735	0.1967962	0.19856	0.196320	−0.72121	−0.33147	−0.33632	−0.337929
	(0.3856)	(0.127829)	(0.119774)	(0.108202)	(0.05152)	(0.0590)	(0.0569)	(0.0596)	(0.0107)	(0.261279)	(0.253900)	(0.252314)
vix		0.22219	0.25475	0.26889		0.0560508	0.05690	0.055436		0.10550	0.11048	0.106533
		(0.165828)	(0.113500)	(0.096569)		(0.0805)	(0.0761)	(0.0842)		(0.245213)	(0.223483)	(0.240688)
vixm		0.06144	0.06701	0.03784		−0.0399398	−0.03664	−0.037028		0.18700	0.17615	0.184436
		(0.706725)	(0.681608)	(0.817043)		(0.2214)	(0.2635)	(0.2611)		(0.043238)	(0.057537)	(0.046445)
ME			−0.36037	−0.27151			−0.03401	−0.017110			0.13613	0.002216
			(0.032729)	(0.028413)			(0.2373)	(0.4757)			(0.160253)	(0.976681)
F-test	14.38	8.628	7.377	7.406	3.313	2.329	2.056	2.063	36.94	23.87	20.1	19.3
	(0.00009)	(0.0000)	(0.0000)	(0.0000)	(0.01027)	(0.01727)	(0.02485)	(0.02434)	(0.0000)	(0.0000)	(0.00009)	(0.0000)

Model 1: $r_{i,t} = \alpha + \beta_1 r_{m,t} + \beta_2 r_{m,t(0.01)} + \beta_3 r_{m,t(0.05)} + \beta_4 r_{m,t(0.1)} + \varepsilon_t$

Model 2: $r_{i,t} = \alpha + \beta_1 r_{m,t} + \beta_2 r_{m,t(0.01)} + \beta_3 r_{m,t(0.05)} + \beta_4 r_{m,t(0.1)} + \zeta_1 vix_{m,t} + \zeta_2 vixm_{m,t} + \varepsilon_t$

Model 3: $r_{i,t} = \alpha + \beta_1 r_{m,t} + \beta_2 r_{m,t(0.01)} + \beta_3 r_{m,t(0.05)} + \beta_4 r_{m,t(0.1)} + \zeta_1 vix_{m,t} + \zeta_2 vixm_{m,t} + \zeta_3 ME_{i,m,t} + \varepsilon_t$

3.2.4. Robustness of market efficiency results

To verify that the results obtained are robust to other market efficiency measures, the Time-Varying Autoregressive (TV-AR) measure of market efficiency by Noda (2016) has also been used to measure the time-varying market inefficiency in the SHA market. The regression tables present the results under *Model 3b*, and the results do not significantly differ from those obtained from the AMIM inefficiency measure. The results from this analysis corroborate our previous results that inefficiency in Bitcoin's price is a driver of its ability to hedge the equity market. In addition to China and the emerging economies, the results from the TV-AR measure also indicate that inefficiency in the gold price enables its functioning as a hedge in Japan and the US. In the case of crude oil, the TV-AR measure suggests that inefficiency enables its hedge function in Japan and the US.

4. Conclusion

Following the differing results on the abilities of safe-haven assets present in the literature (see for e.g., Bouri et al., 2020b; Kumar and Padakandla, 2022; Wen et al., 2022), this study examines the effect of market inefficiency on the hedge and safe-haven abilities of bitcoin, gold and crude oil in different regional equity markets. Although offering some safe-haven benefits during extreme negative shocks, the results indicate that these assets are unsuitable hedge assets for any of the sampled equity markets, including

Table 8

Regression estimates for the regression models. BTC, GLD and USO refer to the safe-haven assets of bitcoin, gold and crude oil, respectively. The sample size of the regression is 2110, and p-values are reported in parentheses. Model 3a is based on the Adjusted Market inefficiency Measure (Tran and Leirvik, 2019), while Model 3b is based on the Time-Varying Autoregressive (TV-AR) measure of market efficiency (Noda,2016).

Estimates of the regression between the safe-haven assets and the equity market in Europe (VGK)												
	Panel 1: BTC				Panel 2: GLD				Panel 3: USO			
	Model 1	*Model 2*	*Model 3a*	*Model 3b*	*Model 1*	*Model 2*	*Model 3a*	*Model 3b*	*Model 1*	*Model 2*	*Model 3a*	*Model 3b*
Intercept	0.20303	0.22739	0.20655	0.21311	−0.004208	−0.07976	−0.08289	−0.09225	−0.01714	0.16833	0.22015	0.21081
	(0.055449)	(0.16287)	(0.21825)	(0.21952)	(0.844)	(0.0150)	(0.0137)	(0.00968)	(0.7724)	(0.06385)	(0.016557)	(0.0267)
vgk	0.68716	0.6738	0.84030	0.98917	0.110901	0.14664	0.13699	0.13031	0.61400	0.41628	0.35495	0.35469
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
vgk q = 0.01	−3.81688	−3.82381	−3.98072	−3.87171	0.243736	0.27937	0.26809	0.27365	−1.08410	−0.32289	−0.30818	−0.32468
	(0.000633)	(0.00208)	(0.00131)	(0.00174)	(0.279)	(0.2628)	(0.2831)	(0.27274)	(0.0823)	(0.64051)	(0.654488)	(0.6382)
vgk q = 0.05	0.36637	0.36770	0.55794	0.52488	0.158032	0.15446	0.15444	0.15092	−0.27773	−0.08217	−0.11908	−0.09860
	(0.577845)	(0.58593)	(0.40787)	(0.43535)	(0.234)	(0.2552)	(0.2554)	(0.26629)	(0.4506)	(0.82710)	(0.750681)	(0.7930)
vgk q = 0.1	0.03161	0.04344	0.26888	0.21961	0.099319	0.06151	0.05431	0.05293	−0.35406	−0.07266	−0.14337	−0.09482
	(0.948167)	(0.93225)	(0.59949)	(0.66691)	(0.311)	(0.5494)	(0.5977)	(0.60723)	(0.1929)	(0.79862)	(0.614065)	(0.7389)
vix		0.03950	0.22890	0.13589		0.05520	0.04598	0.04916		0.39110	0.33192	0.36915
		(0.88394)	(0.40270)	(0.61498)		(0.3104)	(0.4040)	(0.36924)		(0.00956)	(0.028210)	(0.0145)
vixm		−0.02979	−0.08253	−0.04867		−0.07654	−0.07124	−0.07363		0.01508	0.03002	0.03024
		(0.91430)	(0.76528)	(0.85987)		(0.1692)	(0.2023)	(0.18651)		(0.92216)	(0.845551)	(0.8448)
ME			−0.76199	−0.71610			0.03950	0.03411			0.41667	0.23059
			(0.0000)	(0.0000)			(0.2726)	(0.27535)			(0.000316)	(0.0166)
F-test	29.44	14.73	13.62	14.01	7.421	5.305	4.398	4.465	75.48	39.77	34	32.67
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Model 1: $r_{i,t} = \alpha + \beta_1 r_{m,t} + \beta_2 r_{m,t(0.01)} + \beta_3 r_{m,t(0.05)} + \beta_4 r_{m,t(0.1)} + \varepsilon_t$

Model 2: $r_{i,t} = \alpha + \beta_1 r_{m,t} + \beta_2 r_{m,t(0.01)} + \beta_3 r_{m,t(0.05)} + \beta_4 r_{m,t(0.1)} + \zeta_1 vix_{m,t} + \zeta_2 vixm_{m,t} + \varepsilon_t$

Model 3: $r_{i,t} = \alpha + \beta_1 r_{m,t} + \beta_2 r_{m,t(0.01)} + \beta_3 r_{m,t(0.05)} + \beta_4 r_{m,t(0.1)} + \zeta_1 vix_{m,t} + \zeta_2 vixm_{m,t} + \zeta_3 ME_{i,m,t} + \varepsilon_t$

Table 9

Regression estimates for the regression models. BTC, GLD and USO refer to the safe-haven assets of bitcoin, gold and crude oil, respectively. The sample size of the regression is 2110, and p-values are reported in parentheses. Model 3a is based on the Adjusted Market inefficiency Measure (Tran and Leirvik, 2019), while Model 3b is based on the Time-Varying Autoregressive (TV-AR) measure of market efficiency (Noda,2016).

Estimates of the regression between the safe-haven assets and the equity market in Emerging economies (VWO)												
	Panel 1: BTC				Panel 2: GLD				Panel 3: USO			
	Model 1	*Model 2*	*Model 3a*	*Model 3b*	*Model 1*	*Model 2*	*Model 3a*	*Model 3b*	*Model 1*	*Model 2*	*Model 3a*	*Model 3b*
Intercept	0.1624	0.3795	0.39959	0.40438	0.0009804	−0.07396	−0.07910	−0.08711	−0.03477	0.13271	0.17749	0.16653
	(0.127)	(0.0186)	(0.01627)	(0.018947)	(0.96307)	(0.02099)	(0.016014)	(0.012604)	(0.55334)	(0.1355)	(0.048877)	(0.0759)
vwo	0.6843	0.3585	0.44006	0.57666	0.1163324	0.12390	0.13398	0.13420	0.64018	0.45397	0.40903	0.43899
	(0.0000)	(0.0070)	(0.00128)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
vwo q = 0.01	0.5226	2.0391	1.77942	1.65951	0.6880673	0.93400	0.91018	0.90991	−1.77187	−1.05948	−0.82763	−0.97279
	(0.637)	(0.0844)	(0.13418)	(0.161792)	(0.00183)	(0.0000)	(0.000112)	(0.000116)	(0.00376)	(0.1038)	(0.204076)	(0.1388)
vwo q = 0.05	−0.1772	0.3578	0.51067	0.56489	−0.0296679	0.03313	0.04361	0.03710	−0.07317	0.18873	0.04522	0.12376
	(0.791)	(0.5991)	(0.45487)	(0.407397)	(0.82338)	(0.80643)	(0.747440)	(0.783983)	(0.84243)	(0.6150)	(0.904149)	(0.7444)
vwo q = 0.1	0.3109	0.8514	0.90118	0.92492	0.1035588	0.13906	0.14128	0.14571	−0.16868	0.10793	0.09511	0.13570
	(0.528)	(0.0950)	(0.07715)	(0.069376)	(0.29070)	(0.16980)	(0.164091)	(0.152167)	(0.53427)	(0.7010)	(0.734275)	(0.6304)
vix		0.6456	0.71518	0.67727		0.14980	0.15310	0.15004		0.32504	0.32510	0.33011
		(0.0092)	(0.00410)	(0.006205)		(0.00236)	(0.001908)	(0.002326)		(0.0174)	(0.016955)	(0.0158)
vixm		0.2053	0.19056	0.21464		−0.07058	−0.06788	−0.06747		0.10087	0.05939	0.09425
		(0.3944)	(0.42911)	(0.372093)		(0.14062)	(0.156796)	(0.160535)		(0.4479)	(0.654789)	(0.4786)
ME			−0.47462	−0.54897			−0.04336	−0.02383			0.40069	0.06394
			(0.01259)	(0.000386)			(0.193527)	(0.428402)			(0.000746)	(0.4994)
F-test	18.77	11.48	9.866	10.55	11	8.669	7.126	7.068	81.15	42.74	36.16	34.36
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Model 1: $r_{i,t} = \alpha + \beta_1 r_{m,t} + \beta_2 r_{m,t(0.01)} + \beta_3 r_{m,t(0.05)} + \beta_4 r_{m,t(0.1)} + \varepsilon_t$

Model 2: $r_{i,t} = \alpha + \beta_1 r_{m,t} + \beta_2 r_{m,t(0.01)} + \beta_3 r_{m,t(0.05)} + \beta_4 r_{m,t(0.1)} + \zeta_1 vix_{m,t} + \zeta_2 vixm_{m,t} + \varepsilon_t$

Model 3: $r_{i,t} = \alpha + \beta_1 r_{m,t} + \beta_2 r_{m,t(0.01)} + \beta_3 r_{m,t(0.05)} + \beta_4 r_{m,t(0.1)} + \zeta_1 vix_{m,t} + \zeta_2 vixm_{m,t} + \zeta_3 ME_{i,m,t} + \varepsilon_t$

Japan, China, the USA, Europe, and emerging economies. The empirical results indicate that pricing inefficiency within the SHA market influences its ability to function as a hedge in the equity market. High levels of market inefficiency positively influence the function of Bitcoin as a hedge asset in all equity markets. Pricing inefficiency in the Gold market makes it a hedge for the equity markets in Japan, China, the USA and emerging economies. Similarly, market inefficiency in the crude oil market makes hedging possible in the equity markets of Japan and the USA.

The findings of this study are important for the risk management strategies of market traders, especially during market turbulence when bitcoin is found to be more efficient. When investors flock towards Bitcoin bitcoin during a financial crisis, they increase liquidity and pricing efficiency within the market. Consequently, market traders eliminate the hedge abilities of bitcoin, thereby eliminating the effect they seek from this market .

Data availability

Data will be made available on request.

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