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The Bitcoin price and Bitcoin price uncertainty: Evidence of Bitcoin price volatility

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Abstract

This study examines the Bitcoin price by taking into account global factors, including the Chicago Board Options Exchange's Market Volatility Index (VIX), the US dollar index, the gold price, the oil price, and Bitcoin price volatility. The analysis is conducted using the structural vector autoregression (SVAR) model. The variance decomposition findings revealed that the influence of the VIX on the Bitcoin price was initially restricted, but progressively intensified over time. Among the indicators, Bitcoin price volatility had the highest explanatory share in both daily and weekly data analysis. The impulse response functions demonstrated a statistically significant inverse relationship between the VIX and the Bitcoin price. Furthermore, the analysis revealed that the Bitcoin price was mostly impacted by its own volatility. This implies that investing in Bitcoin requires a certain level of risk-taking.

KEYWORDS

Bitcoin, gold price, oil price, SVAR model, VIX

JEL CLASSIFICATION

C32, C58, G12

1 | INTRODUCTION

New investing instruments that are virtually present in the financial system are gaining appeal as the world continues to become increasingly globalized and digitalized. Bitcoin, established in 2008 as an electronic cash system, has become a prominent and widely embraced cryptocurrency, attracting global investment (Nakamoto, 2008). The categorization of this investing instrument has been a topic of extensive deliberation in the financial sphere (Corbet et al., 2019; Hazlett & Luther, 2020; White et al., 2020). The argument around the potential transformation of Bitcoin into a self-sufficient investment vehicle, by mitigating the notion of it being solely speculative, has been discussed (Vo et al., 2022). Examining Bitcoin's correlation with other financial instruments might provide insights into its features as either a conventional asset or a speculative instrument (Zeng et al., 2020). Further discussion on cryptocurrencies is expected in this context, with the potential introduction of new, similar instruments in the global and digital environment. Nevertheless, a thorough discussion is required to elucidate the global indicators of a cryptocurrency.

Investors, portfolio managers, and academics endeavor to evaluate if Bitcoin may serve as a safe haven, a hedging opportunity, and a means of diversification. Furthermore, policymakers are contemplating the feasibility of regulating and formally embracing cryptocurrencies. Umar et al. (2021) highlighted that Bitcoin may serve as a safe haven during times of uncertainty, however this dynamic can fluctuate in both the short and longer term in the United States. González et al. (2021) observed that the correlation between the returns of gold prices and cryptocurrency prices strengthens amid severe economic problems, such as the COVID-19 pandemic. Bouri et al. (2018) examined the impact of the aggregate commodities index and the gold price on the price of Bitcoin. Using the selected determinants, it was discovered that Bitcoin price fluctuations can be anticipated. According to Blau et al. (2021), Bitcoin may serve as a hedge against inflation. Bitcoin is very nascent in comparison to other major financial assets. This invention is significant and there is continuous study being conducted. An array of analytical techniques was used, and several implications were drawn. Nevertheless, there is still a need for the global community to comprehend cryptocurrencies and their impact on financial markets.

Prior research has mostly focused on examining the relationship between Bitcoin and traditional assets as well as the associated risks. Wu et al. (2021) examined the influence of economic policy uncertainty on the returns of Bitcoin. Research has shown that in the majority of nations, there is a positive correlation between uncertainties and Bitcoin returns, while there is a negative correlation between uncertainties and Bitcoin's long-term volatility. The significance of national uncertainty in influencing investment choices was underscored. Chen et al. (2021) discovered a positive connection between the Bitcoin price and various exchange rates, those tied to the US dollar. Entrop et al. (2020) examined the impact of uncertainty and other associated factors on the Bitcoin price. The causal route between the Volatility Index (VIX) and price discovery was reported to be unclear. According to Al-Yahyaee et al. (2019), the VIX has the ability to forecast Bitcoin price returns over various time intervals.

Bitcoin requires a comprehensive worldwide evaluation because of the increasing digitization of the globe. Hence, the primary aim of this study is to scrutinize the causal elements influencing the Bitcoin price, which might provide alternative investment choices for portfolio managers and investors. Digital currencies are anticipated to become more accessible for market operations in the future. Therefore, it is crucial to have a deeper understanding of cryptocurrencies, since they have the potential to serve as innovative economic instruments for investing. Hence, the question of whether cryptocurrencies may replace traditional financial choices needs deliberation. The structural vector autoregression (SVAR) model is implemented in this work. Anticipated were five significant global indications that might potentially prompt fluctuations in the Bitcoin price. These are the VIX, dollar index (DXY) as exchange rate, the gold price, the oil price, and Bitcoin price volatility (uncertainty). The advent of technology and the fast process of globalization have facilitated the attraction of new investors to the digital market for Bitcoin. Consequently, the cryptocurrency witnessed a surge in popularity and eventually became a medium of transaction. Bitcoin operates autonomously without any centralized authority, such as a central bank, and diverges from conventional financial instruments, making it a transnational digital currency. Due to its widespread popularity, there have been inquiries regarding the structure of Bitcoin, its suitability for inclusion in a portfolio, its potential for diversification benefits, and its ability to act as a hedge or safe haven. These questions have been addressed by various studies conducted (Bouri et al., 2017, 2020; Cheikh et al., 2020; Das et al., 2020; Uddin et al., 2020). Furthermore, regulators want to enhance their comprehension of cryptocurrencies, given its growing prominence in financial portfolios, to proactively mitigate any risks. Therefore, the primary inquiries of this study are as follows: What is the influence of the VIX, exchange rate, the gold price, the oil price, and Bitcoin price volatility on the Bitcoin price? What is the significance of Bitcoin price volatility as explanatory factors? On the basis of this study, can Bitcoin be considered a safe haven or a speculative asset for investment? The objective of this effort is to discover solutions to these inquiries.

The VIX is a global indicator that has the potential to influence the investment choices made by investors. Over time, this index has evolved into a significant gauge of apprehension in the financial market. This indicator was used to quantify volatility and utilized in studies to assess risk factors. The index may alternatively be regarded as a fear index or fear gauge. Elevated values of the VIX may correspond with significant levels of upheaval in the financial market, such as during times of war, crises, or more recently, the COVID-19 pandemic. There may be a positive correlation between the VIX and the degree of fear in the market. In other words, when the VIX increases, the level of fear in the market also can increase (Whaley, 2000).

Bitcoin lacks some characteristics of traditional money, such as its limited use as a medium of exchange, unit of account, and store of value. However, it may be categorized alongside other indicators like gold, oil, and the US dollar (Dyhrberg, 2016). The Bitcoin price was assessed by considering various investment choices due to their similarities. The Bitcoin price was anticipated to be influenced by the gold price, thereby impacting this safe asset. Shehzad et al. (2021) aimed to determine if gold or Bitcoin was more advantageous during the COVID-19 pandemic. Their findings supported the notion that gold had a greater advantage over Bitcoin. Wang et al. (2021) examined the capacity of Bitcoin to mitigate risks when compared with other investment instruments, such as gold, the US currency, and oil.

Gold was shown to have superior hedging efficacy in the short term for emerging countries. Będowska-Sójka and Kliber (2021) examined the characteristics of gold, Bitcoin, and Ether as safe havens. Bitcoin was deemed an ineffective haven.

The anticipation was that the presence of uncertainty in financial instruments may have a substantial influence on the choices made by investors. Specifically, high frequency trading may impact the transactional activities inside the financial market. The presence of high risk and volatility might induce stress, leading investors to rethink their decisions and perhaps quit their investments in favor of other derivatives. Hence, it is essential to include Bitcoin price volatility into the investigation to elucidate its influence on the origin of its price fluctuations.

The primary conclusions of the study indicate that Bitcoin price volatility is the most influential element determining the result. Nevertheless, the extent of its influence fluctuates depending on whether daily or weekly data analysis is used. Conventional assets have a restricted impact on the Bitcoin price. These findings indicate that Bitcoin is mostly influenced by speculation, with volatility playing a significant impact. The cryptocurrency market is still evolving to display comparable traits to conventional assets.

The structure of this paper is as follows: Section 2 provides an overview of prior research and examines the novelty and distinctions of this study. Section 3 provides an explanation for selecting variables and collecting data. Section 4 presents an empirical analysis along with its results. Section 5 addresses the policy implications. The study is concluded in Section 6.

2 | PREVIOUS RESEARCH AND THE CURRENT WORK

2.1 | Previous research

The topic of Bitcoin has been the focus of a number of notable works. Conducting research on the indicators of Bitcoin price using econometric methodologies, sample time, and other critical indicators has yielded notable discoveries. Rognone et al. (2020) examined how Bitcoin and major conventional currencies respond to positive and negative news. Vector autoregression with exogenous (VAR-X) models were employed for 15-min data from January 2012 to November 2018. Conventional currencies' returns drop after adverse news and rise after good news. Bitcoin responds positively to both positive and negative news, except for cyberattack and fraud news, which lower returns. Charfeddine et al. (2020) examined Bitcoin and Ethereum's connection with financial assets and commodities from July 18, 2010 to October 1, 2018. Time-varying copula approaches were employed to examine dependence between returns, and structural changes tests were used to determine if regime changes corresponded with digital or conventional financial market events. Cryptocurrencies were deemed ideal for financial diversification. Both cryptocurrency and conventional financial assets were tested for external shock sensitivity. Additionally, cryptocurrency and gold have a positive average reliance. Urquhart and Zhang (2019) used an intraday data sample of Bitcoin covers from November 1, 2014 to October 31, 2017 to determine if Bitcoin might hedge currencies using the asymmetric dynamic conditional correlation model and regression analysis. The cryptocurrency hedged the Swiss franc, euro, and British pound and diversified the Australian dollar, Canadian dollar, and Japanese yen. In periods of market volatility, it might have served as a haven for the Canadian dollar, Swiss franc, and British pound. Guizani and Nafti (2019) utilized daily data from December 19, 2011 to February 6, 2018 to explain Bitcoin price volatility indicators using ARDL model. The conclusion was reached that the exchange rate, transaction volume, stock, and macroeconomic and financial development had no effect on the Bitcoin price in the short or long term. Baumöhl (2019) applied the quantile cross-spectral technique to examine the connection between six forex and six cryptocurrencies from September 1, 2015 to December 29, 2017. Forex and cryptocurrency were expected to be negatively correlated. Thus, diversification between two asset classes was considered appropriate. Furthermore, it was discovered that the relationships between cryptocurrencies were not very robust. Kliber et al. (2019) analyzed Bitcoin's hedge, diversifier, and safe haven potential. Japan, Venezuela, China, Estonia, and Sweden were examined. Using 2014–2017 daily data, the dynamic conditional correlation model was applied to the major stock indexes and Bitcoin prices in local currencies. Bitcoin was a safe haven solely for Venezuela, a diversifier for Japan and China, and a weak hedge for Sweden and Estonia.

Bitcoin is extremely speculative and vulnerable to adverse events, risk, and volatility. The immigration problem and US–China tensions were used by Zhang and Wang (2021) to examine the link between the financial stress index, Bitcoin, and gold. Daily data from May 2, 2013 to March 27, 2020 were analyzed using VAR. Bitcoin is less affected by the US FSI than gold during uncertain times. Bitcoin was expected to be severely influenced by US exchange market financial stress, depending on FSI subcomponent connectivity. Lyócsa et al. (2020) examined Bitcoin news reactions using OLS and quantile regression. Daily data from 2013 to 2018 was analyzed. Bitcoin has extreme volatility relative to other financial assets. Bitcoin volatility was strongly impacted by hacking news regarding cryptocurrencies, while macroeconomic news had little effect on it, unlike conventional assets. De la Horra et al. (2019) investigated whether Bitcoin is a medium of exchange, speculative asset, or safe haven. A demand model examined long-term and short-term indicator correlations using daily data from August 17, 2010 to February 28, 2018. Bitcoin was more impacted by short-term speculation, the research found. Long-term, its behavior as a medium of exchange may drive Bitcoin demand. The GRJ-GARCH model volatility affected cryptocurrencies short-term but not long term. The Model Confidence Set was used by Yu (2019) to determine if leverage and economic policy uncertainty affected Bitcoin using 5-min sample frequency. The conclusion was that the leverage effect was more effective in predicting the Bitcoin volatility. Generalized variance decomposition analysis was performed by Corbet et al. (2018) for daily periods from April 29, 2013 to February 7, 2014. Bitcoin, Ripple, and Litecoin were studied to determine how the VIX, gold, and GSCI index affected them. It was pointed out that there were instances of short-term increases in spillovers from Bitcoin to other assets. Cryptocurrencies were found to be linked to each other and to other assets.

Gold has always been a store of value and a haven from threats and uncertainty. Technological advances have regulators and investors wondering whether cryptocurrencies can compete with gold. Wavelet Multiple Correlation, quantile regression, and VAR were used by Huynh et al. (2020) to study gold and Bitcoin. Daily data from May 1, 2013 to October 28, 2019 was analyzed. Gold-to-platinum ratios were thought to forecast Bitcoin returns. Bitcoin and precious commodities such gold, silver, copper, platinum, palladium, and wheat were analyzed for risk and returns spillover by Rehman (2020) using daily data from April 2013 to January 2018 using ARFIMA-FIGARCH, value at risk (VaR), and conditional VaR tests. Gold was reported to hedge Bitcoin. Gold was a safer investment than other metals. Dutta et al. (2020) applied the dynamic conditional correlation (DCC)-GARCH model to determine whether gold and Bitcoin are safe havens for global crude oil markets during the COVID-19 pandemic. The model indicated that gold was an oil market safe haven and Bitcoin was a diversifier. The report suggested investors to add oil and gold to reduce portfolio risk. Dwita Mariana et al. (2021) evaluated whether Bitcoin and Ethereum were COVID-19 safe havens. Daily data from July 1, 2019 to April 6, 2020 was utilized for DCC-GARCH and regression analysis. These two cryptocurrencies may be short-term safe havens. Before the pandemic, both coins were more volatile than gold and S&P500. Su, Qin, Tao, and Umar (2020) assessed monthly data from July 2010 to January 2020 to determine the causation between Bitcoin and oil prices. It was stated that oil price disruptions may be transmitted to the Bitcoin price in either a positive or negative direction.

2.2 | The research gap and the current work

When the study that was presented before is taken into consideration, this work contains a number of originalities. The SVAR model is a very advantageous research methodology in the field of macroeconomics. It indicates the structural influence of indicators. On the basis of our understanding of the previous works, there has been no prior application of the SVAR model to examine the global metrics of Bitcoin, while including both daily and weekly data over an extended period of time. While many approaches have been used to assess Bitcoin's efficacy as a hedge, diversifier, and safe haven in relation to other assets, more research is required to examine the primary factors driving fluctuations in the cryptocurrency. The SVAR model is a versatile method for investigating a subject and allows for the organization of assumptions based on key questions and hypotheses. This study enhances and broadens the scope of earlier research by including conventional assets, the VIX, and Bitcoin price volatility in the SVAR model. SVAR models need identifying assumptions to establish a causal link between endogenous variables. It is considered one of the most effective approaches for assessing indicators in Bitcoin study. The VAR model is its abbreviated version. The assumptions behind SVAR models are derived from institutional considerations, economic theories, or other limitations. These are molded based on the model's answers. The innovation terms of a VAR model may be obtained by implementing either recursive Cholesky decompositions or non-recursive structural factorizations. This process is referred to as the orthogonalization of reduced-form residuals. This method allows for the imposition of a certain causal sequence instead of investigating causal connections based on the data. It is crucial to have plausible economic explanations to get answers via recursive ordering that are economically sensible (Kilian, 2013). The process of structural factorization, which incorporates underlying assumptions, establishes immediate relationships among the indicators (Bernanke, 1986; Blanchard & Watson, 1986; Sims, 1986). Assumptions, such as the complete VAR, may help identify particular causal linkages (Stock & Watson, 2001). Consequently, the SVAR model offers advantages compared with alternative approaches that use VAR models or single equations (Köse & Ünal, 2021). Given that the study is not subject to changes over time, using the SVAR model is adequate for analyzing the indicators. This will further aid in closing the research disparity and make a valuable contribution to other academic publications. The analysis is conducted using forecast error variance decomposition and impulse response functions. Existing research has examined the correlation between Bitcoin and several factors such as exchange rates, gold, oil, and risk or news in the financial market. However, it is also necessary to analyze these elements by considering the VIX and Bitcoin price volatility. This research assumes a bidirectional contemporaneous relationship between the Bitcoin price and Bitcoin price volatility. In other words, Bitcoin price volatility is contemporaneously influenced by the Bitcoin price, and vice versa. Cholesky decomposition does not provide a bidirectional definition of simultaneous connections. Therefore, it is feasible to achieve a bidirectional definition of simultaneous relationships using structural factorization.

3 | SELECTION OF VARIABLE AND DATA COLLECTION

The selected variables were included in this study to ascertain the potential global factors that impact fluctuations in the Bitcoin price. The link between the Bitcoin price and other indicators has been elucidated via the formulation of assumptions.

Market volatility, driven by fear, panic, or risk, may undermine the perceived stability of assets, compromising their role as safe havens (Chen et al., 2020; Yousaf & Ali, 2020). The inclusion of the VIX was based on the assumption that major fluctuations in the index may potentially impact the demand for Bitcoin. Specifically, the VIX may influence fluctuations in the Bitcoin price since it generates anticipations about future investments. According to Kalyvas et al. (2020), Bitcoin may serve as a hedge during times of uncertainty.

DXY is one of the selected indicators for measuring exchange rates. Several significant justifications exist for the use of this index. The US dollar has universal acceptance worldwide. When nations attempt to reduce the adverse effects of inflation, the significance of the US dollar increases. This currency is extensively used globally and serves as a standard for evaluating exchange rates. Additionally, it is a resilient and robust currency. This currency has been a popular choice for foreign exchange reserves due to globalization and its capacity to provide financial stability. This currency has served as a means of exchange, a store of value, and a unit of account for a considerable period of time. This phenomenon has led to dollarization in some nations, where foreign cash is held as a safeguard against the devaluation of the local currency and excessive levels of inflation. Kwon (2020) examined Bitcoin as a potential substitute for conventional currencies, commodities, or investments. The exchange rate has been shown to be a significant factor that may impact the price of Bitcoin in such circumstances (Zhu et al., 2017). Investors who are affected by exchange rate fluctuates are likely to modify their strategies and exhibit a higher desire for cryptocurrencies. Therefore, the fluctuation in the exchange rate may significantly contribute to understanding the variations in Bitcoin.

The investigation utilized gold because of its established reputation as a secure investment and a reliable asset for preserving value, predating the emergence of cryptocurrencies. Bitcoin and gold have similarities in that both lack regulatory oversight and their value is mostly decided by market forces. While gold remains a popular and reliable investment option, Bitcoin, as an alternative, is impacted by the gold price (Naeem et al., 2020; Shahzad et al., 2020). Diniz-Maganini et al. (2021) discovered that both gold and Bitcoin may serve as safe havens, however, gold shown itself to be the superior choice. Pho et al. (2021) conducted a comparative analysis between Bitcoin and gold specifically for Chinese portfolios. Gold was declared to be a superior portfolio diversifier compared with Bitcoin due to its risk-reducing properties. Moreover, the fluctuations in Bitcoin may be anticipated based on the gold price (Su, Qin, Tao, & Zhang, 2020). If a positive correlation exists between gold and Bitcoin, it implies that the cryptocurrency may serve as a safe haven, similar to gold, in times of financial volatility (Jareno et al., 2020). Therefore, it is hypothesized that fluctuations in the gold price may influence the Bitcoin price.

The oil price is a dynamic global indicator that may influence financial choices. It has the potential to alter economic perspectives. Given that oil is an essential energy resource for production and a significant component of everyday consumption, it is presumed that fluctuations in oil prices may impact the value of Bitcoin. Furthermore, the Bitcoin market might be affected by oil due to the substantial energy demands associated with Bitcoin mining. Energy is a crucial element of the Bitcoin market. The study conducted by Yousaf et al. (2022) examined the transmission of returns and volatility between oil–gold and oil–Bitcoin pairs both before to and during the COVID-19 pandemic. The research demonstrated a significant transmission of volatility from Bitcoin to oil before the onset of the pandemic. Bitcoin was cited as a means of diversification for the oil business throughout the pandemic. In their investigation, Jin et al. (2019) examined the gold price, oil price, and Bitcoin to determine which of these variables provides more valuable insights into price variations. On the basis of the multifractal detrended cross-correlation research, it was found that Bitcoin was more vulnerable to price fluctuations influenced by gold and oil. Therefore, it is advantageous to use the oil price as an indicator for assessing the Bitcoin price in the study.

Significant volatility may lead to the perception that the asset is a high-risk currency rather than a secure investment and may be considered as a speculative asset (Baek & Elbeck, 2015; Cheah & Fry, 2015; Sapuric et al., 2022). Significant declines in price might deter investors, since the asset's abrupt devaluation can result in substantial losses and prompt investors to find a secure shelter (Baur & Hoang, 2020). Conversely, a significant surge in the Bitcoin price might be viewed as a speculative bubble (Geuder et al., 2019). According to Fang et al. (2020), it is further assumed that the Bitcoin price may be influenced by speculative demand.

The indicators were obtained from investing.com as weekly statistics, spanning from the first week of January 2012 to the third week of November 2023. Furthermore, the investigation took into account a daily data set spanning from January 3, 2012 to November 22, 2023 to ensure the model's reliability. The chosen time period corresponds to the early 2010s, a period when Bitcoin began to get interest from investors, portfolio managers, and policy authorities.

These indicators are notated as follows:

vix: The Chicago Board Options Exchange's Market Volatility Index.
exr: US DXY as the exchange rate.
gp: Gold price XAU/USD.
op: Oil price (WTI).
btcvol: Bitcoin price volatility.
btc: Bitcoin price BTC/USD.

Using the logarithmic first differences in the Bitcoin price, Bitcoin price volatilities were calculated by taking conditional variances calculated from the $GARCH(1, 1)$ models for weekly data and $EGARH(5, 5)$ for daily data. With the exception of Bitcoin price volatility, all data is presented in logarithmic form.

4 | EMPIRICAL RESULTS

4.1 | Unit root test

To assess the stationarity of the variables in a robust way, three alternative unit root tests were used, along with two different specifications for deterministic terms. The tests conducted were Augmented Dickey–Fuller (ADF), Phillips–Perron (PP), and Ng–Perron. The test results are shown in Table 1, indicating that the integrated order of each variable, except for variable *vix*, is one. These findings indicate that variable *vix* is stationary at the logarithmic level, whereas the other variables are stationary when considering the first difference in the logarithmic form.

4.2 | Estimating volatility for the Bitcoin price

To be able to estimate volatility for Δbtc, conditional variance models, including ARCH effects, are required. The ARCH effect was tested using the ARCH-Lagrange multiplier (ARCH-LM) method. The mean equation was selected as only a constant term. The ARCH effects for lags from 1 to 8 were tested via the ARCH-LM test and the null hypotheses of the absence of ARCH effects were rejected at a 1% significance level. These results show that conditional variance models can be used to predict Bitcoin price volatility.

The $GARCH(1, 1)$ model, among alternative conditional variance models, such as autoregressive conditional heteroscedasticity (ARCH), generalized ARCH (GARCH), and exponential GARCH (EGARCH), was determined for Bitcoin price volatility using the Schwarz criterion.

The conditional variance model is specified as follows:

Mean equation: $\Delta btc_t = \phi_0 + e_t$.
Variance equation: $h_t = c + \beta e_{t-1}^2 + \gamma h_{t-1}$.

TABLE 1 Unit root test results.

Variable	ADF *t* statistic	PP adjusted *t* statistic	Ng–Perron MZ_α test statistic
Exogenous variable is only intercept			
vix	−6.2608 (−2.8860)	−5.8233 (−2.8660)	−39.9286 (−8.1000)
exr	−1.5162 (−2.8660)	−1.4533 (−2.8660)	−1.4821 (−8.1000)
Δ*exr*	−26.4671 (−2.8660)	−23.9984 (−2.8671)	−248.9990 (−8.1000)
gp	−0.8947 (−2.8660)	−0.8232 (−2.8660)	−2.4336 (−8.1000)
Δ*gp*	−24.4237 (−2.8660)	−24.4488 (−2.8660)	−15.9817 (−8.1000)
op	−2.3571 (−2.8660)	−2.4220 (−2.8660)	−4.0656 (−8.1000)
Δ*op*	−21.4722 (−2.8660)	−21.4608 (−2.8660)	−43.0967 (−8.1000)
btc	−2.0650 (−2.8660)	−1.9909 (−2.8660)	0.8477 (−8.1000)
Δ*btc*	−24.3857 (−2.8660)	−24.5278 (−2.8660)	−309.2420 (−8.1000)
Exogenous variables are trend and intercept			
vix	−6.8029 (−3.4171)	−6.4391 (−3.4171)	−44.4648 (−17.3000)
exr	−2.1932 (−3.4171)	−2.1234 (−3.4171)	−9.2379 (−17.3000)
Δ*exr*	−26.4470 (−3.4171)	−26.4623 (−3.4171)	−308.9100 (−17.3000)
gp	−2.0510 (−3.4171)	−1.9896 (−3.4171)	−2.6255 (−17.3000)
Δ*gp*	−24.4861 (−3.4171)	−24.5379 (−3.4171)	−304.2240 (−17.3000)
op	−2.2771 (−3.4171)	−2.3356 (−3.4171)	−7.9325 (−17.3000)
Δ*op*	−21.4719 (−3.4171)	−18.00361 (−3.4189)	−299.0680 (−17.3000)
btc	−1.8341 (−3.4171)	−2.0081 (−3.4171)	−2.6766 (−17.3000)
Δ*btc*	−24.4554 (−3.4171)	−24.5412 (−3.4171)	−309.3090 (−17.3000)

Note: The number in brackets is the critical values at a 5% significant level.

Appropriate lag length for ADF and Ng–Perron test has been selected using the Schwarz Information Criterion for a maximum lag of 24 periods.

Appropriate Newey–West bandwidth for unit root tests except ADF is selected using Bartlett kernel.

Abbreviations: ADF, Augmented Dickey–Fuller; PP, Phillips–Perron.

The results of the $GARCH(1, 1)$ model are given in Table 2. According to the results, the estimated coefficients of variance equation are positive and their sum is less than one. Therefore, the parameter restrictions for positivity and finiteness are satisfied. The ARCH effect for order q in the residuals was tested using the ARCH-LM F statistic for lags from 1 to 8. Their p values are given in the table. The null hypothesis that "the ARCH effect is not present for order q in

TABLE 2 $GARCH(1,1)$ model results.

Variable	Coefficient	p Value		
Mean equation				
Constant	0.0089	0.0517		
Variance equation				
Constant	0.0028	0.0000		
e_{t-1}^2	0.2867	0.0000		
h_{t-1}	0.5296	0.0000		
ARCH-LM test				
Lag	**1**	**2**	**3**	**4**
F statistic	0.0846	0.1276	0.2204	0.2674
p Value	0.7713	0.8803	0.8822	0.8989
Lag	**5**	**6**	**7**	**8**
F statistic	0.2244	0.3265	0.2881	0.3006
p Value	0.9520	0.9231	0.9586	0.9657

Abbreviations: ARCH, autoregressive conditional heteroscedasticity; GARCH, generalized autoregressive conditional heteroscedasticity; LM, Lagrange multiplier.

the residuals" is not rejected at a 1% level of significance for all orders. Therefore, $GARCH(1,1)$ model residuals do not have ARCH effects. The conditional variances, calculated from the $GARCH(1,1)$ are implemented as Bitcoin price volatility.

Figure 1 depicts the instances of Bitcoin price volatility across the observed timeframe. The Bitcoin price exhibited significant volatility throughout the first stages, notably from 2013 to 2014, but subsequently experienced a reduction in volatility in the following years. The ADF, PP, and Ng–Perron unit root tests were employed to assess the stationarity of Bitcoin price volatility. All unit root test findings indicated that it was stationary at a 1% significance level.

4.3 | Granger causality tests

Maddala and Kim (1998) suggest that Granger causality can be applied to identify leading indicators. Burgstaller (2002) proposes that if the x_t variable is the Granger cause of y_t variable, it serves as a predictor or signal. This is because the idea of Granger causality specifically focuses on the capacity to foresee the short-term connection between variables. For the purpose of identifying the short-term leading indicators for the Bitcoin price, the Granger causality test was performed. The conventional Granger causality test is applicable to time series that exhibit stationarity. Consequently, considering the outcomes of the unit root tests, the Granger causality tests were conducted using transformations that ensure the variables are stationary. In other words, Granger causality tests were carried out by taking the logarithmic form of the VIX, the level of Bitcoin price volatility, and the logarithmic first-order differences of the other variables.

The results of the pairwise Granger causality tests are shown in Table 3 for weekly data and Table 4 for daily data. On the basis of Granger causality tests conducted using both weekly and daily data, it is shown that not all variables in the research are considered Granger causes of the VIX. The data indicate that the VIX is the most exogenous variable. Granger causality tests conducted utilizing both weekly and daily data indicate that the factors influencing the Bitcoin price are the gold price and Bitcoin price volatility. The Granger causality analysis reveals that Bitcoin price volatility is influenced only by the Bitcoin price itself when examining weekly data. However, when examining daily data, all other factors except the exchange rate contribute to the volatility. The findings suggest a bidirectional causal connection between the Bitcoin price and Bitcoin price volatility.

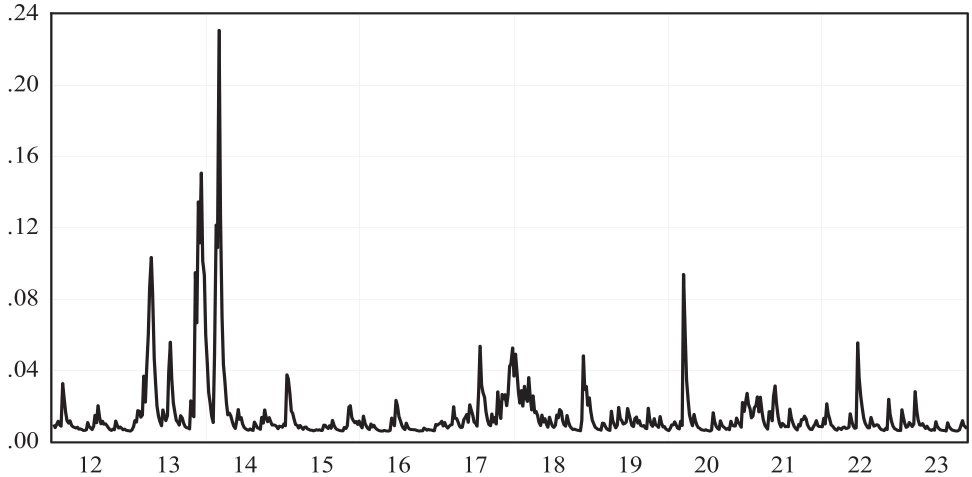

FIGURE 1 Representation of Bitcoin price volatility.

TABLE 3 Granger causality test results for weekly data.

Dependent variable: Volatility index				**Dependent variable: Exchange rate**			
Variable	**Lag**	χ^2	***p* Value**	**Variable**	**Lag**	χ^2	***p* Value**
Δ*exr*	1	0.3805	0.5374	*vix*	1	0.1938	0.6598
Δ*gp*	1	0.2737	0.6009	Δ*gp*	1	0.3620	0.5474
Δ*op*	11	13.2811	0.2754	Δ*op*	4	10.7861*	0.0291
btcvol	3	6.6907	0.0824	*btcvol*	3	8.7848*	0.0323
Δ*btc*	1	3.0266	0.0819	Δ*btc*	1	1.5551	0.2124
Dependent variable: Gold price				**Dependent variable: Oil price**			
Variable	**Lag**	χ^2	***p* Value**	**Variable**	**Lag**	χ^2	***p* Value**
vix	1	0.2737	0.6009	*vix*	11	13.2811	0.2754
Δ*exr*	1	3.0762	0.0794	Δ*exr*	4	12.9332*	0.0116
Δ*op*	4	11.3864*	0.0225	Δ*gp*	4	2.7796	0.5954
btcvol	3	2.4368	0.4868	*btcvol*	3	6.8144	0.0781
Δ*btc*	2	4.8772	0.0873	Δ*btc*	1	2.1676	0.1409
Dependent variable: Bitcoin price volatility				**Dependent variable: Bitcoin price**			
Variable	**Lag**	χ^2	***p* Value**	**Variable**	**Lag**	χ^2	***p* Value**
vix	3	2.3721	0.4988	*vix*	1	1.0992	0.2945
Δ*exr*	3	0.1323	0.9877	Δ*exr*	1	1.5016	0.2204
Δ*gp*	3	7.5359	0.0566	Δ*gp*	2	10.7923**	0.0045
Δ*op*	3	3.1940	0.3627	Δ*op*	1	0.4701	0.4930
Δ*btc*	16	71.9987**	0.0000	*btcvol*	16	32.9850**	0.0074

Note: Appropriate lag length was selected using Akaike information criterion for a maximum lag of 24 periods. Δ is a first-order difference operator.
* and ** correspond to being statistically significant at the level of 5% and 1%, respectively.

TABLE 4 Granger causality test results for daily data.

Dependent variable: Volatility index				Dependent variable: Exchange rate			
Variable	**Lag**	χ^2	***p* Value**	**Variable**	**Lag**	χ^2	***p* Value**
Δexr	2	0.4741	0.7890	*vix*	2	3.9469	0.1390
Δgp	2	0.3226	0.8510	Δgp	1	13.7649**	0.0002
Δop	3	4.1171	0.2491	Δop	1	4.2975*	0.0382
btcvol	16	14.7987	0.5394	*btcvol*	15	11.8225	0.6924
Δbtc	9	11.8640	0.2211	Δbtc	6	11.6147	0.0711
Dependent variable: Gold price				**Dependent variable: Oil price**			
Variable	**Lag**	χ^2	***p* Value**	**Variable**	**Lag**	χ^2	***p* Value**
vix	2	2.2536	0.3241	*vix*	3	17.0197**	0.0007
Δexr	1	3.4672	0.0626	Δexr	1	0.7854	0.3755
Δop	1	1.1533	0.2829	Δgp	1	0.0612	0.8046
btcvol	20	36.7334*	0.0126	*btcvol*	16	62.6978**	0.0000
Δbtc	7	9.0354	0.2501	Δbtc	7	14.0052	0.0511
Dependent variable: Bitcoin price volatility				**Dependent variable: Bitcoin price**			
Variable	**Lag**	χ^2	***p* Value**	**Variable**	**Lag**	χ^2	***p* Value**
vix	16	52.8144**	0.0000	*vix*	9	12.8730	0.1684
Δexr	15	17.9651	0.2645	Δexr	6	3.7626	0.7088
Δgp	29	46.5139**	0.0007	Δgp	7	16.2465*	0.0230
Δop	16	78.2401**	0.0000	Δop	7	4.9794	0.6625
Δbtc	23	591.5056**	0.0000	*btcvol*	23	253.7613**	0.0000

Note: Appropriate lag length was selected using Akaike information criterion for a maximum lag of 24 periods. Δ is a first-order difference operator.
* and ** correspond to being statistically significant at the level of 5% and 1%, respectively.

4.4 | SVAR model

The short-run *SVAR*(*p*) specification for the *A*–*B* model can be written as the following:

$$\boldsymbol{A}(\mathbf{I}_k - \boldsymbol{A}_1\boldsymbol{L} - \boldsymbol{A}_2\boldsymbol{L}^2 - \ldots \boldsymbol{A}_p\boldsymbol{L}^p)\boldsymbol{y}_t = \boldsymbol{A}\boldsymbol{e}_t = \boldsymbol{B}\boldsymbol{u}_t,$$

where $\boldsymbol{L}$ is the lag operator, the vector $\boldsymbol{e}_t$ is the error terms of the standard VAR model with covariance matrix $\sum_{\boldsymbol{e}}$, the vector $\boldsymbol{u}_t$ is the error terms of the structural VAR model with covariance matrix $\mathbf{I}_k$, k is the number of variables in the model, and $\boldsymbol{A}$ and $\boldsymbol{B}$ are the restriction matrices. The order condition requires $k^2 + \frac{k(k-1)}{2}$ restrictions for identification in the short-run *A*–*B* model. The SVAR model is designed to consider the connection between the most exogenous variable and endogenous variable, while imposing certain limits. Furthermore, the SVAR model may be used to examine the impact of the most internally-driven variable on the possible influencing factor. Thus, considering the limitations that the Bitcoin price is impacted by other factors, it may also impact its own volatility, assuming that other exogenous factors do not have an effect on this significant variable. In other words, the model allows for the establishment of a boundary between the Bitcoin price and Bitcoin price volatility. This implies that Bitcoin price shocks are affected by shocks in all other factors. However, its shocks only have a simultaneous effect on Bitcoin price volatility. The SVAR model offers advantages in terms of efficiency and sufficiency for establishing this connection.

The identifying restrictions in this study are given below:

- ✓ Shocks of other variables in the SVAR model are impacted contemporaneously by the VIX, but the shocks of those other variables do not have a contemporaneous effect on the shocks of the VIX. The variable VIX can be considered the most exogenous, according to Köse and Ünal (2023a).
- ✓ Exchange rate shocks have a contemporaneous influence on the gold price, the oil price, and the Bitcoin price. Furthermore, exchange rate shocks are only impacted contemporaneously by VIX shocks. The DXY is regarded as a factor that can affect the prices of gold and oil. In other words, the exchange rate is considered a more exogenous influence when compared with these assets (Köse & Ünal, 2023a; Wang et al., 2022).
- ✓ Gold price shocks are affected contemporaneously by both VIX and exchange rate shocks. Moreover, gold price shocks only have a contemporaneous effect on Bitcoin price shocks. Gold was identified as a potential substitute to Bitcoin (Basher & Sadorsky, 2022; Köse & Ünal, 2023a; Raheem, 2021).
- ✓ Similar to the price of gold, oil price shocks are affected contemporaneously by both VIX and exchange rate shocks. Moreover, oil price shocks only have a contemporaneous effect on Bitcoin price shocks. Ünal and Köse (2023) suggested that the oil price can have a substantial effect on mineable cryptocurrencies. Bitcoin is a cryptocurrency that can be obtained via the process of mining.
- ✓ Bitcoin price volatility shocks are affected contemporaneously by VIX shocks and Bitcoin price shocks. Moreover, Bitcoin price volatility shocks only have a contemporaneous effect on Bitcoin price shocks.
- ✓ The Bitcoin price is assumed to be the most endogenous variable. Hence, Bitcoin price shocks are affected contemporaneously by all of the other variables' shocks but its shocks have contemporaneous effect on only Bitcoin price volatility shocks. Köse and Ünal (2023b) demonstrated that Bitcoin served as the primary indications among the other cryptocurrencies. Hence, it is a factor that has the potential to impact its own value within the context of its volatility.

Under these restrictions, the SVAR model with A and B matrices can be specified as below:

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 & 0 & 0 \\ a_{41} & a_{42} & 0 & 1 & 0 & 0 \\ a_{51} & 0 & 0 & 0 & 1 & a_{56} \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & 1 \end{bmatrix} \begin{bmatrix} e_t^{vix} \\ e_t^{exr} \\ e_t^{gp} \\ e_t^{op} \\ e_t^{btcvol} \\ e_t^{btc} \end{bmatrix} = \begin{bmatrix} b_{11} & 0 & 0 & 0 & 0 & 0 \\ 0 & b_{22} & 0 & 0 & 0 & 0 \\ 0 & 0 & b_{33} & 0 & 0 & 0 \\ 0 & 0 & 0 & b_{44} & 0 & 0 \\ 0 & 0 & 0 & 0 & b_{55} & 0 \\ 0 & 0 & 0 & 0 & 0 & b_{66} \end{bmatrix} \begin{bmatrix} u_t^{vix} \\ u_t^{exr} \\ u_t^{gp} \\ u_t^{op} \\ u_t^{btcvol} \\ u_t^{btc} \end{bmatrix}.$$

The optimum lag length for the VAR model is selected as 3, using Akaike information criterion (AIC) with a maximum lag of 24. Due to the fact that SVAR model is overidentified, the Likelihood Ratio (LR) test for overidentification was performed. The p value for the LR statistic was found to be 0.0139 greater than 0.01, null hypothesis, which indicates that overidentification is valid, and is not rejected at a 1% significant level.

4.5 | Variance decomposition

The outcomes of the forecast error variance decomposition for the Bitcoin price are provided at 24-week periods in Table 5. These outcomes are based on the numerous assumptions that were taken into consideration. This denotes the proportion of changes in the Bitcoin price resulting from the influence of the indicators.

On the basis of the findings, the Bitcoin price was greatly influenced by both the VIX and the oil price. The impact of the VIX was 1.24% in the first week, but it had a substantial rise to 5.64% in the 12th week, and further rose to 5.84% in the 24th week. Over the course of the weeks, the proportion of the movement in the Bitcoin price that can be attributed to the oil price gradually increased. It was found that the oil price had a 0.40 percent influence on the Bitcoin price during the first week. The magnitude of this impact grew to 1.83% during the 12th week and then climbed to 3.90% by the 24th week. The exchange rate has the least significant influence on the Bitcoin price. The influence of the exchange rate on the Bitcoin price was negligible over the first 12 weeks and experienced a little uptick of 0.14% in the 24th week. The gold price had a greater influence on the Bitcoin price in comparison to the exchange rate. The value was 0.08% during the first week. The percentage had a growth from 1.63% to 2.64% throughout the period spanning from the 12th to the 24th weeks. It was found that the Bitcoin price volatility had the most significant

TABLE 5 Results of variance decomposition for the Bitcoin price.

Weeks	VIX	Exchange rate	Gold price	Oil price	Bitcoin price volatility	Bitcoin price
1	1.24	0.06	0.08	0.40	64.67	33.57
2	1.86	0.15	0.06	0.34	60.78	36.81
3	2.91	0.10	0.39	0.46	54.45	41.68
4	3.48	0.08	0.59	0.69	51.87	43.28
5	3.94	0.06	0.80	0.89	50.24	44.07
6	4.32	0.05	0.96	1.05	49.87	43.74
7	4.64	0.05	1.11	1.19	49.97	43.05
8	4.92	0.05	1.23	1.31	50.38	42.12
9	5.15	0.05	1.33	1.44	50.86	41.17
10	5.34	0.05	1.44	1.56	51.34	40.27
11	5.50	0.06	1.53	1.69	51.76	39.45
12	5.64	0.06	1.63	1.83	52.11	38.73
13	5.74	0.07	1.72	1.98	52.38	38.11
14	5.83	0.08	1.81	2.14	52.59	37.56
15	5.89	0.08	1.90	2.30	52.75	37.08
16	5.94	0.09	1.98	2.46	52.86	36.66
17	5.97	0.10	2.07	2.63	52.94	36.29
18	5.98	0.10	2.16	2.81	53.00	35.95
19	5.98	0.11	2.24	2.98	53.04	35.65
20	5.97	0.12	2.32	3.16	53.06	35.37
21	5.95	0.13	2.40	3.34	53.07	35.11
22	5.92	0.13	2.48	3.53	53.07	34.87
23	5.88	0.14	2.56	3.71	53.06	34.64
24	5.84	0.14	2.64	3.90	53.05	34.43

Abbreviation: VIX, Volatility Index.

influence on the Bitcoin price over the course of the weeks. The initial effect was 64.67% during the first week, which then declined to 52.11% by the 12th week. However, it then increased to 53.05% by the 24th week. The explanatory component of the Bitcoin price itself did not show any significant variation throughout the given time periods. The first week had an explanatory share of 33.57%, which increased to 34.43% in the last week.

4.6 | Impulse response functions

The responses of the Bitcoin price to the indicators are illustrated in Figure 2. The factors influencing the Bitcoin price include the VIX, exchange rate, gold price, oil price, and Bitcoin price volatility, while the response is the Bitcoin price itself. The response of the Bitcoin price to structural one standard deviation positive innovations was taken into consideration. In other words, an examination was carried out to determine the statistical significance of the interaction between the indicators and the Bitcoin price.

This figure demonstrates that the relationship between the Bitcoin price and the VIX was statistically significant starting from the first week. Furthermore, the response remained consistently negative until the twelfth week. This outcome demonstrates a significant connection between the price of Bitcoin and the VIX. In other words, an increasing VIX has a negative effect on the Bitcoin price, and conversely, a decreasing VIX has a positive

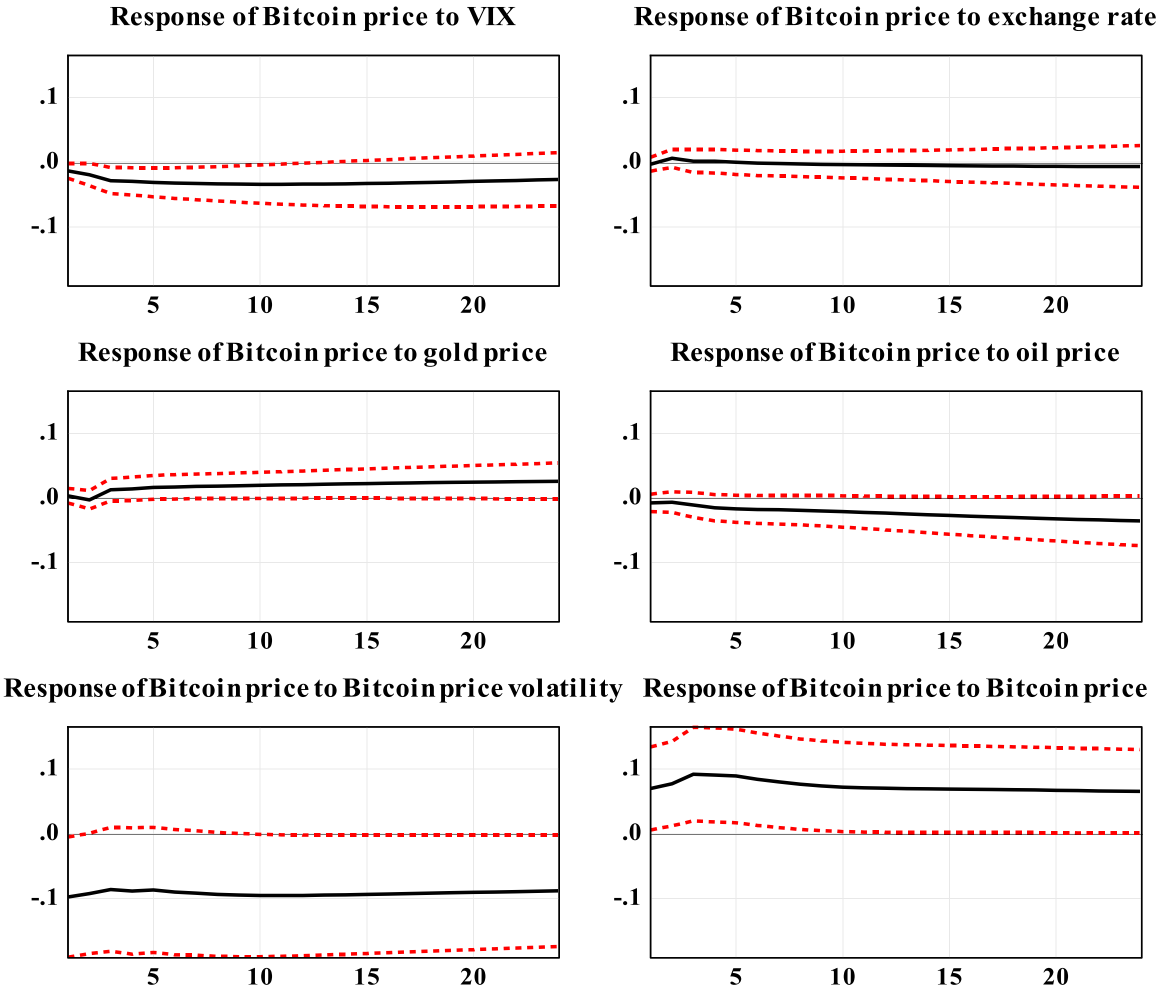

FIGURE 2 Response of the Bitcoin price to structural one standard deviation positive innovations for weekly data analysis. The *Y*-axis shows responses and the *X*-axis shows weeks. VIX, Volatility Index.

influence. There was not a significant connection between the Bitcoin price and the exchange rate, gold price, and oil price across all projected periods. The Bitcoin price exhibited a negative and significant response to Bitcoin price volatility, which persisted until the second week. Starting with the tenth week, the response consistently remained negative and statistically significant for the whole period. This outcome demonstrates the significance of volatility and the willingness of investors to take risks. The Bitcoin price exhibited a positive and statistically significant response to its own price. It experienced a minor decline throughout the given time frame, but the connection between the variables remained statistically significant.

4.7 | Daily test evaluation

To assess the robustness and address the gap in the analysis, the SVAR model was applied utilizing daily data. Therefore, the same processes were also used to the daily data analysis. The unit root tests used in Table 6 were the same as those employed in the weekly data analysis. The findings of all tests were consistent with the weekly data results. The test findings reveal that the integrated order of each variable is one, except *vix*. Other variables become stationary when taking the logarithmic first difference.

The *EGARCH*(5, 5) model, among alternative conditional variance models, such as ARCH, GARCH, and EGARCH, was determined for Bitcoin price volatility using the Schwarz criterion for daily data.

The conditional variance model is specified as follows:

TABLE 6 Unit root test results for daily data.

Variable	ADF t statistic	PP adjusted t statistic	Ng–Perron MZ_α test statistic
Exogenous variable is only intercept			
vix	−6.2648 (−2.8623)	−6.0470 (−2.8623)	−39.3913 (−8.1000)
exr	−1.6481 (−2.8623)	−1.6107 (−2.8623)	0.1970 (−8.1000)
Δexr	−55.1342 (−2.8623)	−55.1840 (−2.8623)	−444.3730 (−8.1000)
gp	−0.9440 (−2.8623)	−0.9346 (−2.8623)	−2.6171 (−8.1000)
Δgp	−54.6219 (−2.8623)	−54.6240 (−2.8623)	−30.4068 (−8.1000)
op	−3.0670 (−2.8623)	−4.1644 (−2.8623)	−2.9473 (−8.1000)
Δop	−55.8162 (−2.8623)	−55.7729 (−2.8623)	−1478.21 (−8.1000)
btc	−2.0554 (−2.8623)	−2.2119 (−2.8623)	0.7972 (−8.1000)
Δbtc	−27.1026 (−2.8623)	−55.3050 (−2.8623)	−296.2500 (−8.1000)
Exogenous variables are trend and intercept			
vix	−6.8105 (−3.4113)	−6.6778 (−3.4113)	−47.7561 (−17.3000)
exr	−2.2191 (−3.4113)	−2.1636 (−3.4113)	−7.9472 (−17.3000)
Δexr	−55.1266 (−3.4113)	−55.1754 (−3.4113)	−905.2510 (−17.3000)
gp	−2.0754 (−3.4113)	−2.0654 (−3.4113)	−2.7312 (−17.3000)
Δgp	−54.6457 (−3.4113)	−54.6498 (−3.4113)	−756.8890 (−17.3000)
op	−2.9640 (−3.4113)	−4.0636 (−3.4113)	−6.0626 (−17.3000)
Δop	−55.8203 (−3.4113)	−55.7796 (−3.4113)	−612.9530 (−17.3000)
btc	−2.0915 (−3.4113)	−2.1808 (−3.4113)	−2.6169 (−17.3000)
Δbtc	−27.1430 (−3.4113)	−55.3293 (−3.4113)	−767.5690 (−17.3000)

Note: The number in brackets is the critical values at a 5% significant level.

Appropriate lag length for ADF and Ng–Perron test has been selected using Schwarz Information Criterion for a maximum lag of 48 periods.

Appropriate Newey–West bandwidth for unit root tests except ADF is selected using Bartlett kernel.

Abbreviations: ADF, Augmented Dickey–Fuller; PP, Phillips–Perron.

Mean equation: $\Delta btc_t = \phi_0 + e_t$.

Variance equation: $\log(h_t) = c + \sum_{j=1}^{5} \alpha_j \left| \frac{e_{t-1}}{\sqrt{h_{t-1}}} \right| + \gamma \frac{e_{t-1}}{\sqrt{h_{t-1}}} + \sum_{i=1}^{5} \beta_i \log(h_{t-i})$.

The results of the $EGARCH(5,5)$ model for daily data are given in Table 7. The ARCH effect for order q in the residuals was tested using ARCH-LM F statistic for lags from 1 to 8. Their p values are given in the table. The null hypothesis that "the ARCH effect is not present for order q in the residuals" is not rejected at a 1% level of significance for all orders. Therefore, $EGARCH(5,5)$ model residuals do not have ARCH effects. The conditional variances, calculated from the $EGARCH(5,5)$ is used as Bitcoin price volatility for daily data. The representation of daily Bitcoin price volatility is given in Figure 3.

The SVAR model was employed to analyze daily data, similar to the investigation conducted on weekly data. The optimum lag length for the VAR model is selected as 10, using AIC with a maximum lag of 30. Due to the fact that the SVAR model is overidentified, the LR test for overidentification was performed. The p value for the LR statistic was found to be 0.0000 less than 0.01, null hypothesis, which indicates that overidentification is not valid, and is rejected at a 1% significant level.

The forecast error variance decomposition findings for the Bitcoin price are shown in Table 8, organized in 30-day periods. The variance decomposition analysis reveals consistent results obtained from the investigation of weekly data. The analysis presented in the table demonstrates that the Bitcoin price was significantly influenced by the VIX in comparison to other factors. The impact of the VIX was 0.83% on the first day. The impact steadily rose to 3.01% on the 30th day. This suggests that the impact of the VIX increases with period. The impact of the exchange rate, the gold price, and the oil price remained relatively limited for the whole time. The daily examination of Bitcoin price revealed that its volatility had the greatest influence on its price, compared with the weekly analysis. The first day experienced a 41.02% effect. However, it witnessed a substantial rise to 67.27% on the 15th day, and then increased to 70.18% on the 30th day. In contrast to the weekly data analysis, this daily research reveals that Bitcoin exhibits more pronounced

TABLE 7 $EGARCH(5,5)$ model results for daily data.

Variable	Coefficient	p Value		
Mean equation				
Constant	0.0027	0.0000		
Variance equation				
Constant	−4.4633	0.0000		
$\lvert e_{t-1}/\sqrt{h_{t-1}}\rvert$	0.3260	0.0000		
$\lvert e_{t-2}/\sqrt{h_{t-2}}\rvert$	0.5562	0.0000		
$\lvert e_{t-3}/\sqrt{h_{t-3}}\rvert$	0.6838	0.0000		
$\lvert e_{t-4}/\sqrt{h_{t-4}}\rvert$	0.5964	0.0000		
$\lvert e_{t-4}/\sqrt{h_{t-4}}\rvert$	0.3261	0.0000		
$e_{t-5}/\sqrt{h_{t-5}}$	−0.0210	0.0020		
$\log(h_{t-1})$	−0.3752	0.0000		
$\log(h_{t-2})$	−0.3948	0.0000		
$\log(h_{t-3})$	0.2924	0.0000		
$\log(h_{t-4})$	0.2066	0.0000		
$\log(h_{t-5})$	0.8255	0.0000		
ARCH-LM test				
Lag	**1**	**2**	**3**	**4**
F statistic	0.0453	0.0540	1.3784	1.0794
p Value	0.8315	0.9474	0.2475	0.3649
Lag	**5**	**6**	**7**	**8**
F statistic	0.9690	0.9344	0.8362	0.7745
p Value	0.4353	0.4689	0.5571	0.6253

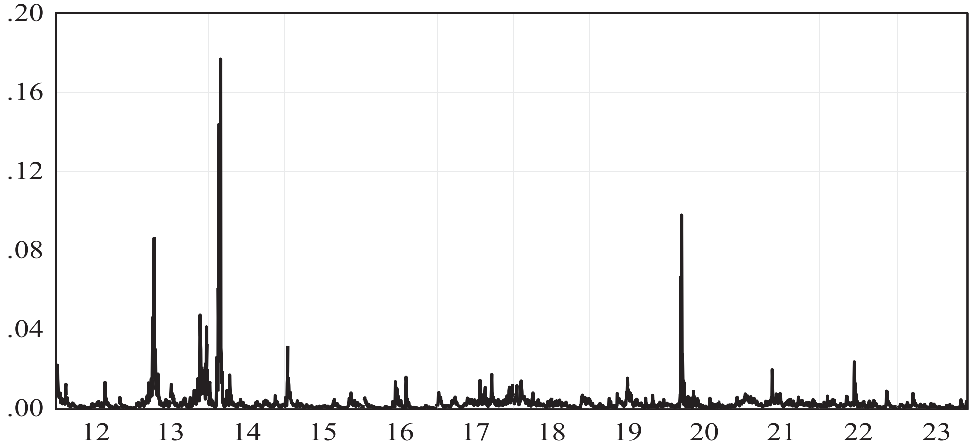

FIGURE 3 Representation of daily Bitcoin price volatility.

responses to Bitcoin price volatility. The explanatory component of the Bitcoin price itself shown substantial fluctuations throughout the time periods. The first day had an explanatory share of 57.92%, which then declined to 26.10% in the last day.

Figure 4 illustrates the responses of the Bitcoin price to the specified factors in the daily data analysis. The analysis indicated in the figure demonstrates that the relationship between the Bitcoin price and the VIX was both statistically significant and consistently negative during the entire time period. As was the case with the weekly analysis, the effect is negative, but the extent of its impact is far greater. In other words, an increasing VIX has a negative impact on the Bitcoin price. The responses of the Bitcoin price to the exchange rate and the oil price did not exhibit statistical significance for all of the prediction periods investigated. The response to the gold price exhibited a positive and significant effect until the fifth period. In the daily case study, the Bitcoin price exhibited a negative and statistically significant response to Bitcoin price volatility, which persisted until the fourth period. Subsequently, the response exhibited a positive and significant effect over the whole duration of each day. In contrast to weekly data analysis, this finding suggests that in the short term, the willingness to take risks is replaced by positive responses in the Bitcoin price. Nevertheless, when examining the weekly data analysis, responses turn out to be negative. In other words, over a longer period of time, the effects are negative. In addition, the connection between the Bitcoin price and its own values was found to be statistically negligible during the whole prediction period.

5 | POLICY IMPLICATIONS

This investigation aims to support investors and portfolio managers in identifying a new asset that has the potential to serve as a safe haven and investment choice for hedging and diversification purposes. Moreover, its purpose is to serve as a guide for policymakers in monitoring the cryptocurrency markets. Unveiling the characteristics of Bitcoin may provide insight into whether the instrument acts similarly to a conventional asset. In order for it to be legitimate, there must be a substantial connection between Bitcoin and other assets. This demonstrates that Bitcoin has a lower level of risk and possesses the same characteristics as any other asset in the market. Unraveling the complexities of Bitcoin may prevent the loss of assets and secure investments.

The findings of the analysis provide significant consequences for policymakers, investors, and portfolio managers. Shahzad et al. (2022) shown that Bitcoin and gold have limited effectiveness as hedging instruments. Furthermore, it has been noted that the VIX may provide enhanced diversification opportunities for nations during moments of turmoil. According to Wang et al. (2021), Bitcoin has favorable hedging characteristics. Al-Yahyaee et al. (2019) identified a connection between the VIX and the price of Bitcoin. However, they did not specify the significance of this correlation as an explanatory indicator, nor did they explain the specific periods in which the VIX had the greatest impact on the price of Bitcoin. The results in this study yields comparable results to Wu et al. (2021), with the exception of their treatment of uncertainty. Uncertainty was demonstrated to have an adverse effect on the long-term volatility of Bitcoin. In contrast to previous investigations, this research demonstrated that Bitcoin is mostly impacted by its own volatility. The impulse response functions revealed that Bitcoin price volatility elicited mostly positive responses in the

TABLE 8 Results of variance decomposition for the Bitcoin price for daily data.

Days	VIX	Exchange rate	Gold price	Oil price	Bitcoin price volatility	Bitcoin price
1	0.83	0.05	0.04	0.14	41.02	57.92
2	0.94	0.03	0.35	0.10	39.80	58.78
3	0.99	0.02	0.63	0.08	40.30	57.98
4	0.94	0.02	0.59	0.16	47.07	51.22
5	0.86	0.02	0.50	0.16	49.99	48.48
6	0.92	0.03	0.42	0.18	53.48	44.98
7	0.93	0.03	0.37	0.20	56.69	41.77
8	1.04	0.04	0.33	0.21	58.62	39.76
9	1.06	0.06	0.29	0.20	60.67	37.72
10	1.10	0.07	0.27	0.20	62.24	36.12
11	1.15	0.08	0.26	0.18	63.59	34.73
12	1.20	0.08	0.26	0.17	64.82	33.46
13	1.28	0.09	0.27	0.17	65.75	32.45
14	1.36	0.08	0.28	0.16	66.61	31.50
15	1.46	0.08	0.29	0.16	67.27	30.74
16	1.57	0.08	0.31	0.15	67.83	30.06
17	1.67	0.08	0.33	0.14	68.29	29.49
18	1.77	0.08	0.35	0.14	68.66	29.00
19	1.88	0.07	0.37	0.13	69.00	28.55
20	1.98	0.07	0.38	0.13	69.24	28.19
21	2.09	0.07	0.40	0.12	69.46	27.86
22	2.20	0.07	0.42	0.12	69.63	27.57
23	2.30	0.07	0.44	0.11	69.76	27.33
24	2.40	0.06	0.46	0.11	69.87	27.09
25	2.51	0.06	0.48	0.10	69.95	26.90
26	2.61	0.06	0.50	0.10	70.02	26.71
27	2.71	0.06	0.52	0.09	70.08	26.54
26	2.81	0.06	0.53	0.09	70.12	26.39
29	2.91	0.06	0.55	0.09	70.15	26.24
30	3.01	0.05	0.57	0.09	70.18	26.10

Abbreviation: VIX, Volatility Index.

short term from the analysis of daily data but yielded negative impacts in the long term from the study of weekly data. Furthermore, Bitcoin price volatility had the most significant impact on explaining changes in the Bitcoin price. Bitcoin is a volatile investment that does not conform to the behavior of traditional assets. The correlation between gold and Bitcoin is rather modest in comparison to the VIX. According to the variance decomposition analysis, the price of gold was a variable that had a lesser power of explanation for the price of this cryptocurrency. From this standpoint, the study reveals that Bitcoin lacks substantial connections with traditional assets, yet it exhibits a notable association with its own volatility. Therefore, it is essential for policymakers to establish a financial system that can facilitate the inclusion of cryptocurrencies as comparable to traditional assets. Enhancing market stability will foster more investor confidence and entice increased participation in cryptocurrencies. Policymakers have the ability to provide a favorable

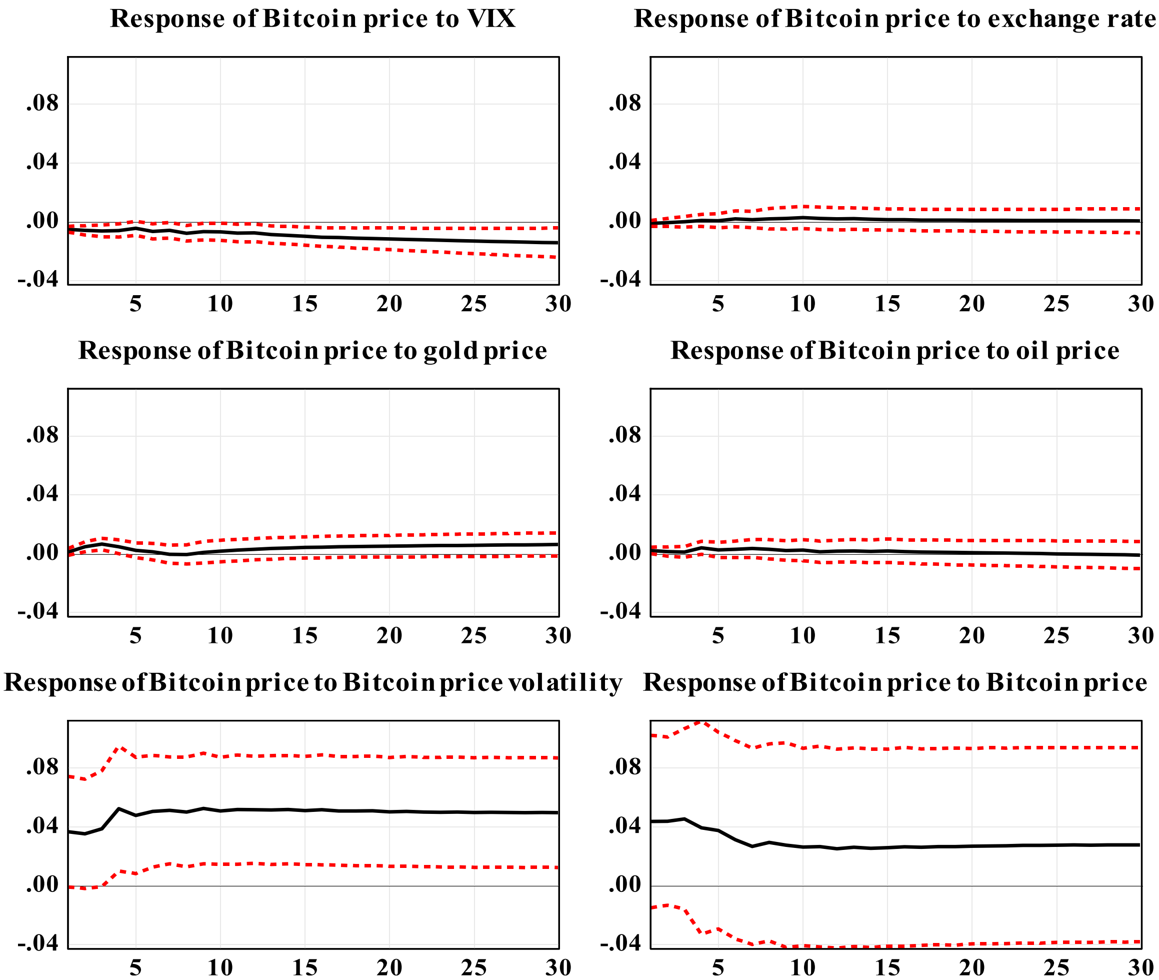

FIGURE 4 Response of the Bitcoin price to structural one standard deviation positive innovations for daily data analysis. The *Y*-axis shows responses and the *X*-axis shows days. VIX, Volatility Index.

trajectory for the growth of cryptocurrencies. The association between the VIX and Bitcoin demonstrates a negative connection. Consequently, an increase in the VIX leads to a decrease in the Bitcoin price. This suggests that the cryptocurrency market lacks protective controls for cryptocurrencies, making them still uncertain. This study also demonstrates that traditional assets and the VIX index have little effects on the price of Bitcoin. Ensuring stability in the cryptocurrency financial markets will lead to a subsequent wave of technological advances and digital trading, playing a crucial role in diminishing both time and transaction expenses. Furthermore, this will also eradicate significant fluctuations and enhance the acceptance of cryptocurrencies as a conventional platform. This research, which examines the interdependence between cryptocurrencies and other assets, will assist regulatory authorities in enhancing the state of the digital financial sector. This study also demonstrates that traditional assets and the VIX index have limited impacts on the Bitcoin price. Ensuring stability in the cryptocurrency financial markets will lead to a subsequent wave of technological advances and digital trading, playing a crucial role in minimizing both time and transaction expenses. Furthermore, this will also eradicate significant fluctuations and enhance the acceptance of cryptocurrencies as a conventional platform. This research examines the interdependence between Bitcoin and other assets, with the aim of assisting regulatory authorities in enhancing the state of the digital financial sector.

The findings also suggest that Bitcoin may serve as a diversification tool for investors with a high tolerance for risk, since it is primarily impacted by its own level of uncertainty. This demonstrates that investors might develop a keen interest in Bitcoin, since it has no connection with traditional assets. Attention, investors and portfolio managers, please be advised of the following cautionary notice. To mitigate potential losses, it is essential to minimize unnecessary exposure to risks associated with Bitcoin, given its high likelihood of enduring financial setbacks. Therefore, it is necessary for governments worldwide to actively participate in the advancement of cryptocurrencies to enhance the stability of the financial sector, rather than rejecting involvement in this expanding sector. The widespread adoption of this technological breakthrough has already been achieved in the majority of nations, and it is highly anticipated that cryptocurrencies will have a significant impact on economies. To do this, it is imperative to implement new legislation that will facilitate the growth of cryptocurrencies and align them more closely with conventional assets. This will pave the path for cryptocurrencies to integrate into a society that presently only depends on traditional assets. If this market grows more consistently, these new assets might potentially have a significant impact on economic and financial indicators worldwide.

6 | CONCLUSION

The aim of this study is to elucidate the global indicators that influence the Bitcoin price and to evaluate whether Bitcoin should be regarded as a secure investment or a speculative asset. To facilitate the application of the SVAR model, data was gathered both on a weekly and daily basis for the analysis. In order for an asset to be considered a hedge, a diversification, or a safe haven, it must have a certain degree of connection with other assets.

The forecast error variance decomposition revealed that the VIX had a more substantial impact on the Bitcoin price compared with the effect of the exchange rate and the gold price. The impact of the VIX remained greater than that of the two other indicators. This demonstrates that the value of Bitcoin is susceptible to fluctuations caused by panic or fear in the financial markets. The impulse response functions revealed a statistically significant, although adverse relationship between the VIX and the Bitcoin price. Contrasting the weekly data analysis, the daily data analysis revealed a more pronounced and adverse effect. This empirical finding suggests a negative connection between the Bitcoin price and the VIX. Investors either sold or stopped purchasing Bitcoins when there was a spike in the VIX. When panic escalates, opting to invest in Bitcoin as a strategy to evade the potential devaluation of assets is not an appealing option. This indicates that Bitcoin will not function as a safe haven during periods when the VIX or prevailing fear takes control of the financial market.

The forecast error variance decomposition findings revealed a lack of significant connection between the exchange rate and the Bitcoin price. This suggests that Bitcoin does not exhibit the characteristics typically associated with a currency in the financial sector. In other words, it remains inappropriate as a form of currency for global commerce. This is an essential factor to consider when evaluating cryptocurrencies as a hedging or diversification alternative. Furthermore, the impulse response functions demonstrated that there was no significant association between the two indicators during all time periods.

Bitcoin was compared with gold because to its limited quantity, comparable supply growth to that of gold, and its autonomy from central banks or governments. Gold is well recognized as a reliable investment in financial markets. However, the forecast error variance decomposition analysis suggests that there is not an important connection between the Bitcoin price and the gold price. This outcome demonstrates that Bitcoin lacks the necessary similarities with gold to be recognized as a safe haven. Furthermore, the results obtained from impulse response functions indicated that there was not a statistically significant association between the Bitcoin price and the gold price, with the exception of a short period of time when daily data analysis is taken into consideration. This further indicates that Bitcoin does not have a significant association with gold. On the basis of the forecast error variance decomposition, there was a limited connection between the oil price and the Bitcoin price. The impulse response functions likewise demonstrated the absence of a statistically significant relationship between these two indicators.

On the basis of the variance decomposition analysis, Bitcoin price volatility had a significant impact on the Bitcoin price in both the daily and weekly data analysis. The data also suggests that the Bitcoin price was significantly impacted by its own dynamics. Bitcoin's behavior demonstrates a significant responsiveness to market expectations. In other words, Bitcoin lacks significant connections with other indicators, but mostly relates to its own performance. The impulse response functions revealed a significant and negative relationship between Bitcoin price volatility and the Bitcoin price, as demonstrated via weekly data analysis. Upon analyzing the daily data, it appeared that the impact becomes positive. These results suggest the market's response. While the short-term impact is positive, the longer-term effect becomes negative. The Bitcoin price remained mostly influenced by its inherent uncertainty. This indicates that investors have a willingness to take on risk. This suggests that Bitcoin is a speculative asset and that the primary driver of Bitcoin price fluctuations is speculators. Bitcoin, which is a stimulant for risk appetite, loses the prospect of becoming an investment that is considered to be a safe haven. There is still a solid basis for the Bitcoin price to account for its own fluctuations. On the basis of the forecast error variance composition, the influence of its own price rose with time, although its impact remained consistently strong. The findings suggest that the determinants of Bitcoin price extend beyond macro-financial variables to include Bitcoin-technology-related factors, the investment appeal of Bitcoin, and the market dynamics of Bitcoin supply and demand. Specifically, this outcome also demonstrates that anticipations about its value have a substantial influence on the Bitcoin price. Lastly, it should be noted that Bitcoin is now in a developing phase and has yet to demonstrate the same behavior as other conventional assets in the market. The volatile nature of the Bitcoin price may provide substantial gains or significant losses for investors. Therefore, given that Bitcoin is a speculative asset, it is essential for investors to diversify their portfolios by selecting several investment instruments instead of just investing in Bitcoin. When making choices on the purchase and sale of Bitcoin, it is crucial to consider the Bitcoin price and the level of uncertainty associated with it. This result suggests that it might be advantageous for investors to use stop loss and take profit orders.

While this study provides an explanation of the indicators for the Bitcoin price, it is important to note that there are still some limitations. Cryptocurrencies are at a nascent stage of development in comparison to traditional assets. Gold has been used for millennia. This commodity has shown its resilience as a viable choice during upheaval. Furthermore, it has widespread acceptance in the financial sector and is used by the majority of nations. Given these characteristics of the asset, Bitcoin is still in its early stages of development. Therefore, more efforts are required to elucidate the indicators of cryptocurrencies. Furthermore, the scope of the investigation may be expanded to include the COVID-19 era, as well as other global currencies, commodities, or assets. In the future, there may be more compelling evidence to support the idea that Bitcoin is acting in a manner similar to traditional assets, leading to its complete integration into the financial markets.

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AUTHOR CONTRIBUTIONS

All authors contributed equally to the paper. All authors read and approved the final manuscript

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request. Various sources were used to collect data for the analyses. Each source of data and materials has been available and pointed out throughout the paper.

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REFERENCES

Al-Yahyaee, K. H., Rehman, M. U., Mensi, W., & Al-Jarrah, I. M. W. (2019). Can uncertainty indices predict Bitcoin prices? A revisited analysis using partial and multivariate wavelet approaches. *The North American Journal of Economics and Finance*, *49*, 47–56.

Baek, C., & Elbeck, M. (2015). Bitcoins as an investment or speculative vehicle? A first look. *Applied Economics Letters*, *22*(1), 30–34.

Basher, S. A., & Sadorsky, P. (2022). Forecasting Bitcoin price direction with random forests: How important are interest rates, inflation, and market volatility? *Machine Learning with Applications*, *9*, 100355.

Baumöhl, E. (2019). Are cryptocurrencies connected to forex? A quantile cross-spectral approach. *Finance Research Letters*, *29*(2019), 363–372.

Baur, D. G., & Hoang, L. T. (2020). A crypto safe haven against Bitcoin. *Finance Research Letters*, *38*, 101431.

Bernanke, B. S. (1986). Alternative explanations of the money-income correlation. *Carnegie-Rochester Conference Series on Public Policy*, *25*, 49–99.

Blanchard, O. J., & Watson, M. W. (1986). Are business cycles all alike? In R. J. Gordon (Ed.), *The American business cycle* (pp. 123–179). NBER and Chicago Press.

Blau, B. M., Griffith, T. G., & Whitby, R. J. (2021). Inflation and Bitcoin: A descriptive time-series analysis. *Economics Letters*, *203*, 109848.

Bouri, E., Gupta, R., Lahiani, A., & Shahbaz, M. (2018). Testing for asymmetric nonlinear short- and long-run relationships between bitcoin, aggregate commodity and gold prices. *Resources Policy*, *57*, 224–235.

Bouri, E., Gupta, R., Tiwari, A. K., & Roubaud, D. (2017). Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. *Finance Research Letters*, *23*(2017), 87–95.

Bouri, E., Shahzad, S. J. H., Roubaud, D., Kristoufek, L., & Lucey, B. (2020). Bitcoin, gold, and commodities as safe havens for stocks: New insight through wavelet analysis. *The Quarterly Review of Economics and Finance*, *77*(2020), 156–164.

Burgstaller, J. (2002). *Are stock returns a leading indicator for real macroeconomic developments*? [Working Paper, No. 0207]. Johannes Kepler University of Linz, Department of Economics.

Będowska-Sójka, B., & Kliber, A. (2021). Is there one safe-haven for various turbulences? The evidence from gold, Bitcoin and Ether. *The North American Journal of Economics and Finance*, *56*, 101390.

Charfeddine, L., Benlagha, N., & Maouchi, Y. (2020). Investigating the dynamic relationship between cryptocurrencies and conventional assets: Implications for financial investors. *Economic Modelling*, *85*(2020), 198–217.

Cheah, E. T., & Fry, J. (2015). Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. *Economics Letters*, *130*(2015), 32–36.

Cheikh, N. B., Zaied, Y. B., & Chevallier, J. (2020). Asymmetric volatility in cryptocurrency markets: New evidence from smooth transition GARCH models. *Finance Research Letters*, *35*(2020), 101293.

Chen, C., Liu, L., & Zhao, N. (2020). Fear sentiment, uncertainty, and Bitcoin price dynamics: The case of COVID-19. *Emerging Markets, Finance and Trade*, *56*(10), 2298–2309.

Chen, T. H., Chen, M. Y., & Du, G. T. (2021). The determinants of Bitcoin's price: Utilization of GARCH and machine learning approaches. *Computational Economics*, *57*, 267–280.

Corbet, S., Lucey, B., Urquhart, A., & Yarovaya, L. (2019). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis*, *62*(2019), 182–199.

Corbet, S., Meegan, A., Larkin, C., Lucey, B., & Yarovaya, L. (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters*, *165*(2018), 28–34.

Das, D., Le Roux, C. L., Jana, R. K., & Dutta, A. (2020). Does Bitcoin hedge crude oil implied volatility and structural shocks? A comparison with gold, commodity and the US dollar. *Finance Research Letters*, *36*(2020), 101335.

Diniz-Maganini, N., Diniz, E. H., & Rasheed, A. A. (2021). Bitcoin's price efficiency and safe haven properties during the COVID-19 pandemic: A comparison. *Research in International Business and Finance*, *58*, 101472.

Dutta, A., Das, D., Jana, R. K., & Vo, X. V. (2020). COVID-19 and oil market crash: Revisiting the safe haven property of gold and Bitcoin. *Resources Policy*, *69*(2020), 101816.

Dwita Mariana, C., Ekaputra, I. A., & Husodo, Z. A. (2021). Are Bitcoin and Ethereum safe-havens for stocks during the COVID-19 pandemic? *Finance Research Letters*, *38*, 101798.

Dyhrberg, A. H. (2016). Bitcoin, gold and the dollar—A GARCH volatility analysis. *Finance Research Letters*, *16*(2016), 85–92.

Entrop, O., Frijns, B., & Seruset, M. (2020). The determinants of price discovery on bitcoin markets. *Journal of Futures Markets*, *40*(5), 816–837.

Fang, T., Su, Z., & Yin, L. (2020). Economic fundamentals or investor perceptions? The role of uncertainty in predicting long-term cryptocurrency volatility. *International Review of Financial Analysis*, *71*(2020), 101566.

Geuder, J., Kinateder, H., & Wagner, N. F. (2019). Cryptocurrencies as financial bubbles: The case of Bitcoin. *Finance Research Letters*, *31*(2019), 179–184.

González, M. O., Jareño, F., & Skinner, F. S. (2021). Asymmetric interdependencies between large capital cryptocurrency and gold returns during the COVID-19 pandemic crisis. *International Review of Financial Analysis*, *76*, 101773.

Guizani, S., & Nafti, K. (2019). The determinants of Bitcoin price volatility: An investigation with ARDL model. *Procedia Computer Science*, *164*(2019), 233–238.

Hazlett, P. K., & Luther, W. J. (2020). Is bitcoin money? And what that means. *The Quarterly Review of Economics and Finance*, *77*(2020), 144–149.

De la Horra, L. P., de la Fuente, G., & Perote, J. (2019). The drivers of Bitcoin demand: A short and long-run analysis. *International Review of Financial Analysis*, *62*(2019), 21–34.

Hussain Shahzad, S. J., Bouri, E., Roubaud, D., & Kristoufek, L. (2020). Safe haven, hedge and diversification for G7 stock markets: Gold versus bitcoin. *Economic Modelling*, *87*(2020), 212–224.

Huynh, T. L. D., Burggraf, T., & Wang, M. (2020). Gold, platinum, and expected Bitcoin returns. *Journal of Multinational Financial Management*, *56*(2020), 100628.

Jareño, F., González, M. O., Tolentino, M., & Sierra, K. (2020). Bitcoin and gold price returns: A quantile regression and NARDL analysis. *Resources Policy*, *67*(2020), 101666.

Jin, J., Yu, J., Hu, Y., & Shang, Y. (2019). Which one is more informative in determining price movements of hedging assets? Evidence from Bitcoin, gold and crude oil markets. *Physica A: Statistical Mechanics and its Applications*, *527*, 121121.

Kalyvas, A., Papakyriakou, P., Sakkas, A., & Urquhart, A. (2020). What drives Bitcoin's price crash risk? *Economics Letters*, *191*(2020), 108777.

Kilian, L. (2013). Structural vector autoregressions. In N. Hashimzade & M. Thornton (Eds.), *Handbook of research methods and applications in empirical macroeconomics* (pp. 515–554). Edward Elgar.

Kliber, A., Marszałek, P., Musiałkowska, I., & Świerczyńska, K. (2019). Bitcoin: Safe haven, hedge or diversifier? Perception of bitcoin in the context of a country's economic situation—A stochastic volatility approach. *Physica A*, *524*(2019), 246–257.

Köse, N., & Ünal, E. (2021). The effects of the oil price and oil price volatility on inflation in Turkey. *Energy*, *226*, 120392.

Köse, N., & Ünal, E. (2023a). The asymmetric effects of the interest rate on the Bitcoin price. *Finance a úvěr-Czech Journal of Economics and Finance*, *73*(2), 189–217.

Köse, N., & Ünal, E. (2023b). Causal relationships between cryptocurrencies: The effects of sampling interval and sample size. *Studies in Nonlinear Dynamics & Econometrics*. https://doi.org/10.1515/snde-2022-0054

Kwon, J. H. (2020). Tail behavior of Bitcoin, the dollar, gold and the stock market index. *Journal of International Financial Markets, Institutions & Money*, *67*(2020), 101202.

Lyócsa, Š., Molnár, P., Plíhal, T., & Širanová, M. (2020). Impact of macroeconomic news, regulation and hacking exchange markets on the volatility of bitcoin. *Journal of Economic Dynamics & Control*, *119*(2020), 103980.

Maddala, G. S., & Kim, I. M. (1998). *Unit roots, cointegration, and structural change*. Cambridge University Press.

Naeem, M. A., Hasan, M., Arif, M., & Shahzad, S. J. H. (2020). *Can Bitcoin glitter more than gold for investment styles?* (pp. 1–17). SAGE Open.

Nakamoto, S. (2008). *Bitcoin: A peer-to-peer electronic cash system*. https://bitcoin.org/bitcoin.pdf

Pho, K. H., Ly, S., Lu, R., Hoang, T. H. V., & Wong, W. K. (2021). Is Bitcoin a better portfolio diversifier than gold? A copula and sectoral analysis for China. *International Review of Financial Analysis*, *74*, 101674.

Raheem, I. D. (2021). COVID-19 pandemic and the safe haven property of Bitcoin. *The Quarterly Review of Economics and Finance*, *81*, 370–375.

Rehman, M. U. (2020). Do bitcoin and precious metals do any good together? An extreme dependence and risk spillover analysis. *Resources Policy*, *68*(2020), 101737.

Rognone, L., Hyde, S., & Zhang, S. S. (2020). News sentiment in the cryptocurrency market: An empirical comparison with Forex. *International Review of Financial Analysis*, *69*(2020), 101462.

Sapuric, S., Kokkinaki, A., & Georgiou, I. (2022). The relationship between Bitcoin returns, volatility and volume: Asymmetric GARCH modeling. *Journal of Enterprise Information Management*, *35*(6), 1506–1521.

Shahzad, S. J. H., Bouri, E., Rehman, M. U., & Roubaud, D. (2022). The hedge asset for BRICS stock markets: Bitcoin, gold or VIX. *The World Economy*, *45*(1), 292–316.

Shehzad, K., Bilgili, F., Zaman, U., Kocak, E., & Kuskaya, S. (2021). Is gold favourable than bitcoin during the COVID-19 outbreak? Comparative analysis through wavelet approach. *Resources Policy*, *73*, 102163.

Sims, C. A. (1986). Are forecasting models usable for policy analysis? *Minneapolis Federal Reserve Bank Quarterly Review*, *10*, 2–16.

Stock, J. H., & Watson, M. W. (2001). Vector autoregressions. *Journal of Economic Perspectives*, *15*(4), 101–115.

Su, C., Qin, M., Tao, R., & Umar, M. (2020). Financial implications of fourth industrial revolution: Can bitcoin improve prospects of energy investment? *Technological Forecasting & Social Change*, *158*, 120178.

Su, C., Qin, M., Tao, R., & Zhang, X. (2020). Is the status of gold threatened by Bitcoin? *Economic Research*, *33*(1), 420–437.

Uddin, M. A., Ali, M. H., & Masih, M. (2020). Bitcoin—A hype or digital gold? Global evidence. *Australian Economic Papers*, *59*(3), 215–231.

Umar, M., Su, C., Rizvi, S. K. A., & Shao, X. (2021). Bitcoin: A safe haven asset and a winner amid political and economic uncertainties in the US? *Technological Forecasting & Social Change*, *167*, 120680.

Ünal, E., & Köse, N. (2023). The impact of the oil price on mineable and non-mineable cryptocurrencies. *Energy Sources, Part B: Economics, Planning, and Policy*, *18*(1), 2266692.

Urquhart, A., & Zhang, H. (2019). Is Bitcoin a hedge or safe haven for currencies? An intraday analysis. *International Review of Financial Analysis*, *63*(2019), 49–57.

Vo, A., Chapman, T. A., & Lee, Y. (2022). Examining Bitcoin and economic determinants: An evolutionary perspective. *Journal of Computer Information Systems*, *62*(3), 572–586.

Wang, J., Ma, F., Bouri, E., & Guo, Y. (2022). Which factors drive Bitcoin volatility: Macroeconomic, technical, or both? *Journal of Forecasting*, *42*, 970–988.

Wang, P., Zhang, H., Yang, C., & Guo, Y. (2021). Time and frequency dynamics of connectedness and hedging performance in global stock markets: Bitcoin versus conventional hedges. *Research in International Business and Finance*, *58*, 101479.

Whaley, R. E. (2000). The investor fear gauge. *The Journal of Portfolio Management*, *26*(3), 12–17.

White, R., Marinakis, Y., Islam, N., & Walsh, S. (2020). Is Bitcoin a currency, a technology-based product, or something else? *Technological Forecasting & Social Change*, *151*(2020), 119877.

Wu, C., Ho, S., & Wu, C. (2021). The determinants of Bitcoin returns and volatility: Perspectives on global and national economic policy uncertainty. *Finance Research Letters*, *45*, 102175.

Yousaf, I., & Ali, S. (2020). Discovering interlinkages between major cryptocurrencies using high-frequency data: New evidence from COVID-19 pandemic. *Financial Innovation*, *6*, 45.

Yousaf, I., Ali, S., Bouri, E., & Saeed, T. (2022). Information transmission and hedging effectiveness for the pairs crude oil–gold and crude oil–Bitcoin during the COVID-19 outbreak. *Economic Research-Ekonomska Istraživanja*, *35*(1), 1913–1934.

Yu, M. (2019). Forecasting Bitcoin volatility: The role of leverage effect and uncertainty. *Physica A: Statistical Mechanics and its Applications*, *533*(2019), 120707.

Zeng, T., Yang, M., & Shen, Y. (2020). Fancy Bitcoin and conventional financial assets: Measuring market integration based on connectedness networks. *Economic Modelling*, *90*, 209–220.

Zhang, H., & Wang, P. (2021). Does Bitcoin or gold react to financial stress alike? Evidence from the U.S. and China. *International Review of Economics and Finance*, *71*, 629–648.

Zhu, Y., Dickinson, D., & Li, J. (2017). Analysis on the influence factors of Bitcoin's price based on VEC model. *Financial Innovation*, *3*, 3.

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