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Factors affecting the volatility of bitcoin prices

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ABSTRACT

To explore the impact of factors from the traditional financial market, such as economic policy uncertainty, oil prices, the NASDAQ index, and gold prices, to identify factors contributing to Bitcoin volatility. This study uses traditional OLS (ordinary least squares) regression analysis to examine how different external factors affect Bitcoin price volatility from January 2014 to March 2023. By employing a comprehensive approach to recognize the distinctive characteristics of the Bitcoin market, namely, 24-hour trading and the short duration of its existence, we've included a wide spectrum of data to ensure a cohesive comparison with other financial datasets. The findings of the statistical analysis indicate that EPU and the NASDAQ index promote positive fluctuations in Bitcoin volatility, whereas gold prices act as a dampener. Conversely, we do not find empirical support for the influence of energy prices, such as oil, on Bitcoin volatility. These findings indicate that we should not undervalue Bitcoin in any financial transaction scenario. It means that all stakeholders should treat the issue of Bitcoin volatility more seriously, even including governments, who should actively regulate the Bitcoin market, and investors, who should recognize the dangers of this volatility, make rational decisions based on individual circumstances, and employ flexible trading strategies.

Contribution/Originality: This article analyses the factors that affect Bitcoin price volatility from different angles. It is helpful for all patriciates (policymakers, investors, and researchers) to take adaptation actions in the finance market.

1. INTRODUCTION

Bitcoin is a decentralized digital currency created in 2009 by an individual or group under the pseudonym Satoshi Nakamoto[1]. It allows users to conduct peer-to-peer transactions without the intervention of a central bank or government. Bitcoin transactions are verified using encryption technology and recorded on a publicly distributed ledger called the blockchain. One of the purposes of creating Bitcoin was to provide an alternative to legal tender and traditional money (Nakamoto, 2008). Nakamoto developed the Bitcoin blockchain as a response to the 2008 financial crisis and to solve some of the problems of the fractional reserve banking system. In the first block of the blockchain, Nakamoto included the message, "The Times 03/Jan/2009 Chancellor on brink of second bailout for banks"; this

[1] The inventor of Bitcoin has not been determined yet.

message highlighted the need for a decentralized system in opposition to the central bank-controlled money supply (Brauneis, Mestel, Riordan, & Theissen, 2022). Bitcoin was also developed to avoid delays in transferring money and costs caused by banks, cards, and even governments (Olvera-Juarez & Huerta-Manzanilla, 2019). It was initially designed to operate independently of governmental or banking control.

One can view Bitcoin as a representation of the currency of ideas. However, as the size of a given group increases and the number of transactions rises accordingly, the cost of achieving consensus and transaction fees also rise. For this reason, a consistent consensus about Bitcoin is difficult to reach among large groups. In addition, it lacks the fundamental functions of currency, such as its use as a means of payment, and its value scale is inconsistent. Consequently, Bitcoin cannot replace fiat currencies that adhere to the consensus rule. At present, Bitcoin is therefore more akin to virtual financial assets (Tong, Chen, & Zhu, 2022).

Bitcoin is, however, still the most prominent cryptocurrency and holds the largest market share today. Nevertheless, it has faced significant challenges and considerable controversy from investors and scholars, mainly due to its incredible growth and price volatility (Lin & An, 2021). The volatility of Bitcoin is considerably higher compared to that of traditional fiat currencies (Blau, 2017; Chu, Chan, Nadarajah, & Osterrieder, 2017; Kurihara & Fukushima, 2018). Understanding the volatility of Bitcoin is essential, regardless of whether it is considered a currency or an asset. Volatility represents the degree to which an asset's price changes over time, and it is a critical aspect of comprehending market risk characteristics. People now widely recognize Bitcoin's extreme volatility and susceptibility to manipulation (Dodd, 2018).

Bitcoin is a virtual currency that differs from traditional currencies in several ways. No central authority guarantees the value of Bitcoin, and it lacks a commodity-backed value. Additionally, the rules governing its supply were established before its initial launch. As a result, Bitcoin is considered a fixed currency, with no need for monetary policy. When a cryptocurrency gains popularity, demand for it tends to increase, which in turn can further boost its popularity through network effects. These dynamics are explored in studies such as that by Gandal and Halaburda (2019). Low volatility is a crucial characteristic of financial products designed with the ambition of becoming a global payment or monetary system (Kristoufek, 2023). However, Bitcoin is known for its high volatility, which has been discussed extensively in numerous previous papers (Bergsli, Lind, Molnár, & Polasik, 2022; Dyhrberg, 2016; Katsiampa, 2017; Köchling, Schmidtke, & Posch, 2020; Lukáš & Taisei, 2017; Ma & Tanizaki, 2019; Sapuric & Kokkinaki, 2014). The prevailing view suggests that Bitcoin's volatility will decrease as its user base and number of transactions increase. However, the facts do not support the notion that Bitcoin volatility is decreasing over time (Baur & Dimpfl, 2021).

In recent years, many studies have investigated various economic and financial factors that affect Bitcoin volatility (De Carvalho, Resende, & Takahashi, 2023; Fang, Bouri, Gupta, & Roubaud, 2019; López-Cabarcos, Pérez-Pico, Piñeiro-Chousa, & Šević, 2021; Wang, Ma, Bouri, & Guo, 2023; Wu, Ho, & Wu, 2022). Researchers have also examined the relationship between Bitcoin and other risky financial assets, as well as safe-haven assets (Bouri, Azzi, & Dyhrberg, 2017). However, the empirical evidence from this growing body of literature on Bitcoin volatility is mixed, and there is no clear consensus on the most significant determinants of Bitcoin volatility, as noted by Bakas, Magkonis, and Oh (2022). In fact, many studies have modeled Bitcoin returns and volatility (e.g., (Baek & Elbeck, 2015; Balcilar, Bouri, Gupta, & Roubaud, 2017; Bouri et al., 2017; Katsiampa, 2017; Pichl & Kaizoji, 2017)). The results indicated that volatility remains very high in the market for Bitcoin compared to that for other financial assets.

Following the work of Kristoufek (2023) and Bakas et al. (2022) we investigate the primary factors contributing to Bitcoin volatility, differentiating our analysis from that of prior research on two key dimensions. First, we study the factors influencing Bitcoin fluctuations from multiple perspectives, taking a multifaceted approach. Second, we find several entry points for future research work. This study is a valuable addition to the vast body of literature on price discovery in various markets and exchanges, as well as the literature on the interconnections between cryptocurrency prices and volatility (Giudici & Abu-Hashish, 2019; Pagnottoni & Dimpfl, 2019; Yi, Xu, & Wang, 2018). Throughout Bitcoin's 10-year history, its existence has always been contentious due to its volatility. Thus, investigation of the factors influencing these fluctuations is imperative. The sample set for our study is diverse, and numerous external factors may influence Bitcoin price volatility. Bitcoin is not an isolated entity; economic policy uncertainty can impact its fluctuations, and there are certain correlations with both the stock market and gold. The results of our study validate those of prior research, and we suggest several insights and directions for future investigations. Moreover, by employing a substitution method to validate the reliability of our research conclusions, we not only confirm the factors influencing Bitcoin but also expand the scope of Bitcoin-related research topics.

The remainder of our paper is organized as follows: Section 2 provides a literature review. Section 3 outlines the data collection method and explains the research model. Section 4 presents the results of our empirical study and tests the stability of the model through various methods. Section 5 summarizes the conclusions based on the findings of the empirical analysis.

2. LITERATURE REVIEW

We review the relevant literature on Bitcoin price volatility from the following perspectives: Bitcoin price volatility, investment portfolios, and factors influencing Bitcoin volatility.

2.1. Bitcoin Price Volatility

Bitcoin price volatility was extensively studied in the early literature. Various models have been employed to explore this topic (Ardia, Bluteau, & Rüede, 2019). Chu et al. (2017) found that Bitcoin is highly volatile compared to traditional currencies. Naimy and Hayek (2018) investigated the volatility of the Bitcoin/USD exchange rate, primarily using the generalized autoregressive conditional heteroscedasticity (GARCH), exponentially weighted moving average, and exponential generalized autoregressive conditional heteroscedasticity (EGARCH) models. Tiwari, Kumar, and Pathak (2019) utilized several GARCH specifications and stochastic volatility models to model the dynamics of Bitcoin returns, revealing that stochastic volatility models outperformed the GARCH models. In contrast, Urquhart (2017) found that heterogeneous autoregressive (HAR) models performed better than GARCH models in modeling Bitcoin volatility. Furthermore, Katsiampa (2017) investigated the performance of various GARCH-type models in explaining Bitcoin volatility and identified an AR-CGARCH model as the preferred specification. Similarly, Conrad, Custovic, and Ghysels (2018) employed the GARCH-MIDAS model to reveal the significant positive effects of the S&P 500 volatility risk premium and Baltic dry index on long-term Bitcoin volatility, suggesting that economic activity is closely related to Bitcoin price volatility. In addition, Blau (2017) rejected the idea that speculative trading contributes to Bitcoin volatility, while Balcilar et al. (2017) found that volume can predict Bitcoin returns but not volatility. Finally, Bystrom and Krygier (2018) found a stronger positive link between Bitcoin volatility and Google search volumes than market-wide risk indicators would suggest. Among these models, they found that the EGARCH (1,1) performed the best both in-sample and out-of-sample.

Qian, Wang, Ma, and Li (2022) focused on the impact of jumps in predicting Bitcoin price volatility using both linear and nonlinear mixed data sampling models. Their results were strong evidence that using a forecasting model with a continuous-time jump and two-stage regimes can make predictions much more accurate and bring big economic benefits. Remarkably, the model with continuous-time jumps outperformed others in predicting highly volatile periods, particularly during a Black Swan event. Numerous studies have suggested that jumps are common in the Bitcoin market; hence, a model with a continuous-time jump can enhance the precision of price forecasting (Gronwald, 2019; Shen, Urquhart, & Wang, 2020). Bariviera (2017) identified nonlinear attributes such as long memory and clustering as factors affecting Bitcoin price volatility. Many studies have reported that the use of regime-switching models can enhance the accuracy of Bitcoin price forecasting (Ardia et al., 2019; Ma, Liang, Ma, & Wahab, 2020). Hau, Zhu, Shahbaz, and Sun (2021) used quantile regression analysis to investigate whether transaction activity can predict Bitcoin returns. By analyzing historical data on Bitcoin prices and trading volumes, they found a predictive relationship between Bitcoin trading activity and related returns, especially in high-return scenarios.

Additionally, that study also showed that, compared to trading activity, Bitcoin price volatility is much less helpful in predicting its future returns.

2.2. Bitcoin Price Volatility in Investment Portfolios

In an early study on the Bitcoin market and its role in portfolio planning, Wu, Pandey, and Dba (2014) analyzed daily Bitcoin prices and other stock indices during the period from July 2010 to December 2013. They concluded from their analysis of correlations and volatility that Bitcoin is a better asset class than a currency, potentially enhancing portfolio efficiency for investors. Dwyer (2015) provided a comprehensive overview of the technical aspects of digital currency and blockchains. He noted that Bitcoin returns have greater average volatility than traditional assets such as gold and currency like the USD, but the volatility of Bitcoin prices remains lower than that of gold and other currencies. Yang and Kim (2015) utilized network theory to analyze returns and volatility in the Bitcoin market and discovered a significant correlation between return volatility and a complexity measure of the Bitcoin trading network flow. Additionally, they discovered that incorporating the residual diversity of the Bitcoin market can enhance return complexity. The results of previous research on the diversification benefits of Bitcoin within a portfolio context (e.g., (Ghabri, Ayadi, & Guesmi, 2021; Guesmi, Saadi, Abid, & Ftiti, 2019; Kajtazi & Moro, 2019; Klein, Thu, & Walther, 2018; Platanakis & Urquhart, 2020; Rehman, Asghar, & Kang, 2020; Symitsi & Chalvatzis, 2019)) showed that the addition of Bitcoin to an equity portfolio can enhance the portfolio's risk–return relationship.

Osterrieder and Lorenz (2017) conducted an extreme value analysis of Bitcoin returns against G10 currencies and the USD, showing that Bitcoin returns exhibited higher volatility with nonnormal (heavy-tail) distributions (Bouri et al., 2017). That study investigated the relationship between return volatility and Bitcoin in the pre-crash period of 2013, finding that positive shocks increased volatility more than negative shocks due to the safe-haven effect. Using a dynamic conditional correlation framework, they also compared Bitcoin's performance against those of major stock indexes, bonds, gold, oil, and a general commodity index, concluding that Bitcoin is an imperfect hedge, but it can perform well in diversified portfolios and can act as a safe haven against extreme weekly movements in Asian stocks. Balcilar et al. (2017) used a nonparametric causality-in-quantile test to model the behavior of volume, returns, and volatility in Bitcoin; they concluded that volume can predict returns except in bull and bear regimes. Katsiampa (2017) fitted an autoregressive conditional GARCH model to estimate the volatility of Bitcoin returns, and concluded that this model is an optimal fit for Bitcoin prices in both the short and long run due to the highly volatile significance of conditional variance.

Zhang, Chen, and Peng (2022) using a GARCH jump model, found that the normal and jump volatility of Bitcoin increased in the short term, changed in opposite directions in the medium term, and decreased in the long term. Baur, Hoang, and Hossain (2022) discovered that adding Bitcoin to a benchmark stock portfolio did not reduce risk at extreme volatility levels. This held not only on average, but also in subsamples, including during the COVID-19 crisis period. Therefore, focusing solely on correlation is inadequate at extreme volatility levels. Qiu, Wang, and Xie (2021) investigated the influence of volatility spillover effects among cryptocurrencies on the prediction of realized volatility in the Bitcoin market. Their findings suggested that a linked-effect model for Bitcoin volatility had better explanatory power within their in-sample dataset and significantly enhanced performance in short-term forecasting.

2.3. Factors Influencing Bitcoin Volatility

Many scholars have studied the factors affecting Bitcoin price volatility from different perspectives. In a nonlinear context, Ardia et al. (2019) provided additional evidence of regime-switching dynamics in Bitcoin volatility, which are influenced by different drivers, as demonstrated by López-Cabarcos et al. (2021). Similarly, Bukovina and Marticek (2016) investigated the impact of investor sentiment on Bitcoin volatility. By dividing Bitcoin prices into rational and irrational components using intraday sentiment data from 12/12/2013 to 12/31/2015, they found that sentiment had significantly higher explanatory power during periods of excessive volatility. Baek and Elbeck (2015) analyzed the volatility of Bitcoin returns utilizing a detrended ratio along with some economic variables. Their findings suggested that the Bitcoin market is characterized by high volatility and speculation. Pichl and Kaizoji (2017) investigated the pattern of Bitcoin returns over a five-year period. They examined the relationship between Bitcoin and the exchange rates of other major currencies using a heterogeneous autoregressive model for realized volatility. To forecast daily returns, they utilized a combination of robust tools, including an artificial neural network. Kristoufek (2023) investigated the factors influencing Bitcoin price volatility and explored potential future developments, focusing on the conditions necessary for a decrease in volatility. The results of their analysis of instrumental variables suggested that a significant influx of small users who perform small transfers, ideally not exchange trades, is needed to decrease volatility. The analysis also showed that increases in exchange volume, on-chain transfer value, and Bitcoin prices alone can increase the volatility of this cryptocurrency asset.

Other scholars have primarily investigated the impact of EPU on Bitcoin price volatility. For example, Wu et al. (2022) investigated the effects of global and national EPU on Bitcoin returns and long-term volatility. They found that EPU in most countries is positively correlated with Bitcoin returns but negatively correlated with long-term volatility in the Bitcoin market. Xia, Sang, He, and Wang (2023) discovered that the Global EPU index and the Uncertainty in Cryptocurrency (UCRY) index had significant negative and positive impacts, respectively, on long-term Bitcoin price volatility. Furthermore, an out-of-sample validation analysis showed that the unilateral heteroskedastic autoregressive GARCH-MIDAS model using the UCRY price index performed the best; in fact, the inclusion of the UCRY index in the forecasting model was a significant improvement over models considering only global and national EPU in out-of-sample predictions. Benhamed, Messai, and El Montasser (2023) utilized the Gets reduction method and found that Bitcoin price volatility was influenced solely by lagged ARCH effects and the trading volume of this cryptocurrency. Nouir and Hamida (2023) studied the impact of EPU and geopolitical risk on Bitcoin price volatility by employing the autoregressive distributed lag model and quantile regression. The results of that study revealed that different factors affected the relationship between uncertainty and Bitcoin price volatility. While uncertainty from the US had a short-term impact on Bitcoin volatility, uncertainty from China had a longer-term effect.

Additionally, many scholars have conducted research on factors related to Bitcoin price volatility from various perspectives. Qian et al. (2022) used linear and nonlinear mixed data sampling models to predict the impact of jumps on Bitcoin volatility. They found that employing a predictive model combining continuous-time jumps and a two-stage regime significantly enhanced prediction accuracy, particularly during Black Swan event periods, and that this combination model demonstrated strong predictive capabilities. Ullah, Attah-Boakye, Adams, and Zaefarian (2022) employing cue utilization theory and signaling theory, discovered a significant positive correlation between positive celebrity tweets, positive government sentiment towards Bitcoin, and the corresponding upward Bitcoin price movement. They concluded that while celebrity endorsements may trigger temporary "exponential surges" in Bitcoin prices, investors must exercise caution in asset allocation to maximize their risk-return trade-off. Bourghelle, Jawadi, and Rozin (2022) employing linear and nonlinear vector autoregressive models, characterized stages of Bitcoin bubbles using investor sentiment and the implied investment intentions and risk aversion embedded within sentiment to explain Bitcoin volatility. That study's findings highlighted the pivotal role of collective sentiment in the formation and collapse of Bitcoin bubbles. Significant time-varying lead-lag effects were also found between Bitcoin volatility and investor sentiment, which bi-directionally influenced each other; the results of that study were effective in capturing the dynamic nature of Bitcoin price volatility. The impact of sentiment exhibited time-varying effects on the market.

Ma and Luan (2022) introduced Bitcoin-Ethereum synchronicity, which is conditional on the upward volatility of Bitcoin, as a proxy for concerns about high Bitcoin prices. They found that when Bitcoin's upward volatility was high, Ethereum's synchronicity had a significantly positive impact on the risk of collapse in the Bitcoin market. Hence, for highly speculative instruments, investor behavior plays a crucial role in asset pricing. Bergsli et al. (2022) investigated which model is most suitable for predicting Bitcoin volatility, considering various GARCH models and two HAR models. They found that EGARCH and APARCH performed best among the GARCH models. The HAR model, which is based on realized variance, outperformed the GARCH model using daily data. The superiority of the HAR model over the GARCH model was most pronounced in short-term volatility forecasting. Bakas et al. (2022) utilizing the dynamic model averaging approach, considered 22 potential determinants to identify the primary drivers of Bitcoin price volatility. Their findings revealed that the most significant factors influencing Bitcoin volatility were Google search trends, total circulation of Bitcoin, US consumer confidence, and the S&P 500 index. Dias, Fernando, and Fernando (2022) investigated a hypothesis regarding the impact of investor sentiment on forecasting Bitcoin returns and volatility using quantile regression. They found a nonlinear relationship between investor sentiment and Bitcoin returns and volatility, with predictability varying according to market conditions.

In summary, the literature above leads us to the conclusion that both intrinsic and external factors influence Bitcoin price volatility. In this paper, we primarily explore the impact of external factors on Bitcoin price volatility. We now propose the following hypotheses:

H_1: The EPU of the US is positively correlated with Bitcoin price volatility.

H_2: Oil prices are positively correlated with Bitcoin price volatility.

H_3: The NASDAQ index is positively correlated with Bitcoin price volatility.

H4: Gold prices are positively correlated with Bitcoin price volatility.

3. DATA, VARIABLES, AND METHODOLOGY

3.1. Sample and Data

Researchers have shown significant interest in predicting the returns and volatility of Bitcoin prices. Some authors have proposed an approach that involves developing trading strategies while also taking into account trading volume (Hau et al., 2021). For accuracy in this study, we use daily data encompassing several types of information. Our dataset includes data from January 2, 2014, to March 21, 2023, covering the past 10 years. We utilized daily opening, closing, highest, and lowest Bitcoin prices to compute volatility in Bitcoin prices. To ensure the robustness of the results, we referenced and compared a series of related studies (Baur & Dimpfl, 2021; Bourghelle et al., 2022) and examined data related to Bitcoin prices from the most commonly used website in Bitcoin research, CoinMarketCap (https://coinmarketcap.com/). The data on EPU, one of our variables of interest, is sourced from Economic Policy Uncertainty (https://www.policyuncertainty.com). Data related to oil, stock, and gold prices is all obtained from Yahoo Finance (https://finance.yahoo.com/). Furthermore, the data used as control variables in our research is from the Coin Metrics website (https://coinmetrics.io/).

3.2. Variables

3.2.1 Dependent Variable

Several studies have identified trading volume as a significant predictor of Bitcoin prices, returns, and volatility (Balcilar et al., 2017; Naeem, Saleem, Ahmed, Muhammad, & Mustafa, 2020). This study aims to explain the values and dynamics of Bitcoin price volatility using the Garman and Klass (1980) range-based estimator as an estimate of volatility, which comprehensively takes into account the opening, closing, highest, and lowest prices on a given day. As a result, this estimator not only captures inter-period price fluctuations but also changes in price from opening to closing. This tool proves invaluable in gathering data on various types of price volatility, as identified in this study: $\sigma_t^2 = 0.5(H_t - L_t)^2 - (2*log(2)-1)*(C_t - O_t)^2$. H_t and L_t respectively represent the logarithm of the highest and lowest prices on day t, and O_t and C_t represent the logarithm of the opening and closing prices on day t, respectively. In the analysis below, we use the volatility σ^2 obtained by taking the square root of σ.

3.2.2. Independent Variable

3.2.2.1. Economic Policy Uncertainty

Numerous previous articles have demonstrated the significant role of EPU in Bitcoin price volatility. Liu, Tsyvinski, and Wu (2022) identified two categories of determinants: those related to price and those related to the broader market. Empirical evidence confirmed that trading volume, investor sentiment (Kraaijeveld & De Smedt, 2020; López-Cabarcos et al., 2021) EPU (Das & Kannadhasan, 2018; Mokni, 2021; Wu et al., 2022) macroeconomic activity (Walther, Klein, & Bouri, 2019) geopolitical risk (Aysan, Demir, Gozgor, & Lau, 2019) and financial market conditions (Yin, Nie, & Han, 2021) all contribute to Bitcoin price volatility. Yen and Cheng (2021) found a negative correlation between China's EPU and Bitcoin volatility, suggesting that Bitcoin can serve as a hedge against EPU risk. Mokni (2021) investigated the quantile causality in the EPU-Bitcoin nexus and identified EPU as a powerful predictor in bullish markets. Fang, Su, and Yin (2020) and Wu et al. (2022) examined the impact of global EPU on Bitcoin volatility but reached mixed conclusions.

3.2.2.2. Stock Prices

Since the US has the largest stock market in the world, accounting for over 50% of global stock market value, fluctuations in the US stock market have a significant impact on stock markets worldwide (Hu, Li, Xiang, & Zhou, 2023; Ren, Zhao, You, & Zhu, 2022; Smales, 2022; Vuong, Nguyen, & Huynh, 2022). The correlation between Bitcoin and traditional asset classes has garnered considerable attention in recent years. Wang, Xie, Wen, and Zhao (2019) combined the US EPU index, stock market uncertainty index, and VIX to represent EPU and observed that in most cases, the risk spillover effect from the stock market uncertainty index to the Bitcoin market was not significant. Bouri, Das, Gupta, and Roubaud (2018) demonstrated that the spillover effect between Bitcoin and financial markets differed in bear and bull markets. Other researchers found that the American stock index exhibited a high degree of predictability for Bitcoin price volatility (Dias et al., 2022; Kapar & Olmo, 2021; Zhu, Dickinson, & Li, 2017).

3.2.2.3. Oil Prices

The relationship between Bitcoin and oil prices has also been studied. Gajardo, Kristjanpoller, and Minutolo (2018) suggested that Bitcoin has a greater multifractal spectrum compared to other currencies with crude oil (WTI). Ghazani and Khosravi (2020) found cross-correlations between three cryptocurrencies (Bitcoin, Ethereum, and Ripple) and crude oils (WTI and Brent). Van Wijk (2013) reported a negative relationship between Bitcoin and oil prices and found that the value of Bitcoin was significantly influenced by the price of WTI oil in the long term. According to Ciaian, Rajcaniova, and Kancs (2016) the price of crude oil is considered a significant determinant of Bitcoin volatility. Vassiliadis, Papadopoulos, Rangoussi, Konieczny, and Gralewski (2017) also provided evidence of cross-correlation between Bitcoin prices and the prices of crude oil and gold. Huynh, Shahbaz, Nasir, and Ullah (2022) demonstrated a close relationship between the movements of most cryptocurrencies and shocks in the US and European crude oil indices, with European crude oil prices acting as a source of shocks to cryptocurrencies and the US oil index acting as a receiver.

3.2.2.4. Gold Prices

Several studies attempted to compare the volatility of Bitcoin, gold, and other financial assets and their usefulness as a safe haven. For example, Bouri, Shahzad, Roubaud, Kristoufek, and Lucey (2020) analyzed differences in volatility factors between Bitcoin and gold and compared their safe-haven properties against various stock market indices. Das, Le Roux, Jana, and Dutta (2020) examined the hedging potential of Bitcoin against crude oil in terms of implied volatility and found that Bitcoin was not a superior asset for this purpose. Pal and Mitra (2019) calculated optimal hedge ratios comparing Bitcoin and other financial assets and demonstrated that gold tended to provide a better hedge against Bitcoin because of its low volatility. Wang, Zhang, Li, and Shen (2019) conducted a comparison of the mean and volatility spillover effects between Bitcoin and other assets, concluding that Bitcoin serves as a hedging asset against stocks and bonds, as well as a safe haven during extreme price changes in the monetary market. Finally, Shahzad, Bouri, Roubaud, Kristoufek, and Lucey (2019) compared the safe-haven and hedging characteristics of gold and Bitcoin in G7 stock markets and identified several distinct properties; interestingly, they also found that, to a certain extent, gold prices were bound to the volatility of Bitcoin.

3.2.3. Control Variables

To enrich our research, we include six control variables strongly related to Bitcoin prices in our model. First, various Bitcoin-related studies extensively utilize the computing power of Bitcoin miners, known as Hashrate. *Hashrate* is the average number of hashes being solved per second, averaged over the course of a given day. Georgoula, Pournarakis, Bilanakos, Sotiropoulos, and Giaglis (2015) found a positive and statistically significant relationship between the price of Bitcoin and its *Hashrate*. Additionally, Kristoufek (2015) established a long-term positive relationship between the *Hashrate* and Bitcoin market variables. Therefore, we include historical data on hash rate as a control variable in our analysis. Second, the effect of Bitcoin trading activity on centralized exchanges (*Volume*) on volatility is ambiguous. Low volume suggests low liquidity, and a large order can cause a significant jump in price, thereby increasing volatility. On the other hand, high trading volumes may indicate nervous trading activity, also leading to increased volatility. Additionally, increased uncertainty can lead to increased trading activity on the exchanges as investors try to close their positions or clear their limit orders due to heightened volatility, resulting in increased realized exchange volumes. Therefore, the traded volume is likely to be endogenous. Third, we also use the number of Bitcoin active addresses (*Addresses*) as a proxy for on-chain activity, with similar expectations and endogeneity issues as for the previous three variables. In addition, *Addresses* represent the number of active addresses on a given day. Fourth, the *Value* of Bitcoin is the overall exchange turn volume in USD multiplied by the average daily value of Bitcoin (the exchange market value of Bitcoin, both the original volume in USD and the daily price, was retrieved from the CoinMarketCap website) (Kristoufek, 2023). Fifth, when the debate over *Blocksize* reaches its peak, market uncertainty may result, subsequently affecting Bitcoin prices. Moreover, delays in the Bitcoin network and high transaction fees might also exert downward pressure on Bitcoin prices. Generally, an increase in Bitcoin price incentivizes more miners to participate due to the increased profitability. Sixth, blocksize increased competition often means that *Mining* difficulty increases.

3.3. Formatting of Mathematical Components

Both internal and external factors influence Bitcoin's price volatility, though the latter may not have a significant long-term impact. Nonetheless, any model seeking to explain any aspect of Bitcoin price volatility must consider both components. To address this, following Kristoufek (2023) we proposed the following model:

$$\sigma_t = \beta_0 + \beta_1 \log(usepu)_t + \beta_2 \log(oil)_t + \beta_3 \log(stock)_t + \\ \beta_4 \log(gold)_t + \beta_{5\sim 10} \log(controls)_t + \varepsilon_t$$

4. RESULTS

In our analysis, the volatility of Bitcoin prices is taken as the dependent variable, with US EPU, crude oil prices, the NASDAQ index, and gold prices as independent variables. The descriptive results are reported in Table 1, where it can be seen that the dependent variable, Bitcoin price volatility, has a maximum value of 0.058, a minimum value of 0.000, an average (mean) of 0.001, and a standard deviation of 0.003. Among the independent variables, US EPU has a maximum value of 6.694, a minimum of 1.200, an average (mean) of 4.544, and a standard deviation of 0.636. The crude oil price variable has a maximum value of 4.818, a minimum of 2.304, a mean of 4.083, and a standard deviation of 0.335. The NASDAQ index variable has a maximum value of 9.716, a minimum of 8.140, an average of 8.878, and a standard deviation of 0.459. The gold variable has a maximum value of 7.626, a minimum of 6.957, a mean of 7.264, and a standard deviation of 0.181Among these four sets of control variables, EPU has the largest standard deviation.

The descriptive statistics in Table 1 indicate that most of the variables are either positively skewed or negatively skewed; in addition, excess kurtosis is evident. Regarding the skewness and kurtosis values, the results indicate that the distributions of Bitcoin price volatility are asymmetric and have heavy tails, suggesting that they follow a leptokurtic and mesokurtic distribution. Therefore, this time period is described as having extremely high fluctuations in Bitcoin prices, indicating the potential for volatility spillover among cryptocurrency markets. The analysis shows high volatility in these data series. Kurtosis values greater than 3 imply that the data does not fit a normal distribution (Balanda & MacGillivray, 1988). In this study, we use the Jarque-Bera statistical method to conduct the normality test. The Jarque-Bera test evaluates whether the skewness and kurtosis of the sample conform to a normal distribution. This test is often applied to residuals resulting from a linear regression test to assess their normality. The Jarque-Bera test is highly effective in detecting normality in residuals. The results of the Jarque-Bera test for normality all reject the null hypothesis of normality at a 1% significance level.

Table 1. Descriptive statistics.

Variable	Mean	Median	Min.	Max.	SD	Skewness	Kurtosis	Jarque-Bera
σ	0.001	0.001	0	0.058	0.003	7.823	88.438	725522***
Log(*Usepu*)	4.544	4.504	1.2	6.694	0.636	0.269	3.532	53.449***
Log(*Oilc*)	4.083	4.056	2.304	4.818	0.335	-0.32	3.918	121.074***
Log(*Nasdaq*)	8.878	8.85	8.14	9.716	0.459	0.207	1.723	173.896***
Log(*Oldc*)	7.264	7.183	6.957	7.626	0.181	0.425	1.663	241.943***
Log(*Address*)	13.315	13.496	11.763	14.128	0.568	-1.07	2.982	439.526***
Log(*Blocksize*)	13.645	13.814	11.866	14.664	0.528	-1.326	3.889	751.545***
Log(*Minidif*)	28.121	29.357	21.07	31.406	2.732	-0.626	2.11	227.006***
Log(*Hashrate*)	16.303	17.484	9.151	19.712	2.705	-0.616	2.074	228.609***
Log(*Transact*)	12.304	12.486	10.906	13.119	0.495	-1.323	3.6	707.441***
Log(*Btcmv*)	24.894	25.457	21.617	27.874	1.881	-0.206	1.64	194.721***

Note: *** means p<0.01; Usepu represents data related to US economic policy uncertainty; Oilc represents the price of oil; Nasdaq represents the NASDAQ index; Goldc represents the price of gold; Address represents the number of active Bitcoin addresses on a given day; Blocksize represents the block size of Bitcoin; Minidif represents mining difficulty; Hashrate represents Bitcoin hash value; Transact represents the trading volume of Bitcoin; Btcmv represents the market value of Bitcoin.

The stationarity of time-series data plays a crucial role in the outcomes of our empirical analyses. For nonstationary time series, the random patterns differ at various time points, making it challenging to capture the overall randomness of the series with known information. To avoid spurious regression, it is essential to perform stationarity tests on each variable. In this study, we employed the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests to inspect each variable; the results are presented in Table 2. The original time series for Bitcoin price volatility, oil prices, and EPU are all stationary. Among the control variables, only the difficulty of mining Bitcoin is stationary. However, nonstationary variables became stationary after first differencing. Hence, in subsequent models, we used the differenced version of variables that were nonstationary in their original series. Thus, the test results suggest that the variables satisfy the model's prerequisites.

Table 2. ADF test.

Variable	ADF	1%	5%	10%	PP	1%	5%	10%	Conclusion
σ	-20.021	-3.430	-2.860	-2.570	-20.630	-3.430	-2.860	-2.570	Stationary
Log(Usepu)	-16.621	-3.430	-2.860	-2.570	-16.576	-3.430	-2.860	-2.570	Stationary
Log(Oilc)	-6.104	-3.430	-2.860	-2.570	-16.576	-3.430	-2.860	-2.570	Stationary
Log(Nasdaq)	-1.011	-3.430	-2.860	-2.570	-0.994	-3.430	-2.860	-2.570	Nonstationary
Log(Oldc)	-0.592	-3.430	-2.860	-2.570	-0.534	-3.430	-2.860	-2.570	Nonstationary
Log(Address)	-0.010	-3.430	-2.860	-2.570	2.912	-3.430	-2.860	-2.570	Nonstationary
Log(Blocksize)	-1.170	-3.430	-2.860	-2.570	1.610	-3.430	-2.860	-2.570	Nonstationary
Log(Minidif)	-4.813	-3.430	-2.860	-2.570	-4.436	-3.430	-2.860	-2.570	Stationary
Log(Hashrate)	-2.148	-3.430	-2.860	-2.570	-2.559	-3.430	-2.860	-2.570	Nonstationary
Log(Transact)	-1.277	-3.430	-2.860	-2.570	1.392	-3.430	-2.860	-2.570	Nonstationary
Log(Btcmv)	0.180	-3.430	-2.860	-2.570	0.222	-3.430	-2.860	-2.570	Nonstationary

Note: Usepu represents data related to US economic policy uncertainty; Oilc represents the price of oil; Nasdaq represents the NASDAQ index; Goldc represents the price of gold; Address represents the number of active Bitcoin addresses on a given day; Blocksize represents the block size of Bitcoin; Minidif represents mining difficulty; Hashrate represents Bitcoin hash value; Transact represents the trading volume of Bitcoin; Btcmv represents the market value of Bitcoin.

Table 3 lists the Pearson correlation coefficients of the variables in the model estimation. The results reveal that the correlation coefficients between our dependent variable, Bitcoin price volatility, and values for the control variables Bitcoin wallet addresses, block size, mining difficulty, hash rate, trading volume, and market value are 0.060, 0.019, -0.002, -0.002, 0.017, and 0.068, respectively. Only Bitcoin wallet addresses and Bitcoin market value show a significant positive correlation with Bitcoin price volatility at the 1% significance level, while the remaining correlation coefficients are not significant. Notably, the correlation coefficient between mining difficulty and Bitcoin price volatility is negative. However, the specifics require further exploration in subsequent empirical models. The correlation coefficient between our main independent variable (EPU) and Bitcoin volatility is 0.040 and is significant at the 10% level. As previously discovered, there is no restriction on the correlation coefficients between the other three independent variables and Bitcoin price volatility. We adjusted the variables in the model to address the instability of the original sequences between them, which is the core issue of this paper. Looking at the entire correlation coefficient matrix, we can see that the correlations between other variables related to the model are mostly significant.

Table 3. Pearson correlation matrix.

Variables	σ	Log(Usepu)	Log(Oilc)	Log(Nasdaq)	Log(Goldc)	Log(Address)	Log(Blocksize)	Log(Minidif)	Log(Hashrate)	Log(Transact)	Log(Btcmv)
σ	1										
Log(Usepu)	0.040*	1									
Log(Oilc)	0.014	-0.191***	1								
Log(Nasdaq)	0.014	0.512***	0.187***	1							
Log(Goldc)	0.018	0.576***	0.209***	0.891***	1						
Log(Address)	0.060***	0.490***	-0.151***	0.823***	0.644***	1					
Log(Blocksize)	0.019	0.458***	-0.211***	0.780***	0.594***	0.960***	1				
Log(Minidif)	-0.002	0.515***	0.015	0.922***	0.760***	0.913***	0.900***	1			
Log(Hashrate)	-0.002	0.516***	0.019	0.922***	0.760***	0.915***	0.895***	0.999***	1		
Log(Transact)	0.017	0.420***	-0.322***	0.651***	0.456***	0.939***	0.938***	0.820***	0.823***	1	
Log(Btcmv)	0.068***	0.491***	0.235***	0.951***	0.824***	0.850***	0.779***	0.926***	0.928***	0.683***	1

Note: *** $p < 0.01$, * $p < 0.1$. usepu represents data related to US economic policy uncertainty; oilc represents the price of oil; nasdaq represents the NASDAQ index; goldc represents the price of gold; address represents the number of active Bitcoin addresses on a given day; blocksize represents the block size of Bitcoin; minidif represents mining difficulty; hashrate represents the Bitcoin hash value; transact represents the trading volume of Bitcoin; btcmv represents the market value of Bitcoin.

Moreover, multicollinearity has always been a significant concern in empirical analysis. Multicollinearity indicates a strong relationship between model variables, which can inflate the variance of the regression coefficients. As a result, precise, accurate estimation of coefficients becomes challenging (Gujarati, 2009; Hair, Black, Babin, & Anderson, 2010). Empirical research methods indicate that if the VIF (variance inflation factor) value of the independent variable in the model exceeds 10, the model can be regarded as having multicollinearity issues. If the VIF value of the independent variable is more than 0 but less than 10, it is generally considered that the model has no multicollinearity problems. Additionally, the inverse of VIF is known as tolerance (TOL), the value of which ranges from 0 to 1. A value of TOL approaching 0 suggests a higher probability of multicollinearity between variables. In contrast, the closer TOL is to 1, the stronger the evidence that the model is free from collinearities (Moore, Craig, & McCabe, 2012). Due to the close relationship between VIF and TOL, they can be used interchangeably. Table 4 shows that the highest VIF value for the independent variables in the model is 4.030, while the other values are close to 1; thus, all values are below the critical value of 10. From these results, we conclude that the regression estimates in Table 5 are not biased due to multicollinearity issues. In other words, the credibility of the model is not compromised due to multicollinearity.

Table 4. VIF test.

Variable	VIF	1/VIF
Log(Hashrate)	4.030	0.248
Log(Address)	3.340	0.300
Log(Blocksize)	3.070	0.326
Log(Transac)	2.300	0.435
Log(Usepu)	1.480	0.674
Log(Minidif)	1.420	0.702
Log(Btcmv)	1.070	0.934
Log(Oilc)	1.070	0.934
Log(Nasdaq)	1.070	0.938
Log(Goldc)	1.010	0.994
Mean VIF	1.990	

Note: Usepu represents data related to US economic policy uncertainty; Oilc represents the price of oil; Nasdaq represents the NASDAQ index; Goldc represents the price of gold; Address represents the number of active Bitcoin addresses on a given day; Blocksize represents the block size of Bitcoin; Minidif represents mining difficulty; Hashrate represents the Bitcoin hash value; Transact represents the trading volume of Bitcoin; Btcmv represents the market value of Bitcoin.

Table 5 presents the results of our regression analysis. Models 1-4 test the influence of our independent variables EPU, oil prices, the NASDAQ index, and gold prices on Bitcoin volatility, respectively, while Model 5 includes all variables. From the models, we see that the linear model demonstrates a statistically significant positive relationship between EPU and Bitcoin price volatility ($\beta = 0.000329, p < 0.05$), thereby supporting Hypothesis 1. This indicates that EPU not only affects traditional financial markets but also has a ripple effect on emerging entities like Bitcoin. In Model 2, we observe that the coefficient for oil prices is negative ($\beta = -0.00011, p > 0.1$) and not statistically significant. Therefore, Hypothesis 2 remains unsupported, implying a minimal relationship between oil prices and Bitcoin volatility. In Model 3, the NASDAQ index shows a statistically significant positive effect on Bitcoin price volatility ($\beta = 0.0154, p < 0.05$), thereby supporting Hypothesis 3. This further underscores the financial nature of Bitcoin. In Model 4, the price of gold shows a statistically significant negative correlation with Bitcoin price volatility, indicating a substitutive relationship between gold and Bitcoin ($\beta = -0.0190, p < 0.05$). Hypothesis 4 is therefore not supported, which to some extent affirms Bitcoin's reputation as "digital gold." The results in the full-variable Model 5 affirm the robustness of the aforementioned conclusions and the model. The coefficients of our main independent variables remain relatively consistent, and their statistical significance remains largely unchanged.

Table 5. Regression results.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Log(Usepu)	0.000329** [0.000]				0.000312** [0.000]
Log(Oilc)		-0.00011 [0.000]			1.34E-05 [0.000]
Log(Nasdaq)			0.0154** [0.006]		0.0147** [0.006]
Log(Goldc)				-0.0190** [0.009]	-0.0195** [0.009]
Log(Address)	0.00273 [0.002]	0.00263 [0.002]	0.00262 [0.002]	0.00275 [0.002]	0.00281* [0.002]
Log(Blocksize)	-0.000505 [0.001]	-0.0004 [0.001]	-0.00048 [0.001]	-0.00046 [0.001]	-0.00062 [0.001]
Log(Minidif)	-0.000042 [0.000]	-1.8E-06 [0.000]	-1.5E-06 [0.000]	-1.3E-06 [0.000]	-3.9E-05 [0.000]
Log(Hashrate)	-0.00107 [0.001]	-0.00102 [0.001]	-0.00106 [0.001]	-0.00113 [0.001]	-0.00119 [0.001]
Log(Transac)	-0.000137 [0.001]	-1.6E-05 [0.001]	6.23E-05 [0.001]	-2.4E-07 [0.001]	-5.2E-05 [0.001]
Log(Btcmv)	-0.0123*** [0.002]	-0.0122*** [0.002]	-0.0134*** [0.002]	-0.0119*** [0.002]	-0.0132*** [0.002]
_Cons	0.00113 [0.001]	0.00194 [0.001]	0.00146* [0.001]	0.00147* [0.001]	0.00105 [0.001]
N	1816	1816	1816	1814	1814
Adj. R^2	0.022	0.02	0.023	0.022	0.026
AIC	-15396.5	-15391.9	-15397.8	-15377.3	-15381.8
BIC	-15352.5	-15347.9	-15353.8	-15333.3	-15321.2

Note: Standard errors in brackets.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; Usepu represents data related to US economic policy uncertainty; Oilc represents the price of oil; Nasdaq represents the NASDAQ index; Goldc represents the price of gold; Address represents the number of active Bitcoin addresses on a given day; Blocksize represents the block size of Bitcoin; Minidif represents mining difficulty; Hashrate represents the Bitcoin hash value; Transact represents the trading volume of Bitcoin; Btcmv represents the market value of Bitcoin.

To ensure the robustness of our primary results, we employed a variable substitution method for verification. In this research, for the independent variables of interest - EPU, oil prices, the NASDAQ index, and gold prices - we substituted them, respectively, with relevant variables: US EPU, natural gas, the S&P 500 index, and silver prices. The regression was conducted similarly, and the results are reported in Table 6. The findings are largely consistent with our previous regression results, thereby validating our research outcomes.

Table 6. Robustness test.

Variable	Model 6	Model 7	Model 8	Model 9	Model 10
Log(Tmuusa)	0.000437*** [0.000]				0.000476*** [0.000]
Log(Gasp)		-0.0016 [0.002]			-0.0018 [0.002]
Log(Sp500)			0.0170** [0.008]		0.0217*** [0.008]
Log(Silverc)				-0.0152*** [0.005]	-0.0166*** [0.005]
Log(Address)	0.00261 [0.002]	0.00265 [0.002]	0.00262 [0.002]	0.00273 [0.002]	0.00269 [0.002]
Log(Blocksize)	-0.0003954 [0.001]	-0.00042 [0.001]	-0.00047 [0.001]	-0.00053 [0.001]	-0.00061 [0.001]
Log(Minidif)	-0.0000766** [0.000]	-2.5E-06 [0.000]	-1.6E-06 [0.000]	-1.4E-06 [0.000]	-0.0000825** [0.000]
Log(Hashrate)	-0.0000766 [0.001]	-0.00104 [0.001]	-0.00106 [0.001]	-0.00123 [0.001]	-0.00119 [0.001]
Log(Transac)	-0.000131	9.6E-06	6.85E-05	7.38E-05	0.000063

Variable	Model 6	Model 7	Model 8	Model 9	Model 10
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Log(Btcmv)	-0.0122***	-0.0122***	-0.0132***	-0.0117***	-0.0130***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
_Cons	0.00162*	0.00150*	0.00146*	0.00147*	0.00160*
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
N	1816	1816	1815	1811	1810
Adj. R^2	0.024	0.02	0.022	0.025	0.033
AIC	-15400.8	-15392.1	-15387.2	-15354.5	-15356.7
BIC	-15356.8	-15348.1	-15343.1	-15310.5	-15296.2

Note: Standard errors in brackets.* p < 0.1, ** p < 0.05, *** p < 0.01; Tmuusa represents data of Twitter US economic policy uncertainty; Gasp represents the price of gas; Sp500 represents the SP500 index; Silverc represents the price of silver; Address represents the number of active Bitcoin addresses on a given day; Blocksize represents the block size of Bitcoin; Minidif represents mining difficulty; Hashrate represents the Bitcoin hash value; Transact represents the trading volume of Bitcoin; Btcmv represents the market value of Bitcoin.

5. CONCLUSIONS

The primary objective of this research is to explore the determinants of Bitcoin volatility from a multivariate perspective, thereby broadening the research on Bitcoin price volatility. In this article, we examine the influence of external factors on Bitcoin volatility, including several control variables related to Bitcoin. The analysis included selected samples spanning from January 2, 2014, to March 21, 2023, an extensive dataset. We performed a series of robustness tests to validate our findings. Consequently, the conclusions of this study are very trustworthy. This study provides an authentic depiction of the Bitcoin market and augments the existing literature by providing empirical evidence that supports behavioral finance theories. Overall, this study offers profound insights into the relationship between external factors and the Bitcoin market.

We focused on the impact on Bitcoin price volatility of external factors such as EPU, oil prices, the NASDAQ index, and gold prices. The results have significant value in enhancing a comprehensive study of factors affecting Bitcoin price volatility. We used the OLS model to conduct a basic regression analysis of the influence of each research variable separately. Our findings indicated that EPU has a positive and statistically significant impact on Bitcoin price volatility. This is in stark contrast to the traditional view that Bitcoin operates independently and is unaffected by conventional economic variables. Interestingly, our research did not support or validate a relationship between the price of Bitcoin and energy prices. Furthermore, we found that the relatively young NASDAQ index, strongly associated with emerging technologies, positively stimulated Bitcoin price volatility. This validates Bitcoin as a financial entity, which is why we chose to include this index in our study. Lastly, the negative relationship between gold prices and Bitcoin volatility suggests that we can accept Bitcoin, often referred to as "digital gold," as a hedge against gold.

These findings have practical implications for policymakers, investors, and researchers. For policymakers, understanding how external factors influence the cryptocurrency market can assist in crafting more targeted regulatory strategies to ensure market stability and fairness. For investors, understanding how traditional financial markets impact the Bitcoin market might help in devising better investment strategies, preventing excessive trading, or making other unwise decisions due to overreactions in the financial markets. For researchers, our study can offer a comprehensive framework to study investor behavior in cryptocurrencies and other financial markets.

However, this research has its limitations. Firstly, while we utilized multiple indicators to study factors influencing Bitcoin price volatility, these might not entirely capture all elements affecting Bitcoin price fluctuations. Secondly, because our sample period is limited to 2014 to 2023, our conclusions might only be pertinent to this specific timeframe. Future studies could consider extending the sample period or delving into other factors potentially affecting the cryptocurrency market, such as macroeconomic elements, technological advancements, or regulatory changes.

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REFERENCES

Ardia, D., Bluteau, K., & Rüede, M. (2019). Regime changes in Bitcoin GARCH volatility dynamics. *Finance Research Letters*, *29*, 266-271.

Aysan, A. F., Demir, E., Gozgor, G., & Lau, C. K. M. (2019). Effects of the geopolitical risks on Bitcoin returns and volatility. *Research in International Business and Finance*, *47*, 511-518. https://doi.org/10.1016/j.ribaf.2018.09.011

Baek, C., & Elbeck, M. (2015). Bitcoins as an investment or speculative vehicle? A first look. *Applied Economics Letters*, *22*(1), 30-34. https://doi.org/10.1080/13504851.2014.916379

Bakas, D., Magkonis, G., & Oh, E. Y. (2022). What drives volatility in Bitcoin market? *Finance Research Letters*, *50*, 103237. https://doi.org/10.1016/j.frl.2022.103237

Balanda, K. P., & MacGillivray, H. (1988). Kurtosis: A critical review. *The American Statistician*, *42*(2), 111-119. https://doi.org/10.2307/2684482

Balcilar, M., Bouri, E., Gupta, R., & Roubaud, D. (2017). Can volume predict Bitcoin returns and volatility? A quantiles-based approach. *Economic Modelling*, *64*, 74-81. https://doi.org/10.1016/j.econmod.2017.03.019

Bariviera, A. F. (2017). The inefficiency of Bitcoin revisited: A dynamic approach. *Economics Letters*, *161*, 1-4. https://doi.org/10.1016/j.econlet.2017.09.013

Baur, D. G., & Dimpfl, T. (2021). The volatility of Bitcoin and its role as a medium of exchange and a store of value. *Empirical Economics*, *61*(5), 2663-2683. https://doi.org/10.1007/s00181-020-01990-5

Baur, D. G., Hoang, L. T., & Hossain, M. Z. (2022). Is Bitcoin a hedge? How extreme volatility can destroy the hedge property. *Finance Research Letters*, *47*, 102655. https://doi.org/10.1016/j.frl.2021.102655

Benhamed, A., Messai, A. S., & El Montasser, G. (2023). On the determinants of Bitcoin returns and volatility: What we get from gets? *Sustainability*, *15*(3), 1761.

Bergsli, L. Ø., Lind, A. F., Molnár, P., & Polasik, M. (2022). Forecasting volatility of Bitcoin. *Research in International Business and Finance*, *59*, 101540.

Blau, B. M. (2017). Price dynamics and speculative trading in Bitcoin. *Research in International Business and Finance*, *41*, 493-499. https://doi.org/10.1016/j.ribaf.2017.05.010

Bourghelle, D., Jawadi, F., & Rozin, P. (2022). Do collective emotions drive Bitcoin volatility? A triple regime-switching vector approach. *Journal of Economic Behavior & Organization*, *196*, 294-306. https://doi.org/10.1016/j.jebo.2022.01.026

Bouri, E., Azzi, G., & Dyhrberg, A. H. (2017). On the return-volatility relationship in the Bitcoin market around the price crash of 2013. *Economics*, *11*(1), 2. https://doi.org/10.5018/economics-ejournal.ja.2017-2

Bouri, E., Das, M., Gupta, R., & Roubaud, D. (2018). Spillovers between Bitcoin and other assets during bear and bull markets. *Applied Economics*, *50*(55), 5935-5949. https://doi.org/10.1080/00036846.2018.1488075

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*, 156-164. https://doi.org/10.1016/j.qref.2020.03.004

Brauneis, A., Mestel, R., Riordan, R., & Theissen, E. (2022). Bitcoin unchained: Determinants of cryptocurrency exchange liquidity. *Journal of Empirical Finance*, *69*, 106-122. https://doi.org/10.1016/j.jempfin.2022.08.004

Bukovina, J., & Marticek, M. (2016). *Sentiment and bitcoin volatility. MENDELU Working Papers in Business and Economics 58/2016. Mendel University in Brno.* Retrieved from http://ideas.repec.org/s/men/wpaper.html

Bystrom, H., & Krygier, D. (2018). What drives bitcoin volatility? *Available at SSRN 3223368.*

Chu, J., Chan, S., Nadarajah, S., & Osterrieder, J. (2017). GARCH modelling of cryptocurrencies. *Journal of Risk and Financial Management, 10*(4), 17. https://doi.org/10.3390/jrfm10040017

Ciaian, P., Rajcaniova, M., & Kancs, D. A. (2016). The economics of BitCoin price formation. *Applied Economics, 48*(19), 1799-1815. https://doi.org/10.1080/00036846.2015.1109038

Conrad, C., Custovic, A., & Ghysels, E. (2018). Long-and short-term cryptocurrency volatility components: A GARCH-MIDAS analysis. *Journal of Risk and Financial Management, 11*(2), 23. https://doi.org/10.3390/jrfm11020023

Das, D., & Kannadhasan, M. (2018). Do global factors impact Bitcoin prices? Evidence from wavelet approach. *Journal of Economic Research, 23*(3), 227-264.

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*, 101335. https://doi.org/10.1016/j.frl.2019.101335

De Carvalho, L. M., Resende, G. P., & Takahashi, M. (2023). An explanatory model for the price of Bitcoin and the public interest in the topic. *Socioeconomic Analytics, 1*, 126-140.

Dias, I. K., Fernando, J. R., & Fernando, P. N. D. (2022). Does investor sentiment predict Bitcoin return and volatility? A quantile regression approach. *International Review of Financial Analysis, 84*, 102383. https://doi.org/10.1016/j.irfa.2022.102383

Dodd, N. (2018). The social life of Bitcoin. *Theory, Culture & Society, 35*(3), 35-56.

Dwyer, G. P. (2015). The economics of Bitcoin and similar private digital currencies. *Journal of Financial Stability, 17*, 81-91. https://doi.org/10.1016/j.jfs.2014.11.006

Dyhrberg, A. H. (2016). Bitcoin, gold and the dollar–A GARCH volatility analysis. *Finance Research Letters, 16*, 85–92. https://doi.org/10.1016/j.frl.2015.10.008

Fang, L., Bouri, E., Gupta, R., & Roubaud, D. (2019). Does global economic uncertainty matter for the volatility and hedging effectiveness of Bitcoin? *International Review of Financial Analysis, 61*, 29-36. https://doi.org/10.1016/j.irfa.2018.12.010

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*, 101566. https://doi.org/10.1016/j.irfa.2020.101566

Gajardo, G., Kristjanpoller, W. D., & Minutolo, M. (2018). Does Bitcoin exhibit the same asymmetric multifractal cross-correlations with crude oil, gold and DJIA as the Euro, great British pound and Yen? *Chaos, Solitons & Fractals, 109*, 195-205.

Gandal, N., & Halaburda, H. (2019). *Competition in the cryptocurrency market.* Retrieved from Bank of Canada Working Paper 2014-33:

Garman, M. B., & Klass, M. J. (1980). On the estimation of security price volatilities from historical data. *Journal of Business*, 67-78.

Georgoula, I., Pournarakis, D., Bilanakos, C., Sotiropoulos, D., & Giaglis, G. M. (2015). Using time-series and sentiment analysis to detect the determinants of Bitcoin prices. *Available at SSRN 2607167.*

Ghabri, Y., Ayadi, A., & Guesmi, K. (2021). Fossil energy and clean energy stock markets under COVID-19 pandemic. *Applied Economics, 53*(43), 4962-4974. https://doi.org/10.1080/00036846.2021.1912284

Ghazani, M. M., & Khosravi, R. (2020). Multifractal detrended cross-correlation analysis on benchmark cryptocurrencies and crude oil prices. *Physica A: Statistical Mechanics and its Applications, 560*, 125172. https://doi.org/10.1016/j.physa.2020.125172

Giudici, P., & Abu-Hashish, I. (2019). What determines Bitcoin exchange prices? A network VAR approach. *Finance Research Letters, 28*, 309-318. https://doi.org/10.1016/j.frl.2018.05.013

Gronwald, M. (2019). Is Bitcoin a commodity? On price jumps, demand shocks, and certainty of supply. *Journal of International Money and Finance, 97*, 86-92. https://doi.org/10.1016/j.jimonfin.2019.06.006

Guesmi, K., Saadi, S., Abid, I., & Ftiti, Z. (2019). Portfolio diversification with virtual currency: Evidence from Bitcoin. *International Review of Financial Analysis, 63*, 431-437. https://doi.org/10.1016/j.irfa.2018.03.004

Gujarati, D. N. (2009). *Basic econometrics.* New Delhi: Tata McGraw-Hill Education.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). Advanced diagnostics for multiple regression: A supplement to multivariate data analysis. *Advanced Diagnostics for Multiple Regression: A Supplement to Multivariate Data Analysis*.

Hau, L., Zhu, H., Shahbaz, M., & Sun, W. (2021). Does transaction activity predict Bitcoin returns? Evidence from quantile-on-quantile analysis. *The North American Journal of Economics and Finance*, *55*, 101297. https://doi.org/10.1016/j.najef.2020.101297

Hu, D., Li, X., Xiang, G., & Zhou, Q. (2023). Asset pricing models in the presence of higher moments: Theory and evidence from the US and China stock market. *Pacific-Basin Finance Journal*, *79*, 102053. https://doi.org/10.1016/j.pacfin.2023.102053

Huynh, T. L. D., Shahbaz, M., Nasir, M. A., & Ullah, S. (2022). Financial modelling, risk management of energy instruments and the role of cryptocurrencies. *Annals of Operations Research*, *313*(1), 47-75. https://doi.org/10.1007/s10479-020-03680-y

Kajtazi, A., & Moro, A. (2019). The role of Bitcoin in well diversified portfolios: A comparative global study. *International Review of Financial Analysis*, *61*, 143-157. https://doi.org/10.1016/j.irfa.2018.10.003

Kapar, B., & Olmo, J. (2021). Analysis of Bitcoin prices using market and sentiment variables. *The World Economy*, *44*(1), 45-63. https://doi.org/10.1111/twec.13020

Katsiampa, P. (2017). Volatility estimation for Bitcoin: A comparison of GARCH models. *Economics Letters*, *158*, 3-6. https://doi.org/10.1016/j.econlet.2017.06.023

Klein, T., Thu, H. P., & Walther, T. (2018). Bitcoin is not the new gold–A comparison of volatility, correlation, and portfolio performance. *International Review of Financial Analysis*, *59*, 105-116. https://doi.org/10.1016/j.irfa.2018.07.010

Köchling, G., Schmidtke, P., & Posch, P. N. (2020). Volatility forecasting accuracy for Bitcoin. *Economics Letters*, *191*, 108836. https://doi.org/10.1016/j.econlet.2019.108836

Kraaijeveld, O., & De Smedt, J. (2020). The predictive power of public Twitter sentiment for forecasting cryptocurrency prices. *Journal of International Financial Markets, Institutions and Money*, *65*, 101188. https://doi.org/10.1016/j.intfin.2020.101188

Kristoufek, L. (2015). What are the main drivers of the Bitcoin price? Evidence from wavelet coherence analysis. *PloS One*, *10*(4), e0123923. https://doi.org/10.1371/journal.pone.0123923

Kristoufek, L. (2023). Will Bitcoin ever become less volatile? *Finance Research Letters*, *51*, 103353. https://doi.org/10.1016/j.frl.2022.103353

Kurihara, Y., & Fukushima, A. (2018). How does price of Bitcoin volatility change? *International Research in Economics and Finance*, *2*(1), 8. https://doi.org/10.20849/iref.v2i1.317

Lin, M.-Y., & An, C.-L. (2021). The relationship between Bitcoin and resource commodity futures: Evidence from NARDL approach. *Resources Policy*, *74*, 102383. https://doi.org/10.1016/j.resourpol.2021.102383

Liu, Y., Tsyvinski, A., & Wu, X. (2022). Common risk factors in cryptocurrency. *The Journal of Finance*, *77*(2), 1133-1177.

López-Cabarcos, M. Á., Pérez-Pico, A. M., Piñeiro-Chousa, J., & Šević, A. (2021). Bitcoin volatility, stock market and investor sentiment. Are they connected? *Finance Research Letters*, *38*, 101399.

Lukáš, P., & Taisei, K. (2017). Volatility analysis of Bitcoin price time series. *Quantitative Finance and Economics*, *1*, 474–485. https://doi.org/10.3934/qfe.2017.4.474

Ma, D., & Tanizaki, H. (2019). The day-of-the-week effect on Bitcoin return and volatility. *Research in International Business and Finance*, *49*, 127-136. https://doi.org/10.1016/j.ribaf.2019.02.003

Ma, F., Liang, C., Ma, Y., & Wahab, M. I. M. (2020). Cryptocurrency volatility forecasting: A Markov regime-switching MIDAS approach. *Journal of Forecasting*, *39*(8), 1277-1290. https://doi.org/10.1002/for.2691

Ma, Y., & Luan, Z. (2022). Ethereum synchronicity, upside volatility and Bitcoin crash risk. *Finance Research Letters*, *46*, 102352. https://doi.org/10.1016/j.frl.2021.102352

Mokni, K. (2021). When, where, and how economic policy uncertainty predicts Bitcoin returns and volatility? A quantiles-based analysis. *The Quarterly Review of Economics and Finance*, *80*, 65-73. https://doi.org/10.1016/j.qref.2021.01.017

Moore, D. S., Craig, B. A., & McCabe, G. P. (2012). *Introduction to the practice of statistics* (7th ed.). New York: WH Freeman.

Naeem, M., Saleem, K., Ahmed, S., Muhammad, N., & Mustafa, F. (2020). Extreme return-volume relationship in cryptocurrencies: Tail dependence analysis. *Cogent Economics & Finance*, *8*(1), 1834175. https://doi.org/10.1080/23322039.2020.1834175

Naimy, V. Y., & Hayek, M. R. (2018). Modelling and predicting the Bitcoin volatility using GARCH models. *International Journal of Mathematical Modelling and Numerical Optimisation, 8*(3), 197-215. https://doi.org/10.1504/ijmmno.2018.088994

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system. *Decentralized Business Review*, 1-9.

Nouir, J. B., & Hamida, H. B. H. (2023). How do economic policy uncertainty and geopolitical risk drive Bitcoin volatility? *Research in International Business and Finance, 64*, 101809. https://doi.org/10.1016/j.ribaf.2022.101809

Olvera-Juarez, D., & Huerta-Manzanilla, E. (2019). Forecasting bitcoin pricing with hybrid models: A review of the literature. *International Journal of Advanced Engineering Research and Science, 6*(9), 161-164. https://doi.org/10.22161/ijaers.69.18

Osterrieder, J., & Lorenz, J. (2017). A statistical risk assessment of Bitcoin and its extreme tail behavior. *Annals of Financial Economics, 12*(01), 1750003. https://doi.org/10.1142/s2010495217500038

Pagnottoni, P., & Dimpfl, T. (2019). Price discovery on Bitcoin markets. *Digital Finance, 1*(1), 139-161.

Pal, D., & Mitra, S. K. (2019). Hedging bitcoin with other financial assets. *Finance Research Letters, 30*, 30-36. https://doi.org/10.1016/j.frl.2019.03.034

Pichl, L., & Kaizoji, T. (2017). Volatility analysis of Bitcoin. *Quantitative Finance and Economics, 1*(4), 474-485.

Platanakis, E., & Urquhart, A. (2020). Should investors include Bitcoin in their portfolios? A portfolio theory approach. *The British Accounting Review, 52*(4), 100837.

Qian, L., Wang, J., Ma, F., & Li, Z. (2022). Bitcoin volatility predictability–The role of jumps and regimes. *Finance Research Letters, 47*, 102687.

Qiu, Y., Wang, Y., & Xie, T. (2021). Forecasting Bitcoin realized volatility by measuring the spillover effect among cryptocurrencies. *Economics Letters, 208*, 110092. https://doi.org/10.1016/j.econlet.2021.110092

Rehman, M. U., Asghar, N., & Kang, S. H. (2020). Do Islamic indices provide diversification to Bitcoin? A time-varying copulas and value at risk application. *Pacific-Basin Finance Journal, 61*, 101326. https://doi.org/10.1016/j.pacfin.2020.101326

Ren, Y., Zhao, W., You, W., & Zhu, H. (2022). Multiscale features of extreme risk spillover networks among global stock markets. *The North American Journal of Economics and Finance, 62*, 101754. https://doi.org/10.1016/j.najef.2022.101754

Sapuric, S., & Kokkinaki, A. (2014). Bitcoin is volatile! Isn't that right? Business information systems workshops: BIS 2014 international workshops, Larnaca, Cyprus, May 22-23, 2014, Revised Papers 17. In (pp. 255-265): Springer International Publishing.

Shahzad, S. J. H., Bouri, E., Roubaud, D., Kristoufek, L., & Lucey, B. (2019). Is Bitcoin a better safe-haven investment than gold and commodities? *International Review of Financial Analysis, 63*, 322-330. https://doi.org/10.1016/j.irfa.2019.01.002

Shen, D., Urquhart, A., & Wang, P. (2020). Forecasting the volatility of Bitcoin: The importance of jumps and structural breaks. *European Financial Management, 26*(5), 1294-1323. https://doi.org/10.2139/ssrn.3449756

Smales, L. A. (2022). Spreading the fear: The central role of CBOE VIX in global stock market uncertainty. *Global Finance Journal, 51*, 100679. https://doi.org/10.2139/ssrn.3336505

Symitsi, E., & Chalvatzis, K. J. (2019). The economic value of Bitcoin: A portfolio analysis of currencies, gold, oil and stocks. *Research in International Business and Finance, 48*, 97-110. https://doi.org/10.2139/ssrn.3127534

Tiwari, A. K., Kumar, S., & Pathak, R. (2019). Modelling the dynamics of Bitcoin and Litecoin: GARCH versus stochastic volatility models. *Applied Economics, 51*(37), 4073-4082. https://doi.org/10.1080/00036846.2019.1588951

Tong, Z., Chen, Z., & Zhu, C. (2022). Nonlinear dynamics analysis of cryptocurrency price fluctuations based on Bitcoin. *Finance Research Letters, 47*, 102803. https://doi.org/10.1016/j.frl.2022.102803

Ullah, S., Attah-Boakye, R., Adams, K., & Zaefarian, G. (2022). Assessing the influence of celebrity and government endorsements on Bitcoin's price volatility. *Journal of Business Research, 145*, 228-239. https://doi.org/10.1016/j.jbusres.2022.01.055

Urquhart, A. (2017). The volatility of Bitcoin. *Available at SSRN 2921082*. http://dx.doi.org/10.2139/ssrn.2921082

Van Wijk, D. (2013). What can be expected from the BitCoin. *Erasmus Universiteit Rotterdam, 18*, 1-21.

Vassiliadis, S., Papadopoulos, P., Rangoussi, M., Konieczny, T., & Gralewski, J. (2017). Bitcoin value analysis based on cross-correlations. *Journal of Internet Banking and Commerce, 22*(S7), 1-12.

Vuong, G. T. H., Nguyen, M. H., & Huynh, A. N. Q. (2022). Volatility spillovers from the Chinese stock market to the US stock market: The role of the COVID-19 pandemic. *The Journal of Economic Asymmetries*, *26*, e00276. https://doi.org/10.1016/j.jeca.2022.e00276

Walther, T., Klein, T., & Bouri, E. (2019). Exogenous drivers of Bitcoin and Cryptocurrency volatility–A mixed data sampling approach to forecasting. *Journal of International Financial Markets, Institutions and Money*, *63*, 101133. https://doi.org/10.2139/ssrn.3192474

Wang, G.-J., Xie, C., Wen, D., & Zhao, L. (2019). When Bitcoin meets economic policy uncertainty (EPU): Measuring risk spillover effect from EPU to Bitcoin. *Finance Research Letters*, *31*. https://doi.org/10.1016/j.frl.2018.12.028

Wang, J., Ma, F., Bouri, E., & Guo, Y. (2023). Which factors drive Bitcoin volatility: Macroeconomic, technical, or both? *Journal of Forecasting*, *42*(4), 970-988. https://doi.org/10.2139/ssrn.4080107

Wang, P., Zhang, W., Li, X., & Shen, D. (2019). Is cryptocurrency a hedge or a safe haven for international indices? A comprehensive and dynamic perspective. *Finance Research Letters*, *31*, 1-18. https://doi.org/10.1016/j.frl.2019.04.031

Wu, C.-C., Ho, S.-L., & Wu, C.-C. (2022). The determinants of Bitcoin returns and volatility: Perspectives on global and national economic policy uncertainty. *Finance Research Letters*, *45*, 102175. https://doi.org/10.1016/j.frl.2021.102175

Wu, C. Y., Pandey, V. K., & Dba, C. (2014). The value of Bitcoin in enhancing the efficiency of an investor's portfolio. *Journal of Financial Planning*, *27*(9), 44-52.

Xia, Y., Sang, C., He, L., & Wang, Z. (2023). The role of uncertainty index in forecasting volatility of Bitcoin: Fresh evidence from GARCH-MIDAS approach. *Finance Research Letters*, *52*, 103391. https://doi.org/10.1016/j.frl.2022.103391

Yang, S. Y., & Kim, J. (2015). *Bitcoin market return and volatility forecasting using transaction network flow properties*. Paper presented at the 2015 IEEE Symposium Series on Computational Intelligence, IEEE.

Yen, K.-C., & Cheng, H.-P. (2021). Economic policy uncertainty and cryptocurrency volatility. *Finance Research Letters*, *38*, 101428. https://doi.org/10.1016/j.frl.2020.101428

Yi, S., Xu, Z., & Wang, G.-J. (2018). Volatility connectedness in the cryptocurrency market: Is Bitcoin a dominant cryptocurrency? *International Review of Financial Analysis*, *60*, 98-114. https://doi.org/10.1016/j.irfa.2018.08.012

Yin, L., Nie, J., & Han, L. (2021). Understanding cryptocurrency volatility: The role of oil market shocks. *International Review of Economics & Finance*, *72*, 233-253. https://doi.org/10.1016/j.iref.2020.11.013

Zhang, C., Chen, H., & Peng, Z. (2022). Does Bitcoin futures trading reduce the normal and jump volatility in the spot market? Evidence from GARCH-jump models. *Finance Research Letters*, *47*, 102777. https://doi.org/10.1016/j.frl.2022.102777

Zhu, Y., Dickinson, D., & Li, J. (2017). Analysis on the influence factors of Bitcoin's price based on VEC model. *Financial Innovation*, *3*(1), 1-13. https://doi.org/10.1186/s40854-017-0054-0