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On the factors of Bitcoin's value at risk



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Abstract

This study investigates the factors of Bitcoin's tail risk, quantified by Value at Risk (VaR). Extending the conditional autoregressive VaR model proposed by Engle and Manganelli (2004), I examine 30 potential drivers of Bitcoin's 5% and 1% VaR. For the 5% VaR, quantity variables, such as Bitcoin trading volume and monetary policy rate, were positively significant, but these effects were attenuated when new samples were added. The 5% VaR responds positively to the Internet search index and negatively to the fluctuation of returns on commodity variables and the Chinese stock market index. For the 1% VaR, variables related to the macroeconomy play a key role. The consumer sentiment index exerts a strong positive effect on the 1% VaR. I also find that the 1% VaR has positive relationships with the US economic policy uncertainty index and the fluctuation of returns on the corporate bond index.

Keywords: Bitcoin, Value at risk, CAVaR

JEL Classification: C58, G15

Introduction

Although it has been approximately a decade since the introduction of Bitcoin by Nakamoto (2008), its scope of usage has been rapidly enlarged. The diverse roles of Bitcoin in the financial market are categorized into three main classes: a medium of exchange, a store of value, and a means of investment. Whelan (2013) argues that Bitcoin is similar to the currency. According to Whelan (2013), Bitcoin is a currency because it is a globally accepted medium of exchange. Cuthbertson (2015) states that there are more than 100,000 retailers accepting Bitcoin as payment for goods and services. Following Faghih Mohammadi Jalali and Heidari (2020), we can use Bitcoin at restaurants, malls, and other large and small businesses in countries such as the United States, Canada, the Netherlands, and Japan. Kou et al. (2021) show that Fintech applications can function as an alternative for payments and money transfers. However, Bitcoin shares many properties with gold, a kind of commodity. Both Bitcoin and gold derive most of their value because they are scarce and costly to extract. This feature enables them to act as a store of value, and they are classified as a commodity. Selgin (2015) puts an emphasis on the fact that Bitcoin is not just contingently but absolutely scarce, which defines it as a synthetic commodity form of money. One can also argue that Bitcoin is another investment asset because investors can hedge the downside risk of their wealth by adjusting the amount of Bitcoin as they have done with other investment assets, such as stocks and

bonds. Glaser et al. (2014) highlight that Bitcoin is now treated as a financial investment asset rather than a currency, acting as a means of investing or borrowing in the financial market. This is confirmed by Brière et al. (2015), who provide evidence that the inclusion of Bitcoin in an investment portfolio offers significant diversification benefits in terms of the risk-return trade-off. This diversification effect is also proven by Qarni and Gulzar (2021), who state that Bitcoin can hedge and minimize the risk related to investment in the foreign exchange market because of the low integration between them. Owing to the wide and rapid spread of Bitcoin, it is natural that economic actors are concerned about the risk of using Bitcoin and the risk factors thereof. However, research on the latter is still in its infancy.

This study aims to uncover the factors of Bitcoin's tail risk, quantified by Value at Risk (VaR). Examining the tail risk of Bitcoin is important for several reasons. First, throughout the series of global and international impacts of economic and financial crises, households, firms, and regulatory authorities have been keen on the tail risk of economic variables. To illustrate this, researchers show that heavy-tailed shocks to economic fundamentals help to explain a certain asset's behavior that has proven otherwise difficult to reconcile with the traditional macro-finance theory. Following the work of Barro (2006), the rare disaster hypothesis shows that the economic model matches several focal asset pricing moments when incorporating tail risk into the model. This leads to the phenomenon wherein investors' demand for the asset, described as the asset's risk premium, is dictated by the tail behavior of economic and financial variables. Bollerslev et al. (2015), Andersen et al. (2015), Kelly and Jiang (2014) and many others argue that tail risk measures have explanatory power for the risk premium on the time series of an asset's return.¹ In Giovannetti (2013), tail risk commands the risk premium in the equilibrium derived from the standard consumption–investment intertemporal problem when a representative agent maximizes the quantile of the utility distribution instead of the expected utility. Zha et al. (2020) review the literature on the application of opinion dynamics models, wherein the interaction between a group of agents can lead to speculative bubbles and crashes in financial markets. Thus, tail risk is one of the main interests of market participants—that is, they are tail risk averse. Therefore, crucial importance should be attached to the investigation of Bitcoin's extreme risk, in which the key point is to find the drivers of Bitcoin's VaR.²

Furthermore, compared to other traditional assets, the analysis of tail risk should be a major issue for Bitcoin, particularly because Bitcoin shows a larger magnitude and frequency of price fluctuations. In other words, Bitcoin exhibits some characteristics of immature market assets, such as sudden and extreme price movements, high volatility, and speculation bubbles. Therefore, in Bitcoin risk management, studying its tail risk and VaR identifying factors are of great significance for asset allocation, portfolio selection, and hedging strategies. A strand of literature reveals Bitcoin's heavy-tailed property. Begušić et al. (2018) provide evidence that extreme prices of Bitcoin are considerably

¹ Given that tail movement of asset returns is governed by higher statistical moments, Kinatader and Papavassiliou (2019) can also be an example of the risk premium generated by tail risk. They find that realized kurtosis is the dominant predictor of subsequent bond returns.

² Strictly speaking, the paper tries to find the factors for the VaR of Bitcoin's return. Bitcoin's VaR is interchangeable with the VaR of Bitcoin's return hereafter.

frequent, implying that Bitcoin has heavier tails than stock returns. Osterrieder et al. (2017) use extreme value analysis of Bitcoin returns and show that Bitcoin is more volatile and much riskier than traditional fiat currencies. Geuder et al. (2019) study the Bitcoin price with a focus on identifying and analyzing bubble behavior. They confirm the existence of frequent bubble periods in Bitcoin prices.

The chief obstacle to the investigation of tail movement is a viable measure of tail risk—the VaR for the returns on Bitcoin over time. Kelly and Jiang (2014) organize the literature on the estimation of tail risk. There are three current approaches to measuring tail risk dynamics for asset returns. The first approach is based on the option price data. Examples of the option-based approach include Bakshi et al. (2003), who study the risk-neutral skewness and kurtosis of stock returns; Bollerslev et al. (2009), who examine how the variance risk premium relates to the equity premium; and Backus et al. (2011) and Gao and Song (2015), who infer disaster risk premia from options. The second approach relies on panel return data. This approach attempts to capture common variations in the tail risks of individual firms. Kelly and Jiang (2014) exploit firm-level price crashes every month to identify common fluctuation in tail risks among individual stocks.

The third approach, adopted in this study, is based on high-frequency data exemplified by Engle and Manganelli (2004). Using regression quantiles suggested by Koenker and Bassett (1978), this method directly computes the conditional VaR from a single time series of returns,³ named as conditional autoregressive VaR (CAViaR). Thus, in contrast to the option-based and panel data approach, Engle and Manganelli's (2004) method does not need a brisk derivatives market nor does it require a large cross-section of asset returns.⁴ There are other lines of reasoning that call for the use of the CAViaR model. Considering the overwhelming evidence against normally distributed Bitcoin's return, CAViaR, a semiparametric method, does not require any assumption on the distribution of a time series and directly computes the VaR inspired by the persistency of quantile of returns. Engle and Manganelli's (2004) demonstrate that the CAViaR model outperforms most of the other VaR methods in general when tackling fat-tailed data through the Monte Carlo simulation. More importantly, the CAViaR model allows explanatory variables to enter directly into the specification of the VaR series, which in turn reduces the number of parameters to be estimated, and consequently, the estimation bias. Given that this study tries to find the factors of Bitcoin's VaR, the main econometric characteristic of the CAViaR model allowing potential drivers for VaR to be incorporated into the specification⁵ would be preferable. The CAViaR specification is also equipped with several test statistics for the validity of VaR: adequacy of candidates in terms of consistency of parameters and robustness of estimated VaR using the dynamic relationship between the returns and the VaR. For these reasons, I refrain from using a two-step approach that consists of estimating VaR and finding drivers. Instead, the CAViaR model allows me to study the link between Bitcoin's VaR and the numerous potential factors representing various economic and financial activities using a single-step procedure.

³ Note that Engle and Manganelli (2004) choose two individual stock returns, daily stock returns of General Motors and IBM, to conduct empirical studies.

⁴ In fact, the first two approaches cannot be implemented for Bitcoin's Value at Risk because Bitcoin's derivatives market is still in its early stages and Bitcoin is the individual financial asset irrelevant to cross-section of returns.

⁵ To be specific, potential drivers are incorporated into an information set of the specification.

Therefore, I first estimate the time series of a conditional 5% VaR and evaluate the performance of factors following Engle and Manganelli (2004), and then investigate a more extreme case, the 1% VaR. According to Feng et al. (2018) and Panagiotidis et al. (2019) who indicate potential structural break, two sample periods are considered. I first estimate the models in a sample covering the period from August 1, 2010 to January 3, 2017, and then, the sample is updated to include the period from August 1, 2010 to December 31, 2019. As potential drivers, I employ a rich dataset of 30 economic variables, categorized into Bitcoin-specific variables, which are related to commodity, macroeconomy, currency, stock market, uncertainty, sentiment, and Internet search intensity (see Table 1). To the best of my knowledge, this list of variables that can affect Bitcoin's VaR is exhaustive, based on previous literature.

The main findings of this study can be summarized as follows: For the 5% VaR, quantity variables determining the liquidity investors hold are found to be important drivers of Bitcoin's VaR in the first period. The more the Bitcoin trading volume and monetary policy rate fluctuate, the higher the tail risk of Bitcoin.⁶ However, these effects are attenuated during the second period. This observation is consistent with the fact that Bitcoin has become more mature after 2017. In other words, as the Bitcoin market gets more depth and maturity, there is little place for the supply side variables to affect Bitcoin's VaR. In both periods, the variations in returns on commodity variables and the Shanghai Composite Index have negative impacts on Bitcoin's VaR. The negative relationship between the variation of returns on the commodity price index and Bitcoin's VaR implies that Bitcoin can be a safe haven for commodities in the tail sense. The negative association between the variation in returns on the Shanghai Composite Index and Bitcoin's VaR might be attributed to the capital inflow from the Chinese financial market to the Bitcoin market. It is well known that investors in the Chinese stock market look for a safer destination for investment when the values of the Chinese stock market and currency are worrisome. Internet search intensity also turns out to be useful in explaining Bitcoin's VaR.

For the 1% VaR, variables related to the macroeconomy play a key role in explaining Bitcoin's VaR. The largest coefficient is attached to consumer sentiment index. Economic actors' expectations and attitudes toward macroeconomic conditions exert crucial effects on Bitcoin's VaR. The variation in returns on the corporate bond index has a positive effect on Bitcoin's VaR. Big swings in interest rates reflecting macroeconomic cycles impinge on Bitcoin's VaR. A positive relationship between the US economic policy uncertainty index and Bitcoin's VaR was also detected. A high variation in economic policy uncertainty drives the increase in Bitcoin's VaR. Moreover, it is noteworthy that variables related to the US market are significantly linked to Bitcoin's VaR. While the responses of Bitcoin's VaR to European, Japanese, Chinese, and international stock market indices and economic policy uncertainty indices are muted, significant coefficients on the American stock market index, corporate bond index, and economic policy uncertainty index are observed.

⁶ In this paper, the high value of VaR means high tail risk.

Table 1 Variables employed

Variable	Name used in the paper	Source
Bitcoin price index	BITCOIN	CoinDesk
Bitcoin trading volume	BIT TRD	Bitcoincharts
Brent oil price index	OIL	Federal Reserve Economic Data
Natural gas index	GAS	Bloomberg
S&P Goldman Sachs commodity index	COMMO	Bloomberg
Gold bullion USD/troy ounce rate	GOLD CASH	Federal Reserve Economic Data
CMX gold futures 100 oz rate in USD	GOLD FUTURE	Bloomberg
Silver price index	SILVER	Federal Reserve Economic Data
US consumer price index	USCPI	Federal Reserve Economic Data
Effective federal funds rate	EFFR	Federal Reserve Economic Data
ECB deposit facility rate	ECB DFR	Bloomberg
Bloomberg US corporate bond index	USCOR BND	Bloomberg
Pimco investment grade corporate bond index	PIMCO BND	Bloomberg
St. Louis Fed financial stress index	STRESS	Federal Reserve Economic Data
EUR/USD exchange rate	EUR/USD	Federal Reserve Economic Data
GBP/USD exchange rate	GBP/USD	Federal Reserve Economic Data
CNY/USD exchange rate	CNY/USD	Federal Reserve Economic Data
New York Stock Exchange index	NYSE	Bloomberg
S&P 500 index	SP 500	Bloomberg
Nasdaq index	NASDAQ	Bloomberg
Financial times stock exchange 100 index	FTSE 100	Bloomberg
Nikkei 225 index	NIKKEI	Quandl
Shanghai composite index	SHANGHAI	Quandl
MSCI world index	MSCI	Bloomberg
Global hedge fund index	HEDGE	Bloomberg
Global economic policy uncertainty index	UNCER WRD	Economic Policy Uncertainty
US economic policy uncertainty index	UNCER US	Economic Policy Uncertainty
UK economic policy uncertainty index	UNCER UK	Economic Policy Uncertainty
Michigan consumer sentiment index	CONSUME	University of Michigan
Google trend for the term 'Bitcoin'	GOOGLE	R package 'gtrendsR'
Wikipedia trend for the article on Bitcoin	WIKI	R package 'wikipediatrend' and Wikimedia Toolforge

This table shows information on the analysis variables. The first column gives the variables employed to explain the VaR of Bitcoin returns. The second column lists their names, as used herein. In the third column, I indicate the sources of the variables from which daily variables are obtained. The sample period is from August 1, 2010 to December 31, 2019

The remainder of this paper is organized as follows: In “[Related studies](#)” section, I provide a review of the literature. In “[Conditional Autoregressive Value at Risk](#)” section, I present an econometric model for estimating the CAViaR of returns on Bitcoin with drivers. The data employed for factors are described in “[Data](#)” section, while the empirical results are presented in “[Empirical Results](#)” section. Section “[Conclusion](#)” concludes this paper.

Related studies

To date, most existing studies have focused on Bitcoin’s return and volatility. However, the literature on the tail risk of Bitcoin is extremely scant. For the determinants of Bitcoin returns, Panagiotidis et al. (2018) examine the significance of 21 potential drivers

of Bitcoin returns using a LASSO regression. As LASSO allows a subset of the covariates to be selected, one can compare the performance among potential drivers. They find that search intensity, gold returns, and policy uncertainty are the most important determinants. These results are confirmed by Demir et al. (2018), who analyze the predictive power of the economic policy uncertainty index on the daily returns of Bitcoin. They conclude that Bitcoin can serve as a hedging tool against uncertainty based on the evidence that Bitcoin returns are negatively associated with the economic policy uncertainty index. While Li and Wang (2017) suggest that measures of financial and macroeconomic activities are drivers of Bitcoin returns, Baek and Elbeck (2015) highlight that Bitcoin returns are not driven by fundamental economic factors but by speculative motives. Aharon et al. (2021) show that the risk factors of the yield curve, that is, the level, slope, and curvature components, are independent of Bitcoin returns, suggesting that the shocks from macroeconomic cycles have no influence on the Bitcoin market. Polasik et al. (2015) demonstrate that Bitcoin returns are driven by the sentiment expressed in newspapers and the total number of transactions. Similar to Polasik et al. (2015), Kristoufek (2015) shows that Bitcoin trading volume and investors' interest, proxied by Google searches, have an influence on Bitcoin returns. Mai et al. (2018) examine the dynamic interactions between social media and Bitcoin returns. They show that forum posts are associated with increasing Bitcoin values.

Meanwhile, the literature considers statistics related to conventional assets as potential drivers of Bitcoin returns. This allows the study of linkages across assets and provides further insights into the classification and identity of Bitcoin. Ji et al. (2019) argue that Bitcoin is a substitute for gold, showing that an increase in gold price decreases the demand for cryptocurrency, and therefore, weakens the connectedness of return spillover for the cryptocurrency market. However, Al-Khazali et al. (2018) reject the claim that Bitcoin and gold are similar. They demonstrate that the return and volatility of gold react to macroeconomic news, whereas those of Bitcoin do not mostly react in a similar manner. An interesting paper by Koutmos (2018) examines the empirical linkages between Bitcoin returns and transaction activity, proxied by the total number of unique Bitcoin addresses. A unique address refers to an identifier that serves as a possible destination for a Bitcoin payment. The bivariate VAR models employed in this study elucidate the strong linkages between Bitcoin returns and transaction activities. This leads to the claim that Bitcoin is traded as an alternative for a medium of exchange. Bouri et al. (2017b) examine whether Bitcoin can act as an alternative financial instrument for major world stock indices, bonds, oil, gold, and the dollar. The empirical results show that Bitcoin has an investment attractiveness in that its returns inversely covary with those on Chinese and Asia-Pacific stocks. By employing alternative VAR and factor-augmented VaR models, Panagiotidis et al. (2019) estimate the dynamics of Bitcoin returns using stock market returns, exchange rates, and gold and oil returns. Their results suggest a significant interaction between Bitcoin and traditional stock markets. In particular, they reveal the increased impact of Asian markets on Bitcoin. Using the daily return series of equity indices, represented by six equity exchange traded funds (ETFs), and five main cryptocurrencies, including Bitcoin, Kristjanpoller et al. (2020) find the asymmetric multifractality in the cross-relationship between Bitcoin and equity ETFs. Baur et al. (2018a) rely on

the general correlation analysis to prove that Bitcoin returns are uncorrelated with other conventional asset returns, implying that there is no similarity between Bitcoin and gold, as well as the dollar. Baur et al. (2018b) enlarge the scope of the assets and conclude that Bitcoin is different from all traditional assets, such as currency, equity, bond, energy, and precious metal.

Another strand of literature studies Bitcoin volatility. Tiwari et al. (2019) employ seven generalized autoregressive conditional heteroskedasticity (GARCH) specifications and stochastic volatility models to assess the model fit for dynamics of Bitcoin returns series. They find that the stochastic volatility models consistently outperform the GARCH models and concomitantly reveal a significant difference in the model specifications between Bitcoin and the stock market index. Urquhart (2017) finds that heterogeneous autoregressive (HAR) models are superior in modelling Bitcoin volatility to traditional GARCH models. He also finds that the inclusion of jumps and continuous components of HAR models adds information to the models. Katsiampa (2017) investigates the performance of several competing GARCH-type models to explain Bitcoin volatility and selects an AR-CGARCH model as the preferred specification. He considers that Bitcoin volatility consists of long- and short-term components, but this is further elaborated by Conrad et al. (2018) with the GARCH-MIDAS model. They provide evidence that the S&P 500 volatility risk premium and Baltic dry index have significantly positive effects on long-term Bitcoin volatility, concluding that economic activity is closely linked with Bitcoin volatility. Blau (2017) also shows roughly similar results. Relying on univariate and multivariate linear regression analyses, Blau (2017) rejects the claim that speculative trading, irrelevant to rational economic decisions, contributes to Bitcoin volatility. Balcilar et al. (2017) analyze the causal relationship between trading volume and Bitcoin returns and volatility over their entire conditional distribution. The results reveal that volume can predict Bitcoin returns over the quantile ranging from 0.25 to 0.75, while there is no predictability for Bitcoin volatility at any point in the conditional distribution. Bystrom and Krygier (2018) compare Google search volumes to market-wide risk indicators in driving Bitcoin volatility. They find a stronger positive link between Bitcoin volatility and search volumes.

Similar to the analyses on Bitcoin returns, an investigation of volatility can help financial scholars clarify the relationship between Bitcoin and traditional assets. Dyhrberg (2016) shows that the GARCH estimation results prove the similarities between Bitcoin and gold, as well as the dollar. She concludes that Bitcoin is somewhere between a commodity and a currency. This is supported by Bouri et al. (2017a), who investigate the return–volatility relationship of Bitcoin and find a similarity between Bitcoin and gold. Based on an asymmetric GARCH framework, their results show that Bitcoin has a safe-haven property similar to gold. Conversely, several papers rebut the statement that there are properties that Bitcoin shares with gold. Klein et al. (2018) concentrate on the volatility behavior to find the distinction between Bitcoin and gold. They compare the conditional variance properties of Bitcoin and gold and find differences in their structures. Glaser et al. (2014) highlight that Bitcoin is treated as a financial investment asset rather than a currency, acting as a means of investing or borrowing in the financial market. They apply ARCH and GARCH estimation approaches, and document that it is not Bitcoin network volume but Bitcoin trading volume that is closely linked with the

new user's attention. Dissimilar results are reported by Ennis (2013). Using a GARCH analysis, he reports that Bitcoin returns are statistically independent of equity and bond markets, while it acts as a hedge for the euro, supporting the idea that Bitcoin is an alternative monetary asset. Stavroyiannis and Babalos (2017) rely on a variety of econometric approaches, such as asymmetric GARCH and full BEKK model, and investigate the dynamic properties of Bitcoin, the S&P 500 index, and gold. They conclude that Bitcoin does not hold any of the attributes of the stock market index or gold has.

Indeed, recent studies have focused on the tail risk of Bitcoin, which consists of two main strands of literature. The first strand addresses tail risk dependence among cryptocurrencies. Borri (2019) use CoVaR to estimate the conditional tail risk for cryptocurrencies. He finds that cryptocurrencies, including Bitcoin, are exposed to tail risk within cryptocurrency markets, while they are not exposed to tail risk with respect to other assets, such as the US equity market or gold. Huynh (2019) investigates the contagion risks among cryptocurrencies. The Student's *t* copula indicates that cryptocurrencies have a joint distribution in extreme value, which causes a simultaneous downside trend. Xu et al. (2020) analyze the tail risk interdependence among 23 cryptocurrencies by applying the Tail-Event driven NETwork (TENET) framework. They find that a significant risk spillover effect exists in cryptocurrency markets.

The second strand focuses on the relationship between Bitcoin and traditional assets in the tail sense. Feng et al. (2018)⁷, Bouri et al. (2020) and Hussain Shahzad et al. (2019)⁸ compare the tail movement of Bitcoin with that of the stock market index. Feng et al. (2018) assert that Bitcoin is a good diversification asset for stocks because its left tail is uncorrelated with the left tails of S&P 500, Euro Stoxx 50, Nikkei 225, and CSI 300 index. Similar to Feng et al. (2018), Bouri et al. (2020) report that Bitcoin is a safe haven for US equity indices. Conversely, Hussain Shahzad et al. (2019) show that Bitcoin does not exhibit a safe-haven property for stock market investments during extreme market periods. A few studies have investigated the distinct drivers of Bitcoin tail risk. Using the measure of crash risk suggested by Chen et al. (2001), Kalyvas et al. (2020) demonstrate that economic uncertainty is negatively associated with Bitcoin price crash risk. Using the same measure of crash risk, Anastasiou et al. (2021) show that sentiment index has a positive impact on cryptocurrencies' market price crash risk. However, the above mentioned literature presents an incomplete picture of the tail risk of Bitcoin because they only examine the direct cross-correlation of time series and fail to adopt a more precise measure of tail risk,⁹ which do not investigate the exhaustive list of candidate factors for Bitcoin's VaR. Thus, I seek to contribute in this respect.

⁷ In this paper, conditional VaR is estimated by the combination of the extreme value theory and ARMA-GARCH model. This method has a strong assumption and is not empirically convincing when considering the large number of potential polynomials in the mean and variance equations.

⁸ These two papers employ the approach of Han et al. (2016) that measure the directional quantile dependence between two time series. Since this method does not contain the specification describing the persistence in tail behavior, this relies on large sample sizes for the validity. Recall that the sample size of Bitcoin is still small due to its recent emergence.

⁹ Recall that two crash-risk measures Kalyvas et al. (2020) and Anastasiou et al. (2021) adopt are based only on the second and third moments of daily returns. Tail risk should be expected to be correlated with the higher moments of the corresponding variable. This is well documented in Kim and White (2004), Sihem and Slaheddine (2014), and Gormsen and Jensen (2020).

Conditional autoregressive value at risk

This section presents the estimation method of the series of conditional VaR via CAViaR specifications using daily returns on the Bitcoin price index and explanatory variables, following Engle and Manganelli (2004). The key idea of CAViaR is the recognition of the persistent quantile of the return. CAViaR is obtained by modeling the quantile of the daily return directly with the specifications. The general CAViaR specification is as follows:

$$VaR_{\theta,t}(\boldsymbol{\beta}) = \beta_0 + \sum_{i=1}^q \beta_{1,i} VaR_{\theta,t-i}(\boldsymbol{\beta}) + \sum_{j=1}^r \beta_{2,j} l(z_{t-j}). \tag{1}$$

where $VaR_{\theta,t}(\boldsymbol{\beta})$ is the quantile of the distribution of returns on the corresponding variable with a level of confidence $\theta \in (0,1)$ at time t , θ is 5% and 1% associated with VaR in this study,¹⁰ $\boldsymbol{\beta}$ is a vector of unknown parameters, and z is a vector of observable explanatory variables. $p = q + r + 1$ is the dimension of $\boldsymbol{\beta}$, and l is a function of a finite number of lagged values of the observables. The autoregressive terms $\beta_{1,i} VaR_{\theta,t-i}(\boldsymbol{\beta})$ ensure that the quantile changes “smoothly” over time. The role of $l(z_{t-j})$ is to link $VaR_{\theta,t}(\boldsymbol{\beta})$ to explanatory variables belonging to the information set. This study extends Engle and Manganelli’s (2004) two specifications: symmetric absolute value and asymmetric slope.

$$VaR_{\theta,t}(\boldsymbol{\beta}) = \beta_1 + \beta_2 VaR_{\theta,t-1}(\boldsymbol{\beta}) + \beta_3 |r_{t-1}| + \beta_4 |x_{t-1}| \tag{2}$$

$$VaR_{\theta,t}(\boldsymbol{\beta}) = \beta_1 + \beta_2 VaR_{\theta,t-1}(\boldsymbol{\beta}) + \beta_3 (r_{t-1})^+ + \beta_4 (r_{t-1})^- + \beta_5 (x_{t-1})^+ + \beta_6 (x_{t-1})^- \tag{3}$$

I use the notation $(r)^+ = \max(r, 0)$, $(r)^- = -\min(r, 0)$. As a proxy for the information set, the lagged return on Bitcoin, r_{t-1} , is used following Engle and Manganelli (2004). In addition, the potential drivers of Bitcoin’s VaR, x_{t-1} , are included next to lagged returns as another component of the information set, which is composed of 30 economic and financial variables, as explained in the next section.¹¹ By incorporating an explanatory variable into the specification directly, the CAViaR model has the ability to capture complex tail dynamics via a parsimonious parameter structure.

In the symmetric absolute value specification, β_1 and β_2 are constant and the coefficients of the lagged VaR, respectively. Two coefficients, β_3 and β_4 , capture the response to past returns and the explanatory variable. In the asymmetric slope specification, two terms are needed for each lagged return and driver to allow the response to positive and negative returns and driver to be different. For the factors of Bitcoin’s VaR, the parameters of interest are β_4 in the symmetric absolute value specification and β_5 and β_6 in the asymmetric slope specification. In the symmetric absolute value specification, one can estimate the unconditional relationship between the driver and Bitcoin’s VaR. In the asymmetric slope specification, the conditional relation between the driver and Bitcoin’s

¹⁰ It should be noted that the conventional choice of the confidence level for the tail risk is 95% and 99%, which correspond to the 5% and 1% VaR.

¹¹ The spirit of this paper is close to that of Engle et al. (2013). Engle et al. (2013) measure the contribution of economic sources to stock market volatility. Specifically, they extend the GARCH-MIDAS model to link stock market volatility to each economic variable by imputing macroeconomic time series into the volatility component.

VaR is estimated because β_5 (β_6) shows a state-dependent relation when the driver is on an upward (downward) trajectory. Both specifications are mean-reverting in the sense that the coefficient of the lagged VaR is not constrained to 1.

The unknown parameters are estimated using regression quantiles, as introduced by Koenker and Bassett (1978). The return dynamics of Bitcoin are as follows:

$$r_t = VaR_{\theta,t}(\beta) + e_{\theta,t}, \quad Quant_{\theta}(e_{\theta,t}|\Omega_t) = 0. \tag{4}$$

where daily Bitcoin returns are defined as $r_t = \ln(P_t) - \ln(P_{t-1})$, Ω_t is the information set at time t , and $Quant_{\theta}(e_{\theta,t}|\Omega_t) = 0$ means that the θ -quantile of the error term is zero. Then, the θ th regression quantile is defined as any $\hat{\beta}$ that solves

$$\hat{\beta} = \underset{\beta}{\operatorname{argmin}} \frac{1}{T} \sum_{t=1}^T [\theta - I(r_t < VaR_{\theta,t}(\beta))] \cdot [r_t - VaR_{\theta,t}(\beta)] \tag{5}$$

Engle and Manganelli (2004) establish the conditions under which the estimates are consistent and asymptotically normal.

$$\sqrt{T}A_T^{-1/2}D_T(\hat{\beta} - \beta) \xrightarrow{d} N(0, I) \tag{6}$$

where

$$A_T = E \left[T^{-1} \theta(1 - \theta) \sum_{t=1}^T \nabla' VaR_t(\beta) \nabla VaR_t(\beta) \right], \tag{7}$$

$$D_T = E \left[T^{-1} \sum_{t=1}^T h_t(0|\Omega_t) \nabla' VaR_t(\beta) \nabla VaR_t(\beta) \right]. \tag{8}$$

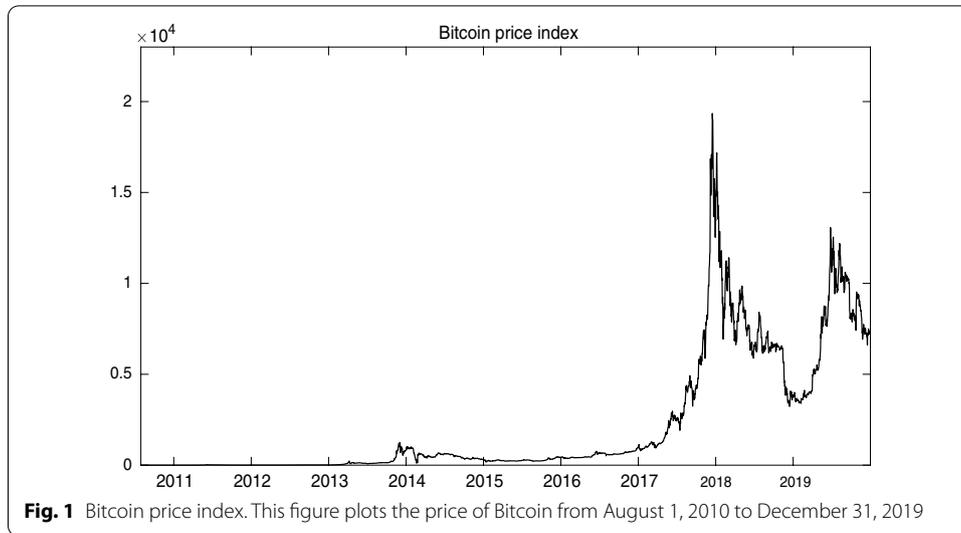
I suppress the subscript θ from VaR_{θ} for notational convenience. We denote the conditional density of $e_{\theta,t}$ evaluated at zero by $h_t(0|\Omega_t)$ and the $1 \times p$ gradient of $VaR_t(\beta)$ by $\nabla VaR_t(\beta)$. $\nabla VaR(\beta)$ is a $T \times p$ matrix with a typical row $\nabla VaR_t(\beta)$. Note that the only assumption in the model is that the quantile process is correctly specified. No assumption on the distribution of the error terms is required, thereby reducing the risk of misspecification.

I use a consistent estimator of the variance-covariance matrix and the statistic of the dynamic quantile (DQ) test to evaluate the performance of potential drivers. First, the variance-covariance matrix of β is calculated using

$$\hat{A}_T = T^{-1} \theta(1 - \theta) \nabla' VaR(\hat{\beta}) \nabla VaR(\hat{\beta}), \tag{9}$$

$$\hat{D}_T = (2T\hat{c}_T)^{-1} \sum_{t=1}^T I(|r_t - VaR_t(\hat{\beta})| < \hat{c}_T) \nabla' VaR_t(\hat{\beta}) \nabla VaR_t(\hat{\beta}). \tag{10}$$

where \hat{c}_T is the bandwidth and its probability limit, c_T , satisfies $c_T = o(1)$ and $c_T^{-1} = o(T^{1/2})$.



Second, the DQ test is a type of specification test for the accuracy of a VaR model. This test is set up to determine whether the conditional expectation of $Hit_t(\beta)$ is equal to zero, where $Hit_t(\beta) = I(r_t < VaR_{\theta,t}(\beta)) - \theta$. This function assumes that the value $(1 - \theta)$ every time r_t is less than the quantile, and $-\theta$ otherwise.¹² The test statistic asymptotically chi-square distributed is given by:

$$DQ = \frac{Hit'(\hat{\beta})X(\hat{\beta})(\hat{M}_T\hat{M}'_T)^{-1}X'(\hat{\beta})Hit'(\hat{\beta})}{\theta(1 - \theta)} \tag{11}$$

where $X_t(\beta)$ is different element wise from $\nabla VaR_t(\beta)$ which is measurable with respect to Ω_t and $\hat{M}_T = X'(\hat{\beta}) - \left[(2T\hat{c}_T)^{-1} \sum_{t=1}^T I(|r_t - VaR_t(\hat{\beta})| < \hat{c}_T) X'_t(\hat{\beta}) \nabla VaR_t(\hat{\beta}) \right] \hat{D}_T^{-1} \nabla' VaR(\hat{\beta})$. $X_t(\hat{\beta})$ and $Hit_t(\hat{\beta})$ are the typical rows of $X(\hat{\beta})$ and $Hit(\hat{\beta})$, respectively.

In the empirical application, I use the empirical θ -quantile of the first 300 observations as the initialization to compute the VaR series. Because VaR is usually reported as a positive number, the estimated VaR is set to be positive. A high value of the estimated VaR indicates a high tail risk.

Data

The data employed are daily and cover the period from August 1, 2010, to December 31, 2019. The dependent variable is always the VaR of the return on Bitcoin. Following Panagiotidis et al. (2018), the price index of Bitcoin (BITCOIN) is taken from Coin-desk and plotted in Fig. 1. Before the first boom in late 2013, the Bitcoin price index was characterized by low volatility. Between 2010 and 2012, the price remained near zero. The price index was below 50 until March 2013, and then it went over 100 in April 2013 for the first time. Bitcoin trade started to become more active as Bitcoin grew in

¹² Christoffersen and Pelletier (2004) summarize the two methods of backtesting for conditional VaR. Their first way, based on the Hit_t sequence, is qualitatively same as the dynamic quantile test in this paper. Note that, in this paper, the distribution and the t-statistic associated with DQ can be used to test not only the validity of the forecasting model, but also the misspecification of the information set.

popularity since 2013. To address this, the US authorities began a full-scale investigation into Bitcoin trade and its exchanges. As the debate and the following regulations on Bitcoin became confused with many conflicting opinions—Bitcoin possesses the potential to help international business, as suggested by the Federal Reserve Board in November and Bitcoin is fully characterized by its speculation motive warned by the People's Bank of China in December—Bitcoin experienced unprecedented huge price fluctuations. During 2016, the price of Bitcoin showed a gradual upward movement, as the second Bitcoin halving event occurred in July. It is well known that Bitcoin prices respond positively to the Bitcoin halving event. Interestingly, the price action in 2017 was dramatic. After the period of moderate growth between 2014 and 2016, the price index consistently soared by early 2018 and showed high fluctuations afterward. This is considered to be the result of self-fulfilling phenomena. As the value of other financial instruments also showed gradual growth, Bitcoin's popularity accelerated its rapid growth. In October 2017, the CME group announced the launch of Bitcoin futures, and its first contract began in December 2017. After Bitcoin's price continuously decreased in 2018, the price again spiked due to a series of favorable events. In January 2019, Bakkt, a cryptocurrency exchange, announced the launch of bitcoin futures contracts, and Facebook said it was loosening its ban on advertisements related to blockchain and cryptocurrency. Moreover, several influential institutions' digital coins, such as Facebook Libra and People's Bank of China's CBDC, have seemed to provide psychological support to the appetite of Bitcoin since the mid of 2019.

With the Bitcoin price index, the list of all 30 employed variables for the factors of Bitcoin's VaR, their mnemonics, and data sources are available in Table 1. I follow prior researchers to select candidates of drivers trying to make the most extensive dataset examined in the literature. These potential drivers can fall into several categories: Bitcoin-specific variables, variables related to commodity, macroeconomy, currency, stock market, uncertainty, sentiment, and internet search intensity.

Bitcoin trading volume (BIT TRD), one of the most renowned Bitcoin-specific variables, was retrieved from Bitcoincharts. The Bitcoin trading volume is simply the sum of all Bitcoins traded in a selected period. The motivation for including Bitcoin trading volume is based on the work of Balcilar et al. (2017), who examines whether trading volume can predict Bitcoin's returns and volatility. The variables related to commodities consist of the following: Brent oil price index (OIL), natural gas index (GAS), S&P Goldman Sachs commodity index (COMMO), gold bullion USD/troy ounce rate (GOLD CASH), CMX gold futures 100 oz rate in USD (GOLD FUTURE), and silver price index (SILVER) obtained from the Federal Reserve Economic Data and Bloomberg's databases. To investigate the sensitivities to macroeconomic variables, I include the US consumer price index (USCPI), effective federal funds rate (EFFR), ECB deposit facility rate (ECB DFR), Bloomberg US corporate bond index (USCOR BND), Pimco investment-grade corporate bond index (PIMCO BND), and St. Louis Fed Financial Stress Index (STRESS).

Turning to currency-related variables, EUR/USD exchange rate (EUR/USD), GBP/USD exchange rate (GBP/USD), and CNY/USD exchange rate (CNY/USD) are taken from the Federal Reserve Economic Data. The inclusion of currency as an explanatory variable is justified by the phenomenon where cryptocurrencies are asserted to replace traditional currency, such as euros, dollars, and pounds, due to Bitcoin's advantages over

fiat currency. Given that Bitcoin is another type of investment asset, I try to measure the risk of Bitcoin against various stock market indices: the New York Stock Exchange index (NYSE), S&P 500 index (SP 500), Nasdaq index (NASDAQ), Financial times stock exchange 100 index (FTSE 100), Nikkei 225 index (NIKKEI), Shanghai composite index (SHANGHAI), MSCI world index (MSCI), and Global hedge fund index (HEDGE) collected from Federal Reserve Economic Data, Quandl, and Bloomberg's databases. Following Demir et al. (2018), three economic policy uncertainty indices are examined (UNCER WRD, UNCER US, UNCER UK). It is suspected that uncertainties about the decisions of governments and regulatory bodies lead to decreases in the trust of investors to mainstream currencies and/or to the entire economy, and then affect Bitcoin's VaR.

Considering the viewpoints of Bitcoin users, variables related to sentiment and Internet search intensity are investigated. First, a variable related to consumer sentiment, namely the Michigan Consumer Sentiment Index (CONSUME), is considered. Additionally, because Bitcoin has been receiving more attention in the news, I follow Panagiotidis et al. (2019) and utilize Google and Wikipedia trend data to see how Internet search intensity contributes to Bitcoin's VaR. Google trend data (GOOGLE) are retrieved using the R package 'gtrendsR' and for Wikipedia trend (WIKI), the package 'wikipediatrend' was used. The data for Wikipedia trends are available till the 21st of January 2016. The most recent data are available from tools.wmflabs.org.

Table 2 provides summary statistics. Values for variables that are not in daily frequency have been linearly interpolated. Note that BITCOIN, OIL, GAS, COMMO, GOLD CASH, GOLD FUTURE, SILVER, USCOR BND, PIMCO BND, EUR/USD, GBP/USD, CNY/USD, NYSE, SP 500, NASDAQ, FTSE 100, NIKKEI, SHANGHAI, MSCI and HEDGE are used in returns on the corresponding price index.¹³ When comparing the average of daily Bitcoin's returns to that of commodity, currency and stock market index, Bitcoin is much higher than its counterparts. More importantly, the skewness and the kurtosis of Bitcoin's returns are also much more extreme than those of other variables. They are the third highest among variables in the list, indicating that Bitcoin's return process deviates from the normal distribution.¹⁴ These findings, therefore, call for the analysis of the tail risk of Bitcoin which seems to be relatively more important than focusing on the return and volatility. Note that the third and fourth moments of the corresponding variable are the components of tail behavior measure (Groeneveld and Meeden 1984; Moors 1988; Kim and White 2004). The high fluctuation of returns is also bolstered by the large proportion of noise components in Bitcoin's returns verified by low autocorrelation.

Empirical results

This section contains empirical results from the application of the CAViaR model to find the drivers of Bitcoin's VaR. The determinants of the 5% VaR of Bitcoin returns and 1% VaR of Bitcoin returns are investigated in "5% VaR" and "1% VaR" sections, respectively. Prior to the estimation of the VaR, all explanatory variables are standardized. This

¹³ For the empirical analysis in the next section, these variables are used in returns while the others are used in levels. Therefore, depending on the variables, mnemonics refers to the returns on the price index or the price index itself hereafter.

¹⁴ Like Balcilar et al. (2017), the null hypothesis of Jarque-Bera test is rejected at a 1% significance level.

Table 2 Summary statistics

	Mean	SD	Skew	Kurt	AR(1)
BITCOIN	0.596	8.915	17.229	610.629	− 0.014
BIT TRD	246296.517	867752.692	9.314	114.451	0.831**
OIL	0.008	1.610	0.352	10.263	− 0.067**
GAS	0.003	2.327	0.419	10.071	− 0.046**
COMMO	0.036	2.801	23.782	1030.892	0.000
GOLD CASH	0.010	0.774	− 0.217	12.546	− 0.008
GOLD FUTURE	4.573	221.516	57.524	3348.719	0.000
SILVER	0.011	1.460	− 0.701	22.354	− 0.039*
USCPI	1.754	0.853	0.038	3.332	0.998**
EFFR	0.641	0.774	1.202	2.915	0.999**
ECB DFR	− 0.125	0.312	0.991	3.334	0.999**
USCOR BND	0.014	0.236	− 0.345	6.228	− 0.059**
PIMCO BND	0.015	0.894	− 0.429	12.080	0.060**
STRESS	− 0.984	0.322	0.728	2.849	0.997**
EUR/USD	− 0.003	0.462	− 0.312	9.355	− 0.006
GBP/USD	− 0.004	0.455	− 1.650	36.587	− 0.005
CNY/USD	− 0.001	0.160	− 0.599	18.421	− 0.010
NYSE	0.023	0.760	− 0.542	11.716	− 0.50**
SP 500	0.034	0.751	− 0.461	11.167	− 0.055**
NASDAQ	0.044	0.873	− 0.397	9.333	− 0.058**
FTSE 100	0.013	0.757	− 0.175	7.799	− 0.011
NIKKEI	0.032	1.062	− 0.515	12.660	− 0.051**
SHANGHAI	0.010	1.101	− 0.942	13.264	− 0.0110.011
MSCI	0.024	0.669	− 0.557	10.633	0.074**
HEDGE	0.003	0.167	− 1.018	9.627	0.141**
UNCER WRD	155.924	50.102	0.986	3.307	0.994**
UNCER US	108.299	64.072	1.711	8.025	0.637**
UNCER UK	324.096	157.934	1.809	8.912	0.991**
CONSUME	85.998	11.162	− 0.583	2.298	0.998**
GOOGLE	32.170	19.424	0.620	3.349	0.922**
WIKI	14369.668	29671.088	14.526	359.518	0.779**

This table reports the descriptive statistics for the variables employed. BITCOIN, OIL, GAS, COMMO, GOLD CASH, GOLD FUTURE, SILVER, USCOR BND, PIMCO BND, EUR/USD, GBP/USD, CNY/USD, NYSE, SP 500, NASDAQ, FTSE 100, NIKKEI, SHANGHAI, MSCI, and HEDGE are used in returns on the corresponding price index. The data are all daily, from August 1, 2010 to December 31, 2019. The table presents the mean (Mean), standard deviation (SD), skewness (Skew), kurtosis (Kurt), and first-order autocorrelation (AR(1)) with its significance. The significance levels at 95% and 99% are denoted by one and two stars, respectively

allows for a comparison of the performance of the explanatory variables. Considering the concern of potential structural breaks due to regime shifts or critical social events, two sample periods are considered. I first estimate the models in a sample covering the period from August 1, 2010 to January 3, 2017, and then I update the sample to include the period from August 1, 2010 to December 31, 2019. According to Feng et al. (2018) and Panagiotidis et al. (2019), there are two reasons for this. First, the WannaCry ransomware attack in 2017 used Bitcoin as the only payment method, and it represented a natural advertisement for Bitcoin. Market speculation activities quickly follow. Second, numerous initial coin offerings were launched in 2017, which raised the demand for Bitcoin and attracted considerable market attention. These correspond to the recently alleged Bitcoin bubble since 2017.

Table 3 Estimates and relevant statistics for the 5% and 1% CAViaRs of Bitcoin's returns

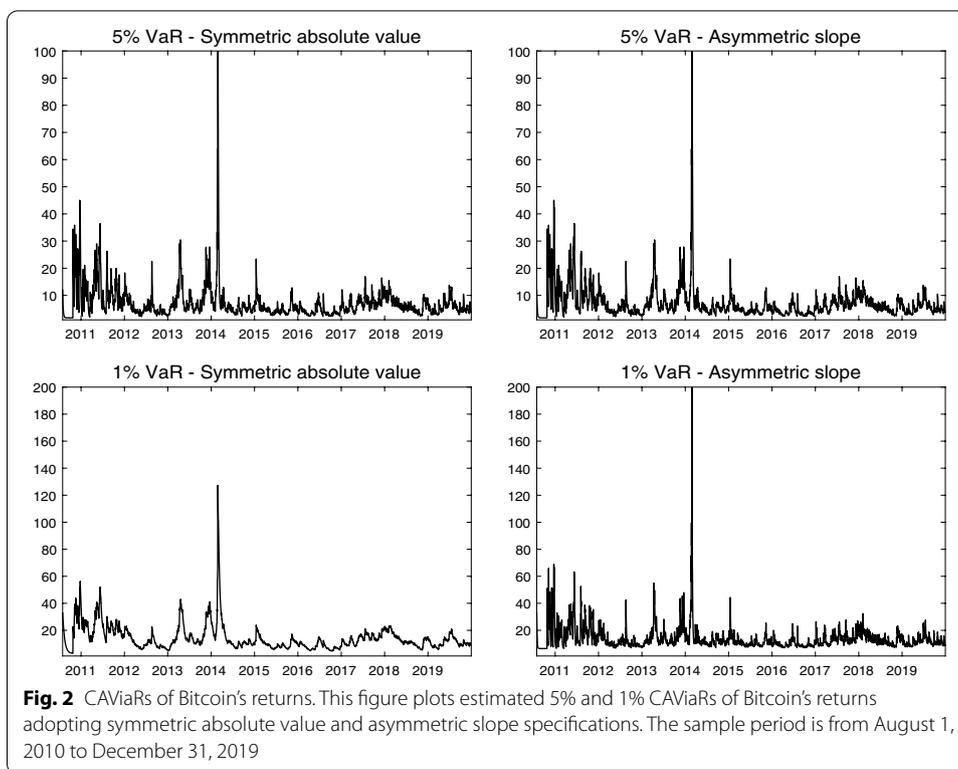
	5% VaR		1% VaR	
	Symmetric absolute value	Asymmetric slope	Symmetric absolute value	Asymmetric slope
β_1	0.359	0.527	0.169	1.837
Standard errors	0.174	0.143	0.102	0.722
<i>p</i> values	0.020	0.000	0.048	0.005
β_2	0.795	0.715	0.941	0.719
Standard errors	0.036	0.037	0.010	0.077
<i>p</i> values	0.000	0.000	0.000	0.000
β_3	0.327	0.294	0.197	0.445
Standard errors	0.087	0.045	0.023	0.147
<i>p</i> values	0.000	0.000	0.000	0.001
β_4		0.658		0.835
Standard errors		0.075		0.152
<i>p</i> values		0.000		0.000
RQ	2110.147	2070.816	686.464	672.943
Hits (%)	5.000	5.000	0.988	0.988
DQ <i>p</i> values	0.249	0.986	0.489	0.577

This table presents the values of the estimated parameters, the corresponding standard errors, (one-sided) *p* values, the values of the regression quantile objective functions (RQ), the percentage of times the VaR is exceeded (Hits), and the *p* value of the dynamic quantile test (DQ) when computing the series of CAViaR of return on the price index of Bitcoin. For specification, symmetric absolute value, and asymmetric slope are adopted. The second and third columns are about the 5% VaR estimates, and the fourth and fifth columns are about the 1% VaR estimates. The sample period is from August 1, 2010 to December 31, 2019

Before examining 30 potential factors, I check whether the CAViaR model is appropriate for estimating Bitcoin's VaR. To this end, I include only the lagged Bitcoin returns in the information set and estimate the conditional VaR of Bitcoin's returns as a benchmark. In Table 3, the estimation results of the two CAViaR specifications for 5% and 1% VaRs of Bitcoin returns are reported. The table presents the values of the estimated parameters, the corresponding standard errors, (one-sided) *p* values, the values of the regression quantile objective functions (RQ), the percentage of times the VaR is exceeded (Hits), and the *p* value of the DQ when computing the series of CAViaR of returns on Bitcoin. Both the 5% and 1% VaRs of Bitcoin are stably estimated based on the significant coefficients of lagged VaRs (β_2) at the 1% level of significance. CAViaRs of returns on Bitcoin show a significant autoregressive term, which is consistent with the persistence of tail behavior. β_3 in the symmetric absolute value specification, and β_3 and β_4 in the asymmetric slope specification are also significant at the 1% level. The value of 5 for Hits of 5% VaR and around 1 for Hits of 1% VaR and their corresponding DQ *p* values by which models are not rejected confirm that CAViaR models do a good job in describing the evolution of the left tail for Bitcoin. Figure 2 plots the estimated time series of the VaRs.

5% VaR

In this section, the factors of the 5% VaR of Bitcoin returns are analyzed. As mentioned above, the potential drivers are directly entered into the specifications, which allows them to vary with Bitcoin's VaR. Their significance and performance are evaluated based



on the coefficients of the variance–covariance matrix and DQ tests. Table 4 presents the parameter estimates for the 5% CAViaR models with explanatory variables adopting a symmetric absolute value specification. The results of the first period are shown in the second column, and those of the second period are shown in the seventh column. The values of the estimated parameters (Beta), the corresponding (one-sided) p values (in parentheses), the values of the RQ, the percentage of times the VaR is exceeded (Hits), and the p value of the DQ test are reported. Coefficients of explanatory variables that are significant at the 5% or better level are in bold. One and two stars denote the statistical significance of the DQ at the 5 or 1% level, respectively.

In the first period, several explanatory variables have significant coefficients. BIT TRD significantly influences Bitcoin's VaR, and its absolute value, 3.948, is the highest among the potential drivers. This is consistent with the intuition that the more the trading amount of Bitcoin fluctuates, the higher the tail risk of Bitcoin. This evidence contradicts that of Balcilar et al. (2017), who show that there is no significant relationship between the BIT TRD and the tail of Bitcoin. The second highest value is EFR. This is related to the impact of monetary policy. When dramatic tightening and easing monetary policies take place, these affect the liquidity market participants hold to determine their participation in the Bitcoin market, and it is therefore likely that demand for Bitcoin will vary in turn. This evidence can also explain the positive relationship between the

Table 4 Estimation results of the 5% CAViaRs with explanatory variables adopting symmetric absolute value specification

Variables	From August 1, 2010 to January 3, 2017				From August 1, 2010 to December 31, 2019			
	Beta	RQ	Hits	DQ	Beta	RQ	Hits	DQ
BIT TRD	3.948 (0.027)	1567.712	4.983	0.577	-0.057 (0.000)	2107.714	4.971	0.285
OIL	-0.272 (0.016)	1572.006	4.983	0.143	-0.188 (0.013)	2105.785	5.000	0.044*
GAS	0.063 (0.412)	1576.575	5.026	0.039*	0.308 (0.084)	2107.965	5.000	0.023*
COMMO	-0.062 (0.413)	1576.712	4.983	0.067	-0.173 (0.000)	2108.357	4.971	0.228
GOLD CASH	0.039 (0.455)	1576.683	4.983	0.067	0.023 (0.461)	2110.118	5.000	0.262
GOLD FUTURE	-0.041 (0.389)	1576.730	4.940	0.020*	-0.086 (0.000)	2109.118	5.000	0.262
SILVER	0.053 (0.439)	1576.581	4.983	0.180	-0.037 (0.317)	2110.067	5.000	0.191
USCPI	-0.031 (0.338)	1576.499	5.026	0.112	-0.047 (0.220)	2109.217	5.000	0.123
EFFR	1.762 (0.010)	1562.922	4.940	0.845	0.032 (0.375)	2110.071	5.000	0.340
ECB DFR	0.425 (0.031)	1567.808	5.026	0.035*	0.439 (0.007)	2101.926	5.029	0.063
USCOR BND	0.021 (0.468)	1576.788	5.026	0.011*	-0.006 (0.479)	2110.137	5.000	0.328
PIMCO BND	0.443 (0.079)	1564.426	4.983	0.203	0.359 (0.008)	2100.639	4.971	0.548
STRESS	0.237 (0.156)	1572.957	4.940	0.317	0.078 (0.291)	2109.265	5.000	0.130
EUR/USD	-0.246 (0.028)	1575.527	5.026	0.030*	-0.127 (0.188)	2108.595	5.029	0.105
GBP/USD	-0.128 (0.164)	1575.916	4.983	0.344	-0.181 (0.134)	2108.944	5.000	0.315
CNY/USD	-0.097 (0.275)	1576.106	4.983	0.023*	0.147 (0.151)	2108.108	5.000	0.056
NYSE	0.316 (0.331)	1574.785	4.983	0.096	0.042 (0.426)	2110.040	4.971	0.239
SP 500	0.428 (0.145)	1574.069	4.983	0.095	0.095 (0.353)	2109.781	5.000	0.187
NASDAQ	0.389 (0.315)	1574.131	5.026	0.177	0.076 (0.367)	2109.881	5.000	0.308
FTSE 100	0.369 (0.046)	1572.632	5.026	0.100	0.023 (0.422)	2110.092	5.000	0.312
NIKKEI	0.547 (0.037)	1566.951	4.983	0.296	0.388 (0.070)	2107.628	5.029	0.402
SHANGHAI	-0.395 (0.001)	1569.658	4.940	0.034*	-0.379 (0.000)	2102.015	4.971	0.067
MSCI	0.483 (0.143)	1572.601	4.983	0.078	0.267 (0.251)	2109.441	4.971	0.241
HEDGE	0.328 (0.169)	1575.157	5.026	0.098	0.349 (0.049)	2106.333	5.029	0.149
UNCER WRD	0.199 (0.217)	1574.090	5.026	0.460	0.050 (0.258)	2109.569	4.971	0.448
UNCER US	-0.018 (0.447)	1576.766	5.026	0.005**	-0.056 (0.138)	2109.861	4.971	0.122
UNCER UK	-0.085 (0.266)	1575.368	4.983	0.052	-0.038 (0.164)	2109.979	4.971	0.230
CONSUME	0.462 (0.089)	1570.049	4.983	0.284	0.446 (0.115)	2102.529	5.000	0.195
GOOGLE	0.125 (0.333)	1576.098	4.983	0.105	0.059 (0.352)	2109.372	5.000	0.212
WIKI	0.459 (0.208)	1572.901	5.026	0.147	0.140 (0.045)	2106.927	5.029	0.126

The table reports the estimation results for the 5% CAViaRs of Bitcoin returns with explanatory variables adopting a symmetric absolute value specification. The values of the estimated parameters (Beta), the corresponding (one-sided) p values (in parentheses), the values of the regression quantile objective functions (RQ), the percentage of times the VaR is exceeded (Hits), and the p value of the dynamic quantile test (DQ) are reported. All explanatory variables are standardized. Coefficients of explanatory variables that are significant to at least the 5% level are in bold. One and two stars denote statistical significance of the DQ at the 5 or 1% level, respectively. Two sample periods are considered: August 1, 2010–January 3, 2017 and August 1, 2010–December 31, 2019

demand for Bitcoin and the short-term interest rate documented by De la Horra et al. (2019).¹⁵ The monetary policy effect is similarly investigated by Nguyen et al. (2019), who show the responses of returns on four major cryptocurrencies, including Bitcoin,

¹⁵ They argue that Bitcoin does not seem to be demanded as a medium of exchange because, if so, there should be an inverse relationship between demand for money and interest rates. However, taken together with the evidence from the movement of Bitcoin's tail, this argument is rather hasty, since the liquidity effect appears to dominate many other possible impacts of interest rate on Bitcoin.

to monetary policy.¹⁶ ECB DFR is also associated with Bitcoin's VaR, but the model in this case turns out to be a significant lack of fit based on the DQ test. The table shows evidence of a negative relationship between the variation in returns on OIL and Bitcoin's VaR. It appears that Bitcoin can be a safe haven for commodities, especially OIL, in the tail sense because the tail risk of Bitcoin is reduced in response to a large swing in OIL. In contrast, the variables related to the stock market and Bitcoin's VaR increase together. The relatively high values of coefficients for FTSE 100 and NIKKEI can be interpreted as follows: like stocks, Bitcoin is a similar kind of investable asset in the financial market because Bitcoin's VaR is dragged up by the variation of stock market returns. These results are somewhat consistent with those of Glaser et al. (2014), who show that Bitcoin users utilize it as an alternative investment asset.

The true factors of Bitcoin's VaR in the first period can be characterized as quantity variables. The high values of coefficients on BIT TRD and EFR indicate that Bitcoin's VaR is susceptible to how much money market participants put into the Bitcoin market. Taken together with the evidence of Panagiotidis et al. (2018), market liquidity is the key factor not only for Bitcoin's return, but also for its tail risk.¹⁷ However, this quantity issue is diminished to some extent in the second period. The magnitude and sign of the coefficient on the BIT TRD become small and negative, respectively. This is because the Bitcoin market has been growing and maturing since 2017, and thereby its tail risk is not heavily dependent on the variation in trading volume. After all, the negative relationship between BIT TRD and Bitcoin's VaR is reported in the sense that recent economic actors' demand and participation give the Bitcoin market more depth and maturity. This is also confirmed by the reduced effect of the ECB DFR in the second period. Although there is a positive coefficient on monetary policy variables, the value for ECB DFR (0.439) is not as high as EFR in the first period, 1.762.

The second period reveals the same effect of the variables related to commodities. The effects of commodity variables remain significant, with consistently negative signs. Although the effect of OIL disappears, COMMO and GOLD FUTURE show negative relationships with Bitcoin's VaR. This finding is consistent with the evidence from De la Horra et al. (2019). They show a negatively significant relationship between Bitcoin demand and the price of gold, and therefore, I conclude that Bitcoin serves as a substitute for gold, not a complement, even in the tail sense. Conversely, Bitcoin's VaR no longer exhibits significant responses to FTSE 100 and NIKKEI. While HEDGE has a positive relationship with Bitcoin's VaR, there are no effects of the typical stock market indices in the second period. However, it should be noted that SHANGHAI exerts a negative effect on Bitcoin's VaR. This implies that Bitcoin is considered a safe haven for the Chinese stock market rather than categorized into the same investable asset group with FTSE 100 and NIKKEI. It is a well-known fact that investors in the Chinese market today look for a safer destination for investment when the values of the Chinese stock market and currency are worried. This phenomenon, the so-called flight-to-safety, brings about the Chinese capital inflow to Bitcoin and helps the Bitcoin market to be

¹⁶ Lobo (2000) finds the capital flight from stock market based on the relationship between monetary policy rates and stock returns.

¹⁷ According to Panagiotidis et al. (2018), EFR and ECB DFR are positively covarying with Bitcoin's return, and the effect of ECB DFR is more pronounced than that of EFR.

healthy. A variation in WIKI positively contributes to Bitcoin's VaR. Interestingly, Glaser et al. (2014) and Kristoufek (2015) indicate that the increasing attraction of Bitcoin, proxied by WIKI and GOOGLE, also positively influences Bitcoin's return. A potential explanation might be that investors with speculative motives decide whether to enter or exit the Bitcoin market based on an internet search. These investors tend to foster herd behavior in the Bitcoin market, which is skittish about outside news due to shortsightedness, which leads to an increasing extreme risk.

Next, I turn to Table 5 to check the asymmetric responses of Bitcoin's 5% VaR to determinants. By using asymmetric slope specification, the significance uncovered in Table 4 remains, but there are new implications. First, the commodity variable still has significant explanatory power for Bitcoin's VaR in both the first and second periods. Interestingly, Bitcoin's VaR responds negatively to COMMO's large change, especially when the market of COMMO is in a boom. This is consistent with the view in Table 4, where Bitcoin is asserted to be a safe haven for commodities. A degree of caution should be exercised when interpreting the results. In this paper, recall that explanatory variables enter the CAViaR specifications after taking absolute values. The large absolute value in an information set of the specification is interpreted as a high risk in the corresponding variable.¹⁸ The increasing absolute values in both boom and bust times are considered as indicators of risky conditions in the sense that the price of an asset deviates from the trend reflecting the intrinsic value.¹⁹ Therefore, the negative value of Beta (+) from COMMO does not imply a positively covarying relationship between commodities and Bitcoin. The negative relationship between OIL and Bitcoin's VaR is still observed in the second period, and it is newly found that these negative responses emerge when the market of OIL is in a boom. Second, the negative relationship between SHANGHAI and Bitcoin's VaR is a result of the negative response of Bitcoin's VaR to SHANGHAI when the Chinese stock market accelerates. For both the first and second periods, considerable responses (-0.333 and -0.307, respectively) are detected. With the positive relation between Bitcoin's return and SHANGHAI documented in Panagiotidis et al. (2019), these results corroborate the existence of capital inflows from the Chinese stock market to the Bitcoin market. It can be viewed that investors in Chinese stock market consider Bitcoin a safer asset and diversify the investment addresses by using Bitcoin when there is an excessive upward movement in Chinese stock price.

As for quantity variables, the hypothesis that Bitcoin's market becomes mature due to more participation in Table 4 is supported by the negative relationship between BIT TRD and Bitcoin's VaR in the second period. Despite the small value of -0.063, it is evident that growing participation in Bitcoin's trade leads to a reduced tail risk of Bitcoin. Tightening monetary policy, rather than easing, is found to be a more important driver of Bitcoin's VaR because Bitcoin's VaR responds positively to the increase in ECB EFR in the first period. Consistent with the finding that quantity variables matter, a reduction in money supply is a factor for the tail risk of Bitcoin.

¹⁸ It can be well understood through the concept of realized volatility. Similar to squared returns, a common proxy for volatility, taking absolute value is another way to measure an asset's riskiness. These are based on the methods of computing distance, L^1 distance, and L^2 distance. This is well illustrated by Zheng et al. (2014).

¹⁹ The price deviated from the actual value eventually accompanies the large fluctuation in return. Alan Greenspan commented that unduly escalated asset values would become subject to contractions.

Table 5 Estimation results of the 5% CAViAs with explanatory variables adopting asymmetric slope specification

Variables	From August 1, 2010 to January 3, 2017					From August 1, 2010 to December 31, 2019				
	Beta (+)	Beta (-)	RQ	Hits	DQ	Beta (+)	Beta (-)	RQ	Hits	DQ
BIT TRD	-1.965	4.199	1538.771	4.983	0.949	-0.063	0.348	2068.363	5.000	0.980
OIL	-0.216	-0.291	1541.161	5.026	0.989	-0.255	-0.184	2069.235	5.029	0.987
GAS	-0.115	-0.083	1543.858	5.026	0.948	0.312	0.108	2068.465	5.000	0.922
COMMO	-0.217	0.455	1541.432	4.983	0.938	-0.176	0.378	2067.544	5.000	0.985
GOLD CASH	-0.065	0.167	1543.057	4.898	0.936	-0.017	-0.006	2070.772	4.971	0.946
GOLD FUTURE	-0.033	0.231	1543.820	5.026	0.996	-0.096	7.183	2064.469	5.000	0.954
SILVER	0.051	-0.038	1543.770	4.983	0.996	0.272	-0.172	2069.028	5.058	0.887
USCPI	0.293	-0.102	1536.595	4.983	0.993	0.180	-0.105	2064.773	5.000	0.915
EFFR	-11.588	1.083	1537.914	5.026	0.958	0.004	0.139	2070.097	5.000	0.984
ECB DFR	0.512	-0.029	1529.459	5.026	0.986	0.412	0.086	2058.703	5.000	0.989
USCOR BND	-0.229	0.310	1541.567	5.068	0.994	-0.223	0.293	2067.776	5.000	0.928
PIMCO BND	0.304	0.848	1534.122	4.983	0.921	0.192	0.648	2060.767	5.029	0.734
STRESS	0.276	0.102	1539.646	4.983	0.961	0.299	0.120	2066.222	4.942	0.949
EUR/USD	-0.014	-0.370	1541.572	5.026	0.944	0.019	-0.292	2068.332	5.000	0.873
GBP/USD	-0.240	0.006	1542.940	4.983	0.991	-0.203	-0.033	2069.746	5.000	0.965
CNY/USD	0.003	-0.205	1542.898	5.026	0.985	0.241	-0.108	2067.652	5.029	0.876
NYSE	0.210	0.283	1542.839	4.940	0.944	0.055	0.150	2069.511	5.000	0.971
SP 500	0.207	0.260	1543.069	4.940	0.951	-0.115	0.150	2068.973	5.029	0.891
NASDAQ	0.051	0.137	1543.689	4.983	0.983	-0.099	0.148	2069.478	4.971	0.949
FTSE 100	0.309	0.035	1541.056	4.983	1.000	0.189	-0.149	2069.523	5.000	0.902
NIKKEI	0.455	0.552	1537.358	4.983	0.996	0.213	0.319	2068.638	5.000	0.991
SHANGHAI	-0.333	-0.168	1539.670	4.940	0.946	-0.307	-0.184	2064.549	5.000	0.985
MSCI	0.222	0.231	1542.700	4.983	0.988	0.087	0.171	2069.563	4.971	0.796
HEDGE	-0.007	0.322	1541.908	4.983	0.995	0.080	0.249	2067.819	4.971	0.933
UNCER WRD	0.015	0.335	1539.057	5.026	0.903	-0.021	0.209	2066.658	5.000	0.946

Table 5 (continued)

Variables	From August 1, 2010 to January 3, 2017					From August 1, 2010 to December 31, 2019				
	Beta (+)	Beta (-)	RQ	Hits	DQ	Beta (+)	Beta (-)	RQ	Hits	DQ
UNCER US	-0.259 (0.102)	-0.769 (0.085)	1540.114	5.026	0.985	-0.119 (0.061)	-0.226 (0.188)	2069.052	5.000	0.991
UNCER UK	-0.044 (0.246)	0.281 (0.200)	1539.455	4.940	0.963	-0.021 (0.361)	0.137 (0.142)	2067.554	5.000	0.990
CONSUME	-0.050 (0.440)	0.517 (0.232)	1536.090	4.898	0.998	0.267 (0.226)	0.494 (0.184)	2062.636	5.000	0.970
GOOGLE	0.377 (0.317)	0.232 (0.360)	1541.789	5.068	0.955	0.117 (0.189)	0.078 (0.338)	2069.444	4.971	0.530
WIKI	1.040 (0.023)	-0.039 (0.483)	1543.184	4.983	0.961	0.045 (0.256)	-0.205 (0.309)	2069.178	5.029	0.721

The table reports the estimation results for the 5% CAViaRs of Bitcoin returns with explanatory variables adopting an asymmetric slope specification. The values of the estimated parameters (Beta (+) and Beta (-)), the corresponding (one-sided) *p* values (in parentheses), the values of the regression quantile objective functions (RQ), the percentage of times the VaR is exceeded (Hits), and the *p* value of the dynamic quantile test (DQ) are reported. All explanatory variables are standardized. The coefficients of explanatory variables that are significant to at least the 5% level are in bold. One and two stars denote the statistical significance of the DQ at the 5 or 1% level, respectively. Two sample periods are considered: August 1, 2010–January 3, 2017 and August 1, 2010–December 31, 2019

In addition, it is worth noting that a market interest rate, currency variables, and an Internet search variable constitute determinants of Bitcoin's VaR in the first period. The large fluctuation in the PIMCO BND is strongly linked to the increase in Bitcoin's VaR when it is decreasing. It can be reasoned that bad market conditions, reflected by a decreasing market interest rate, depress Bitcoin's value. The negative response of Bitcoin's VaR to EUR/USD and CNY/USD implies that Bitcoin can act as a stable medium of exchange without huge potential losses.²⁰ Recall that the depreciation of the Chinese currency encourages Chinese capital inflow to the Bitcoin market. Since the significance of WIKI is detected in the first period when adopting asymmetric slope specification, a close relationship between WIKI and Bitcoin's VaR holds in both the first and second periods. The finding of the response of Bitcoin's VaR to the swing in WIKI supports the idea that herd behavior of momentum strategy generated by Internet search has impinged the Bitcoin market.²¹ These results are in line with those of Anastasiou et al. (2021), who exhibit a positive relationship between Internet search variables and cryptocurrencies' crash risk. Another notable thing is that Bitcoin's tail risk is especially aggravated when the search trends are increasing. This finding is compatible with Glaser et al. (2014) and Panagiotidis et al. (2018), who confirm an asymmetric response of Bitcoin returns, that is, the return is more driven by positive events than negative news. Meanwhile, neither period detects significant relationships between Bitcoin's VaR and variables related to uncertainty and sentiment. This is in stark contrast to the evidence of Panagiotidis et al. (2018), who show that all uncertainty indices significantly affect Bitcoin returns.

1% VaR

I now turn to 1% VaR. Table 6 reports the estimation results for 1% CAViaR with explanatory variables when adopting the symmetric absolute value specification. In the first period, the largest significant coefficient is attached to the PIMCO BND. Because a variety of risks in the market, such as credit risk, liquidity risk, and interest rate risk, are reflected in the PIMCO BND, it can be concluded that the unstable movement of market risk plays a key role in explaining Bitcoin's VaR. The second largest is the NASDAQ. Unlike the results for the 5% VaR, 1% VaR is responsive to the US stock market. Although a variable related to economic policy uncertainty, UNCER UK, has a significant relationship with 1% Bitcoin's VaR, this link is relatively weak, based on the value of -0.061.

²⁰ This interpretation differs from that of De la Horra et al. (2019) who use EUR/USD exchange rate as a proxy for the price level of Bitcoin. Based on Ciaian et al. (2016), they link the appreciation and depreciation of the US dollar against the euro to the depreciation/appreciation of Bitcoin because Bitcoin data are denominated in US dollars. In contrast, I consider exchange rates as exogenously time-varying currency variables not related to Bitcoin's price following Dyhrberg (2016), Baur et al. (2018a), and Kwon (2020).

²¹ To get the detailed view of WIKI's effect, I additionally verify the relation between the regulation of Bitcoin and Bitcoin's 5% VaR. Adopting a regulation variable is suggested by a referee of an earlier version of this paper. The method of constructing a regulation variable is based on the work of Liu and Tsyvinski (2021), and the initial value of the time series starts from March 2017. The results using the whole sample are summarized as follows: In the symmetric absolute value specification, the variation of regulation has a positive effect on Bitcoin's VaR. In the asymmetric slope specification, I find an asymmetric association between regulation and Bitcoin's tail risk. While Bitcoin's VaR is diminished when regulation is favorably changed, Bitcoin's VaR is negatively affected by regulation when it is adversely amended. The table is available upon request.

Table 6 Estimation results of the 1% CAViaRs with explanatory variables adopting symmetric absolute value specification

Variables	From August 1, 2010 to January 3, 2017				From August 1, 2010 to December 31, 2019					
	Beta	RQ	Hits	DQ	Beta	RQ	Hits	DQ		
BIT TRD	1.254	(0.198)	516.262	0.937	0.105	−0.010	(0.336)	686.350	0.988	0.491
OIL	−0.218	(0.064)	518.122	0.980	0.169	−0.036	(0.459)	686.375	0.988	0.495
GAS	0.386	(0.081)	514.755	0.937	0.001**	0.504	(0.000)	675.484	0.988	0.037*
COMMO	−0.011	(0.462)	519.193	1.022	0.220	0.011	(0.471)	686.404	0.988	0.489
GOLD CASH	0.117	(0.328)	518.797	1.022	0.191	0.184	(0.239)	684.015	0.959	0.492
GOLD FUTURE	−0.052	(0.336)	519.043	0.980	0.187	−0.064	(0.404)	686.298	0.988	0.496
SILVER	0.304	(0.311)	515.786	1.022	0.175	0.675	(0.010)	674.397	0.930	0.349
USCPI	0.031	(0.328)	517.914	0.980	0.159	0.791	(0.041)	690.345	0.988	0.041*
EFFR	0.303	(0.143)	517.697	0.980	0.173	−0.007	(0.459)	686.419	0.988	0.491
ECB DFR	0.403	(0.008)	506.703	0.980	0.002**	0.275	(0.066)	674.680	0.988	0.041*
USCOR BND	0.873	(0.064)	506.187	0.980	0.289	0.752	(0.047)	668.576	1.047	0.668
PIMCO BND	0.778	(0.001)	502.295	0.980	0.210	0.800	(0.000)	669.635	0.959	0.423
STRESS	0.098	(0.325)	517.044	0.980	0.181	0.075	(0.353)	686.043	1.017	0.172
EUR/USD	0.444	(0.179)	514.748	1.022	0.019*	0.840	(0.023)	666.964	1.017	0.025*
GBP/USD	−0.130	(0.326)	519.059	0.980	0.223	0.072	(0.378)	686.068	0.988	0.506
CNY/USD	0.110	(0.286)	519.112	1.022	0.200	0.062	(0.299)	685.930	0.988	0.521
NYSE	0.541	(0.249)	509.090	0.980	0.218	0.573	(0.098)	672.554	0.959	0.440
SP 500	0.640	(0.174)	510.012	0.980	0.220	0.507	(0.046)	675.625	1.017	0.535
NASDAQ	0.592	(0.035)	510.318	1.022	0.177	0.401	(0.180)	678.296	0.959	0.430
FTSE 100	0.181	(0.224)	516.947	1.022	0.200	0.167	(0.241)	684.036	0.988	0.524
NIKKEI	0.016	(0.431)	519.299	0.980	0.176	0.663	(0.080)	688.391	1.017	0.524
SHANGHAI	0.026	(0.406)	518.840	0.980	0.168	0.040	(0.360)	685.654	0.988	0.494
MSCI	0.592	(0.264)	508.863	0.937	0.150	0.660	(0.106)	672.781	0.959	0.395
HEDGE	0.345	(0.145)	515.716	0.980	0.002**	0.248	(0.153)	683.254	0.959	0.398
UNCER WRD	0.100	(0.281)	517.688	0.980	0.120	0.078	(0.169)	684.398	1.017	0.575
UNCER US	0.271	(0.068)	511.079	0.980	0.002**	0.328	(0.000)	670.986	1.017	0.064
UNCER UK	−0.061	(0.004)	518.302	1.022	0.229	0.069	(0.267)	685.608	0.959	0.442
CONSUME	2.497	(0.019)	502.906	1.022	0.012*	1.343	(0.008)	675.500	0.959	0.144
GOOGLE	0.014	(0.454)	519.238	0.980	0.201	0.478	(0.184)	695.833	0.959	0.061
WIKI	0.133	(0.416)	519.156	0.980	0.206	−0.049	(0.204)	686.406	0.959	0.444

The table reports the estimation results for the 1% CAViaRs of Bitcoin returns with explanatory variables adopting a symmetric absolute value specification. The values of the estimated parameters (Beta), the corresponding (one-sided) p values (in parentheses), the values of the regression quantile objective functions (RQ), the percentage of times the VaR is exceeded (Hits), and the p value of the dynamic quantile test (DQ) are reported. All explanatory variables are standardized. The coefficients of explanatory variables that are significant to at least the 5% level are in bold. One and two stars denote the statistical significance of the DQ at the 5 or 1% level, respectively. Two sample periods are considered: August 1, 2010–January 3, 2017 and August 1, 2010–December 31, 2019

Similar results are observed in the second period. The macroeconomic variable is one of the most important factors for Bitcoin's VaR. Both PIMCO BND and USCOR BND have a significant impact on Bitcoin's VaR. Except for CONSUME, the values of 0.800 and 0.752 for PIMCO BND and USCOR BND are the highest among the potential drivers for Bitcoin's VaR. It is natural that the large variation in cyclical macroeconomic movement described by interest rates has a significant influence on Bitcoin's tail risk. The explanatory power of the stock market is also preserved in the second period. Even though NASDAQ is eradicated, the considerable effect of SP 500, 0.507, suggests

that the tail risk of Bitcoin and the riskiness in the stock market covary. These results are in contrast to those of Baur et al. (2018a). They conclude that Bitcoin is different from investment assets because Bitcoin's returns are not correlated with any of the asset returns, returns on corporate bond index, or stock market index.

It should be noted that several explanatory variables play a part in explaining Bitcoin's 1% VaR in the second period. First, CONSUME becomes significant and its power is remarkable. This suggests that the transmission channel by which economic actors' expectations and attitudes on macroeconomic conditions are linked to Bitcoin's market. Second, a wide variation in US economic policy uncertainty, UNCER US, aggravates the tail risk of Bitcoin. With the positive relationship between UNCER US and Bitcoin's return reported by Panagiotidis et al. (2019), this result implies that UNCER US can be considered as a crucial adverse factor of both normal and extreme risks of Bitcoin. This contradicts those of Demir et al. (2018) and Kalyvas et al. (2020), who claim that Bitcoin has a hedging capability against economic policy uncertainty. Lastly, I find a significantly positive effect of SILVER on Bitcoin's VaR. These results for the 1% VaR are quite different from those for the 5% VaR. The sign of SILVER is inconsistent with that of OIL, COMMO, and GOLD FUTURE for 5% VaR. This finding suggests that the associations between Bitcoin's VaR and variables related to commodities are individually different. Unlike OIL and COMMO, Bitcoin cannot be a safe haven for SILVER in the tail sense.

In Tables 4 and 5, the effects of USCOR BND, UNCER US, CONSUME, SP500, and NASDAQ are not observed. In contrast, these variables are strongly associated with 1% VaR. This is noteworthy for two reasons. First, the 1% VaR is influenced by macroeconomic forces. Recall that USCOR BND is a macroeconomic variable, and UNCER US and CONSUME are constructed from several components related to the macroeconomy. This is not captured in the return analysis by Polasik et al. (2015) and Baek and Elbeck (2015), who conclude that the association between Bitcoin returns and macroeconomic factors is weak and insignificant. A potential explanation for the power of macroeconomic variables for the 1% VaR might be that the systematic risk leading to the crash of the whole economy is accompanied by macroeconomic shocks. While normal risks or tail risks that occur somewhat frequently (5% VaR) could be locally responsive to economic actors' demand and their perspective on the Bitcoin market, the more extreme tail risk must entail the systematic risk that universally switches the macroeconomic dynamics (Benoit et al. 2017; Commendatore et al. 2018). Recall that the duration of time between two tail events is approximately 3 weeks and 14 weeks for the 5% VaR and 1% VaR, respectively, which is well documented in Christoffersen and Pelletier (2004).

Second, based on the significance of SP 500, NASDAQ, and UNCER US, the US market has more explanatory power than other countries. FTSE 100 and SHANGHAI become insignificant, as UNCER WRD and UNCER UK remain insignificant and marginal.

The results of the asymmetric slope specification in Table 7 corroborate these findings. The variables related to the commodity still drive 1% VaR, but their signs on the variables vary. In both periods, OIL was negative, whereas GAS was positive. GOLD CASH and GOLD FUTURE are negative in the first and second periods, respectively. SILVER was positive during the second period. Therefore, it can be concluded that Bitcoin can be a safe haven for OIL, GOLD CASH, and GOLD FUTURE in terms of 1% VaR.

Several variables related to the macroeconomy are significant. In the first period, the explanatory power of CONSUME is the highest, and USCOR BND is the second strongest driver of the 1% VaR. The tail risk of Bitcoin goes up with the swing of CONSUME and returns on US corporate bonds when they decrease. In the second period, Bitcoin's VaR is equally driven when both the ups and downs of these two variables occur. In particular, Bitcoin's VaR is more sensitive when CONSUME and USCOR BND decrease. Conversely, Bitcoin's 1% VaR has an asymmetric response to STRESS. As the value of STRESS is designed to be zero and values below zero suggest below-average financial market stress, the finding that a positive (negative) response of Bitcoin's VaR to STRESS when there is an upward (downward) movement is not surprising. This evidence confirms the importance of STRESS emphasized by Kristoufek (2015), who find that increasing STRESS leads the Bitcoin price to go up.

The impact of the variables related to the US market on Bitcoin's VaR is established. As previously mentioned, the USCOR BND shows the second-highest coefficient in the first period. In the second period, Bitcoin's VaR exhibits a significant relationship with UNCER US, and this finding is intuitively plausible. When uncertainty generating vulnerability and riskiness of the financial market increases, Bitcoin's VaR also increases, and vice versa. With respect to the relationship between Bitcoin's VaR and the US stock market, Bitcoin's VaR is found to be positively related to the US stock market, especially when NYSE and SP 500 are decreasing. These results contradict those of Feng et al. (2018), Bouri et al. (2020) and Hakim das Neves (2020), who argue that Bitcoin can act as a safe-haven for US equity index because Bitcoin's left tail is uncorrelated with that of SP 500.

When focusing on the second period, there are several new findings relative to Table 6. I find a strong linkage between Bitcoin's VaR with the BIT TRD and currency. The BIT TRD exacerbates Bitcoin's tail risk when it decreases. However, the effect of BIT TRD is limited when it is increasing because the mature Bitcoin market with expanding trading volume would be less vulnerable to fluctuations in BIT TRD. I also find that EUR/USD and GBP/USD are important determinants of Bitcoin's VaR.²²

Conclusion

Rapach et al. (2010) state that "applied asset pricing models could benefit from the consideration of more complex data-generating processes with more variables." In this respect, several works in the literature have focused not only on mean and variance but also on the tail of stock market and bond returns. Unfortunately, to date, the literature on the tail risk of Bitcoin remains relatively scarce. To address the literature gap, this study tried to identify the drivers of Bitcoin's VaR. Considering that Bitcoin becomes a mainstream financial instrument and acts as an alternative for currency, commodity, and investment assets, the findings of this study offer useful insights to practitioners, traders, financial modelers, and policymakers, thus enabling them to use and manage it more efficiently. As tail risk is another dimension to consider in addition to traditional

²² Like Engle et al. (2013), most of the variables are no longer statistically significant when estimating the model that combines all employed variables. This implies strong evidence of collinearity among the variables employed. The results of the kitchen sink model are available on request.

Table 7 Estimation results of the 1% CAViARs with explanatory variables adopting asymmetric slope specification

Variables	From August 1, 2010 to January 3, 2017					From August 1, 2010 to December 31, 2019				
	Beta (+)	Beta (-)	RQ	Hits	DQ	Beta (+)	Beta (-)	RQ	Hits	DQ
BIT TRD	0.670	3.363	497.537	1.022	0.011*	0.330	6.946	662.770	0.988	0.746
OIL	-0.399	0.092	494.777	1.022	0.294	-0.915	-0.490	670.377	1.017	0.050*
GAS	0.429	0.422	493.568	0.980	0.230	0.928	0.258	662.721	0.988	0.174
COMMO	0.021	-0.111	499.470	1.022	0.276	-0.145	-0.447	672.084	1.017	0.051
GOLD CASH	0.171	-0.706	493.899	0.937	0.191	1.054	-0.114	672.145	0.988	0.419
GOLD FUTURE	0.049	-0.543	498.914	1.022	0.274	-0.187	5.146	670.485	1.017	0.623
SILVER	0.930	-0.505	493.267	1.022	0.316	1.442	-0.241	657.354	0.988	0.447
USCPI	0.092	-0.019	498.062	1.022	0.464	0.195	-0.043	670.213	0.959	0.561
EFFR	-20.425	-0.141	499.161	1.022	0.140	0.311	1.320	670.071	0.959	0.637
ECB DFR	0.299	0.154	490.234	1.022	0.362	1.180	-0.271	651.040	0.988	0.648
USCOR BND	0.707	1.100	490.983	0.980	0.422	0.778	1.165	657.581	0.988	0.700
PIMCO BND	0.797	0.696	489.971	0.980	0.000**	0.686	1.015	659.146	1.017	0.059
STRESS	0.138	-0.232	490.986	0.937	0.321	0.870	-0.651	652.670	1.017	0.645
EUR/USD	0.871	0.493	488.243	1.022	0.372	0.928	1.363	649.756	0.959	0.469
GBP/USD	0.142	0.170	499.001	1.022	0.125	-0.922	-0.209	671.945	1.017	0.062
CNY/USD	0.143	-0.067	499.562	0.937	0.194	0.356	0.207	671.678	0.959	0.623
NYSE	0.167	0.670	494.524	0.980	0.277	0.540	0.806	664.562	0.988	0.629
SP 500	0.282	0.694	495.000	0.980	0.009**	0.066	0.703	665.988	0.959	0.589
NASDAQ	-0.218	0.264	497.568	1.065	0.186	0.031	0.713	669.407	1.017	0.034*
FTSE 100	-0.237	0.125	496.891	0.937	0.204	-0.417	0.453	670.555	0.988	0.600
NIKKEI	-0.301	0.407	498.444	0.980	0.330	0.164	0.416	667.929	1.047	0.757
SHANGHAI	-0.129	0.159	498.753	1.022	0.353	-0.587	0.054	670.824	0.988	0.610
MSCI	0.478	0.486	495.901	0.937	0.258	0.465	0.763	666.945	0.988	0.635
HEDGE	-0.323	0.103	496.747	0.980	0.315	-0.256	0.560	668.393	1.017	0.453
UNCER WRD	-0.011	0.081	500.850	0.980	0.010**	0.184	0.337	669.719	1.047	0.691

Table 7 (continued)

Variables	From August 1, 2010 to January 3, 2017					From August 1, 2010 to December 31, 2019				
	Beta (+)	Beta (-)	RQ	Hits	DQ	Beta (+)	Beta (-)	RQ	Hits	DQ
UNCER US	0.206 (0.087)	-0.565 (0.067)	489.176	0.980	0.530	0.480 (0.001)	-1.574 (0.000)	650.095	0.988	0.635
UNCER UK	-0.081 (0.000)	-0.266 (0.041)	498.451	0.980	0.005**	-0.242 (0.099)	0.350 (0.324)	670.543	0.988	0.576
CONSUME	1.057 (0.099)	1.929 (0.000)	482.740	1.022	0.596	1.043 (0.017)	2.013 (0.000)	639.670	0.988	0.930
GOOGLE	0.082 (0.413)	0.117 (0.262)	500.015	0.980	0.399	-0.012 (0.487)	0.282 (0.312)	670.974	1.017	0.131
WIKI	0.076 (0.225)	0.995 (0.071)	492.293	1.022	0.016*	0.242 (0.383)	1.983 (0.132)	669.051	0.959	0.797

The table reports the estimation results for the 1% CAViaRs of Bitcoin returns with explanatory variables adopting an asymmetric slope specification. The values of the estimated parameters (Beta (+) and Beta (-)), the corresponding (one-sided) *p* values (in parentheses), the values of the regression quantile objective functions (RQ), the percentage of times the VaR is exceeded (Hits), and the *p* value of the dynamic quantile test (DQ) are reported. All explanatory variables are standardized. The coefficients of explanatory variables that are significant to at least the 5% level are in bold. One and two stars denote the statistical significance of the DQ at the 5 or 1% level, respectively. Two sample periods are considered: August 1, 2010–January 3, 2017 and August 1, 2010–December 31, 2019

risks, estimates and determinants of Bitcoin's VaR are important for formulating optimal portfolios. Specifically, the tail analysis of Bitcoin is useful for managing and diversifying a portfolio, including Bitcoin, to avoid devastating losses in extreme circumstances, as excessive price fluctuation is a major issue in trading Bitcoin. Uncovering the relationship between Bitcoin's VaR and conventional asset is a reference source for the hedging strategy because Bitcoin can be a safe haven for other financial assets in the tail sense.²³

This study extends the CAViaR model proposed by Engle and Manganelli (2004) to find the factors of Bitcoin's 5% and 1% VaR. The model allows 30 potential drivers to enter directly into the conditional VaR specification. For the 5% VaR, I find that quantity variables, such as Bitcoin trading volume and monetary policy rate, have significant explanatory power in the first period. However, the links become weaker in the second period, and this phenomenon may be attributed to the mature Bitcoin market in recent years. Variables related to commodities and the Chinese stock market show a negative relationship with Bitcoin's 5% VaR. Meanwhile, a variation in internet search intensity proxied by Wikipedia trend data positively affects Bitcoin's 5% VaR. It appears that herd behavior fostered by outside news can be a factor in the tail risk of Bitcoin. Different from the 5% VaR, variables related to the macroeconomy play a key role in explaining Bitcoin's 1% VaR. The four most powerful factors are in the following order (larger absolute value of coefficient first): consumer sentiment index, US economic policy uncertainty index, exchange rates for EURO to US dollar, and returns on the corporate bond index. Interestingly, variables related to the US market emerge as significant explanatory variables for the 1% VaR. While the effects of European, Japanese, Chinese, and international stock market variables and economic policy uncertainty indices are insignificant or marginal, the American stock market variables, corporate bond index, and economic policy uncertainty index exert significant effects on the 1% VaR.

For market participants trading Bitcoin, more research is needed to further complement the work in this paper. First, by developing a new class of tail risk models combining the insights of CAViaR and mixed data sampling (MIDAS) filters, it would be interesting to disentangle short- and long-run sources of Bitcoin's tail risk. The more challenging question is to explore the extent to which each economic and speculative variable can explain the short- and long-run components of Bitcoin's VaR. Given that Bitcoin can be an alternative for investment assets in the tail sense, it would also be an interesting avenue for future research to evaluate the change of efficient frontier in three-dimensional space, which is the mean-variance-skewness efficient frontier, when Bitcoin is considered as an element of the investment opportunity set. After estimating the series of Bitcoin's VaR, one can concurrently conduct an experiment in which mean-variance-skewness investors can gain sizable benefits relative to a naive strategy based on the historical mean and variance benchmark only with conventional assets.

²³ On a practical level, some hedge funds keep buying cheap deep out-of-the-money put options to hedge against black swan events.

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Authors' contributions

As a single author of the paper, I have not received any contribution from non-authors and taken responsibilities for all categories of contribution: conceptualization, methodology, investigation, writing, supervision, and so on. All authors read and approved the final manuscript.

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Availability of data and materials

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Declarations**Competing interests**

The authors declare that they have no competing interests.

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