Re-examining Bitcoin Volatility: A CAViaR-based Approach

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Abstract
The paper aims to explore the heterogeneous feature in the determination of Bitcoin volatility using a Markov regime-switching model and test its forecasting ability. The forecasting methodology of the risk measurement of Bitcoin’s returns is based on the Conditional Autoregressive Value at Risk models (CAViaR) approach. Our results show that Bitcoin’s volatility is significantly related to the volatility of the crypto-asset’s return and the main determinants of volatility are speculation, investor attention, market interoperability and the interaction between speculation and market interoperability. In addition, we present evidence that investors’ attention is the main source of volatility. Speculation and the interaction term are related in a “U-shaped” form, whereas investor attention and market interoperability show a linear trend on the volatility of Bitcoin.

Keywords: Bitcoin, Heterogeneous, CAViaR, Markov regime-switching regression model

JEL Codes: C44, C51, G17
1 Introduction

Bitcoin (BTC) appears on the China (CNY) markets as a virtual financial asset (VFA). The CNY market for Bitcoin rapidly gained increasing popularity and became the leading market in terms of active trading volume (see coinmarketcap.com). Though, these markets continue to work in an unregulated status, which forced the Chinese government to close the Initial Coin Offering (ICO) processes in China since October 2017, in an effort to guarantee financial stability, but as a short-lived asset traded in BTC market, it provides us with an invaluable dataset for the statistical research on trader’s behavioral characters in BTC market. On the other hand, blockchain, and competitive technologies that underpinning crypto-assets, is an instance of institutional evolution and sparked a new wave of financial innovation, which may start to revolutionize markets microstructure (Chen, 2018; Davidson, De Filippi and Potts 2018).

Compared with the prices and return of Bitcoin in China (CNY) and United States (USD) markets, as shown in Figure 1, price of Bitcoin in the CNY market is more highly volatile than it in the USD market. Besides, the return fluctuations in the CNY market play a leading role in the American market. Therefore, we re-examine bitcoin volatility in the CNY market.

It is of great significance, for both institutional investors and noise traders, the exploration of the determinants of Bitcoin’s volatility and Value at Risk in different regimes. Further, the research results could be useful for market microstructure analysis and regulatory decision making. More specifically, the determination of Bitcoin’s risk could be significantly heterogeneous in different regimes as its market is highly speculative (Cheah and Fry, 2015; Baur, Hong and Lee, 2018). This is our core hypothesis to test and provide originally reliable results. The significant positive effect of prior returns and volatility on the leading cryptocurrency turnover suggests extremely speculative trading elements (Baur and Dimpfl, 2018; Selmi Tiwari and Hammoudeh, 2018). Speculators could react differently in different
regimes due to behavioral biases, such as over-confidence or beliefs for taking advantage the
market information. Consequently, the deeper understanding of the existence of heterogeneity
in the determinants of Bitcoin’s volatility under different regimes is crucial for the decision-
making process of investors, as mentioned above, but also of high importance for policy makers
and regulators.

**Error! Not a valid embedded object.**

Figure 1. Bitcoin price and return in China and the United states markets. Note: CNY stands for
the China market, whereas USD is the United states markets. Datasource: https://bitcoincharts.com/ and author estimation.

Specifically, the volatility of Bitcoin enhances a positive effect on the difference in its
price (Sornette, Cauwels and Smilyanov, 2018; Pabuçcu , Ongan and Ongan, 2020), which
might result to the complexity of speculators and investors. This ultimately could affect the
expected returns and the formation of Bitcoin prices. Furthermore, the behavior and reactions
of speculators in correspondence to volatility might be more complex, due to differences in their
goals, investment strategies and investing horizon. All of them might exert heterogeneous
features in different regimes. Therefore, it is necessary for policy makers and regulatory bodies
to emphasize on their ability to monitor trading in real-time.

The present work firstly tries to link Bitcoin with Value-at-Risk (VaR). Romero, Muela,
and Martin (2013) review the full range of methodologies developed to estimate the VaR and
present their relative strengths and weaknesses from theoretical and practical perspectives. In
the existing literature there are many studies focus on the application and some alternative risk
measures (Bernardi and Catania, 2016; Ferraty and Quintela-Del-Río, 2016; Gerlach Lu and
Huang, 2013; Gkillas and Katsiampa 2018; Li et al, 2018; Righi and Ceretta, 2015; Whitea,
As the nature of the risk has changed over time, methods of measuring these risks must adapt to recent experience. Based on the regression quantile framework (Chernozhukov and Umantsev 2001; Koenker and Bassett, 1978), Engle and Manganelli (2004) propose a conditional autoregressive specification for VaR, namely Conditional Autoregressive Value at Risk (CAViaR) that models not the entire distribution but rather the quantile directly. Since it is proposed, this approach has been attracted more attention by academics and practitioners from different markets (Drakos Kouretas and Zarangas, 2015; Jeon and Taylor, 2013; Joëts, 2014; Laporta, Merlo and Petrella, 2018; Meng and Taylor, 2018; Rubia and Sanchis-Marco, 2013).

The determinant of VFAs risk is a topic that has received much attention in financial stability (Cobbinah, Zhongming and Ntarmah, 2020). One common feature of related literature is that it has assumed that the determinants are homogeneous. The first determinant is speculation (Balcilar et al, 2017; Blau, 2017). As a speculative asset, it is critical for trading strategies to understand the volume-return relationship and furthermore shed light on potential implications. Due to the volatility of price, speculators could get speculative profits by using Bitcoin (Yermack, 2013; Latunde, Akinola and Dare, 2020). Thus, in the VFAs trading platform, the determinant of speculation should be heterogeneous.

Investor attention, as a scare cognitive resource (Kahneman, 1973), could produce a large influence on determining market prices (De, 1995). Kristoufeck (2013 and 2018) found that internet (Google) searches is a significant determinant of the price of Bitcoin. Garcia et al (2014) extended these results by showing that word-of-mouth information on social media and information on both Google Trends and new Bitcoin users have a significant influence on
Bitcoin price changes (Hayes, 2016). Therefore investor attention might be an important determinant of Bitcoin volatility, a hypothesis that will be tested.

Market interoperability plays a key role on crypto-assets volatility, since the adoption of any regulatory restrictions in regulated markets). It is defined as “the ability of the transfer of assets abroad at two or more different market unit”. Crypto-assets provide a new channel for capital flow that can be untraceable. Such cash flows show the functions that crypto-assets can be considered as production factors (Li et al., 2017). In addition, because of characteristics such as anonymity status, irrevocability and low-cost, it is a convenient vehicle for criminals/terrorists and participants in the shadow economy to transfer “illicit” money across the different markets bypassing any supervision or control (Gunter, 2017). Above all, there is no empirical investigation for the heterogeneous on the determinant of BTC volatilitys. Thus in this paper, we would explore it through the Markov regime-switching regression model.

Otherwise, speculation also exerts its effect in conjunction with market interoperability. The interaction mainly refers that the speculators realize arbitrage opportunities between different crypto-asset markets, throughout a combination existing information, with the judgment of the price difference. The asymmetry of different market information leads to the heterogeneity of expected returns, which in turn affects the Bitcoin price, and ultimately causes changes in the crypto-asset volatility (Barillas and Nimark, 2018; Frijns and Zwinkels, 2020). Arbitrageurs try to detect and take advantage of any opportunity between different markets, and speculators who trade on price trends, generate a synergy effect on market volatility. Speculators use their advantage of information and market trends to invest between different crypto-asset markets and achieve arbitrage gains. Further, the disruption of market liquidity by
speculators’ transactions leads to an increase in market price uncertainty, which in turn increases Bitcoin volatility.

In this paper we provide evidence that the heterogeneous feature under different regimes by estimation the Markov regime-switching regression Model. Furthermore, we empirically investigate that investors’ attention is main determinant on BTC volatility at all regimes while market interoperability has no significant role under medium-risk regime.

For example, Wang et al. (2019) implement the MVQM-CAViaR approach to test the existence of risk spillover between Bitcoin returns and Economic Policy Uncertainty, using three volatility indices (US EPU index, equity market uncertainty index, and VIX). More recently Ardia, Bluteau and Ruede (2019) check for regime changes using MSGARCH models to estimate and forecast the dynamics Bitcoin volatility. Their results support the rejection of the hypothesis of a single regime and support that Markov-switching GARCH models (the symmetric GARCH(1,1) and the asymmetric GJR(1,1) model) provide higher predictive ability for one–day Value–at–Risk during the out-of-sample period. For their estimations they consider three regimes. Their results show that for the in-sample time-span the two–regime MSGARCH model provide the best-fit, with an inverted leverage effect in both low– and high–volatility regimes. To the best of our knowledge, the present paper is the first paper that examines the determinants of Bitcoin volatility in different regimes.

We aim to contribute to the existing literature by exploring the heterogeneous on the determinants under different volatility regimes. The recent emergence of Markov regime-switching regression model allows coefficients to switch under different BTC volatility regimes. It may provide a more realistic depiction of the driving on BTC volatility. It is more reasonable to take account the heterogeneous under different regimes into crypto-assets market operation,
which could be benefit for the investors to make an efficient financial decision. The present study has a serious contribution as the literature in examining Bitcoin volatility in different regimes and examining expected shortfall using CAViaR approach is very limited. Moreover the variables used differentiate from the traditional used in the Bitcoin related literature.

Our analysis makes significant contributions in three areas. First, the CAViaR method is implemented in order to forecast the volatility of Bitcoin daily returns for the first time in the related literature, to our knowledge. In general, the difficulty of policy supervision and the complexity of capital flows make BTC risks more dynamic (Bouri, 2017a, 2017b; Lan, Lu and Tu, 2016). CAViaR is a dynamic method that describes time-varying risk under the hypothesis of an auto-correlated distribution. Second, unlike existing studies, the Markov regime-switching regression model can reasonable refer to the heterogeneous of different regimes. This ensures the estimation accuracy and a better understanding the determinants of BTC volatility in different regimes.

Third, given the decentralized nature and its global character, we originally aim to study the determinants of its volatility, applying four different aspects. The aspects examined in our analysis are the following: a) speculation, b) investors’ attention, c) market interoperability and d) the common interaction of speculation and market interoperability (or “interaction”). By analyzing the driving of these four aspects on different Bitcoin volatility regimes, we are able to comprehensively analyze the main drivers of Bitcoin prices.

The paper is organized as follows. Section 2 proposes research hypotheses on the examination of Bitcoin volatility based on the suggested aspects. In Section 3, we introduce the proposed model applied in the paper and consequently we present the measurement of variables and tests used for performance evaluation. Section 4 shows the forecasting results of Bitcoin
volatility. In Section 5, the extensive empirical analysis on Bitcoin is carried out. Finally, conclusions are given in Section 6.

2 Hypotheses

In accordance with the previous review, the following five hypotheses will be examined in the next sections:

H1: Speculation is a determinant of Bitcoin’s volatility.

H2: Investor attention is a determinant of Bitcoin’s volatility.

H3: Market interoperability is a determinant of Bitcoin’s volatility

H4: Different determinant factors have significant heterogeneous under the same regime.

H5: All of determinants exert heterogeneous features in different regimes.

Our first hypothesis considers information and its flow as vital elements for market’ stability and efficiency. Since the initiation of Bitcoin trading a vast literature has examined the main characteristics of Bitcoin returns, its volatility and their relationship. Under this scope, speculation is a core determinant factor. In the present study, speculation is regarded as informed trading, which is different from other financial assets markets (Feng 2018). Since the beginning of Bitcoin trading, large speculative amounts have been invested attracted by its decentralization feature. The increase of market liquidity, leads to excess volatility and hedging capabilities (Balcilar et al., 2017 and Gandal et al., 2018). In that sense, the speculative behavior of investors might be associated with large inflows and their perspective to take advantage of the available information. The increasing participation of speculative investors in a market tends to attract others, due to herding behavior. Whether those actions are rational or irrational (Ajaz and Kumar, 2018; Vidal-Tomás, 2018 and Bouri, Gupta and Roubaud, 2019), which further provides excess market liquidity to some extent, although leads to irrational exuberance. Then, the speculators have gradually been the leading players in future prices and if the volume has a
predictive power, this equals that volume-driven strategies are profitable. In addition, information is a key factor of hedging trading. Speculators can take advantage of the available information and quickly respond to subtle changes in market prices and implement more reliable risk management strategies (Auer and Claessens, 2018). Finally, Balcilar et al. (2017) find a strong predictive ability of the Bitcoin trading volume and its returns. Using non-parametric causality-in-quantiles tests to detect the occurrence of any causal relationship between the volume with either returns or the volatility.

On second hypothesis, investor attention necessarily requires a substitution of cognitive resources from others. When it comes to investment decisions, given the vast amount of information available and the inevitability of limited attention, investors should be selective in information processing (Peng and Xiong, 2006; Wen et al., 2019). The main proxies for investor attention are Google trends data and Wikipedia search queries. In the existing literature Kristoufek (2013) detects a strong causality between both the databases and the prices formation, while Bouoiyour and Selmi (2015) show that the lags of Google trends also explain the Bitcoin price. In addition, overconfidence of investors could lead them to believe that their judgment on information is so accurate that they could find potential information from crypto-assets market operations. Based on this, they might think that they are more able to predict the crypto-trading operations and further earn the expect return on Bitcoin. Similarly, they are more convinced that they could affect the outcome of uncontrollable events because of the increase in attention to information. As the interests of investors increase, more investment data are available, making them feel that they could better control the results of investments, thereby increasing the frequency of transactions (Ciaian, 2016; He, He and Wen, 2019).
The third hypothesis is based on a macro-financial perspective, supporting that market interoperability is an important determinant in the stability of the virtual financial system. Market interoperability can be defined simply as the inter-relationship and communication channels between different markets (El Bahrawy et al., 2017). In addition, market interoperability would provide an opportunity for speculators to generate excess returns in the crypto-assets market. Given the state of anonymity and the lack of central authorization in the clearing process, in comparison with other traditional financial assets (such as equities, bonds, exchange rates etc), there is an considerable opportunity to hedge with other markets and furthermore cause the capital flight (Pieters and Vivanco 2017; Zhang, 2018). The occurrence of abnormal capital flows makes any effort for regulatory foreign exchange regulation more difficulty. It also shows higher requirements on maintaining the balance of international payment. From the perspective of micro, market interoperability is correlated with the expect return of crypto-assets. Capital outflows which caused by abnormal capital flows might easily result in market instability and extreme volatility.

The fourth and fifth hypothesis consider the differentiation of the Bitcoin’s volatility determinants seem to present significant heterogeneous patterns under the same and different regimes.

3 Model and Variables

As mentioned above, the heterogeneous features for analyzing the core determinants of Bitcoin volatility are based on the Markov regime-switching regression model (Hamilton 2008). In this section, we briefly explain the methods implied for the generation of Bitcoin volatility forecasts, as well as the measurement approaches of the explanatory variables used in the model specification. Afterwards the Markov regime-switching model is described.
3.1 CAViaR and The measurement of explanatory variables

Prior to the theoretical investigation on how the heterogeneous patterns (speculation, investor attention and market interoperability) drive the Bitcoin volatility, it would be useful to describe and explain the special features of the main variables that are used in our models.

The dependent variable is Bitcoin volatility, as it is described by its realized historical volatility as a measure. Value-at-Risk (VaR) represents the maximum expected amount of loss exposed in Bitcoin, during a specific holding period $T$. VaR could be regarded as an effective tool for the estimation of the risk. Defining $\{R_t\}_{t=1}^T$ as the daily logarithmic returns of Bitcoin and $T$ is the time-span of the returns. It can be calculated as (1).

$$R_t = \ln P_{Bitcoin_t} - \ln P_{Bitcoin_{t-1}}.$$  

where $P_{Bitcoin_t}$ and $P_{Bitcoin_{t-1}}$ stands for the closing price of Bitcoin at time $t$ and $t-1$ respectively.

In this case, VaR is defined as the left $\theta$-quantile of the conditional probability distribution of Bitcoin returns, which is subject to (2).

$$Pr[R_t < Risk_t|\Omega_{t-1}] = \theta.$$  

where $Risk_t$ stands for the Bitcoin volatility at time $t$, and $\Omega_{t-1}$ is the information set available at time $t-1$.

In the $Risk_t$ calculation process, researchers usually fall into two groups, one is factor mapping models, and another is portfolio models (Qureshi, 2016). But these approaches often assume that the distribution of Bitcoin return is invariable across time. The empirical works fact that volatility of Bitcoin returns cluster over time, thus the distribution of Bitcoin is time-varying (Begušić et al., 2018; Takaishi, 2018). Consequently, the measurement of $Risk_t$, which is tightly link to the standard deviation of the distribution, must exert similar behavior. In this
paper, we use conditional autoregressive quantile specification (CAViaR), proposed by Engle and Manganelli (2004). The CAViaR can be generally written as in equation (3).

\[ \text{Risk}_t(\beta) = \beta_0 + \sum_{i=1}^{q} \beta_i \text{Risk}_{t-i}(\beta) + \sum_{j=1}^{r} \beta_j l(R_{t-j}). \]  

(3)

with \( p = q + r + 1 \) being the dimension of \( \beta \) and \( l \) is a function of a finite number of Bitcoin lagged realized return. In addition, \( \beta_i \text{Risk}_{t-i}(\beta) \), \( i = 1, 2, \cdots q \) represent the autoregressive variables used to guarantee the smoothness in Bitcoin volatility over time. The role of \( l(R_{t-j}) \) is to link \( \text{Risk}_t(\beta) \) to Bitcoin returns that belong to \( \Omega_{t-1} \).

Furthermore, based on Engle and Manganelli (2004) process we also develop four CAViaR models, as described in equations (4)-(7).

Symmetric absolute value:

\[ \text{Risk}_t(\beta) = \beta_1 + \beta_2 \text{Risk}_{t-1}(\beta) + \beta_3 |R_{t-1}|. \]  

(4)

Asymmetric slope:

\[ \text{Risk}_t(\beta) = \beta_1 + \beta_2 \text{Risk}_{t-1}(\beta) + \beta_4 (R_{t-1})^+ + \beta_3 (R_{t-1})^- \]  

(5)

GARCH (1,1):

\[ \text{Risk}_t(\beta) = (\beta_1 + \beta_2 \text{Risk}_{t-1}^2(\beta) + \beta_3 R_{t-1}^2)^{1/2}. \]  

(6)

Adaptive:

\[ \text{Risk}_t(\beta_1) = \text{Risk}_{t-1}(\beta_1) + \beta_1 [1 + \exp( G[R_{t-1} - \text{Risk}_{t-1}(\beta_1)])]^{-1} - \theta. \]  

(7)

where \( (R_{t-1})^+ = \max(R_{t-1}, 0) \), \( (R_{t-1})^- = -\min(R_{t-1}, 0) \) and \( G > 0 \in \mathbb{N} \).

Furthermore, the test of Engle and Manganelli (2004) is implied for the evaluation of the results. The test can be defined as in (8).

\[ Hit_t(\beta) \equiv I(R_t < \text{Risk}_t(\beta)) - \theta. \]  

(8)
where $\text{Hit}_t(\beta)$ is assumed to follow the value $(1-\theta)$ for Bitcoin returns smaller than the quantile and $-\theta$ for returns greater than the quantile, with $\text{E}[\text{Hit}_t(\beta)] = 0$ and $\text{E}[\text{Hit}_t(\beta) | l_{t-1} = 0] = 0$. For the particular purpose, $\text{Hit}_t(\beta)$ is defined without the existence of autocorrelation and uncorrelated with $\text{Risk}_t(\beta)$. Only if $\text{Hit}_t(\beta)$ satisfies these assumptions, we can verify the elimination of any misspecification error, of autocorrelation autocorrelation in the hits and that be able retrieve the correct fraction of exceptions.

Furthermore, in order to test the adequacy of the models, we extend an in-sample dynamic quantile test and an out-of-sample dynamic quantile test, as in equations (9)-(10).

\[
DQ_{IS} = \frac{\text{Hit}'(\hat{\beta}) X(\hat{\beta}) (M_T - M'_{r}) - X'(\hat{\beta}) \text{Hit}'(\hat{\beta})^d}{\theta(1-\theta)} \sim \chi^2_q
\]

\[
DQ_{OOS} = N^{-1}_R \text{Hit}'(\hat{\beta}_r) X(\hat{\beta}_r) [(X'(\hat{\beta}_r) X(\hat{\beta}_r))^{-1} \times X'(\hat{\beta}_r) \text{Hit}'(\hat{\beta}_r)]^{-1}
\]

where

\[
M_T = X'(\hat{\beta}) - \left\{(2Tc_T)^{-1} \sum_{t=1}^T I [R_t < \text{Volatility}_t(\hat{\beta}) < c_T] \times \text{Volatility}_t(\hat{\beta})\right\}
\]

\[
\times D_T^{-1}\text{Volatility}_t(\hat{\beta}).
\]

Both $DQ_{IS}$ and $DQ_{OOS}$ enhance quite a different role. More specifically, $DQ_{IS}$ is a specification test for any of the particular CAViaR process, contributing for the model selection.

On the other hand, $DQ_{OOS}$, instead, could be very useful for regulatory purposes, so that they could check whether the VaR forecast satisfies the minimum requirements of a good quantile, such as unbiasedness, independent hits and independence of the quantile estimates.
According to our previous analysis and our hypothesis, the main driver of Bitcoin volatility is speculation. Bitcoin returns and volumes are associated with speculation variable. Following the Llorente et al (2002) approach, we estimate daily turnover at time $t$ as we describe in the following equations (12) and (13).

\[ \log \text{turn}_t = \log (\text{Turnover}_t + 0.00000255). \]  
\[ v_t = \log \text{turn}_t - \frac{1}{50} \sum_{s=-50}^{s=50} \log \text{turn}_{t+s}. \]  

where $\text{turn}_t$ is the trading volume of Bitcoin at time $t$ and $v_t$ stands for the (50-day) detrended measure of trading activity\(^1\). In addition, a small constant 0.00000255 was added for days with zero-volume\(^2\), as in Llorente et al (2002). The constant value was chosen as a best fit so that volume could follow the normal distribution. As a result we measure the speculation as presented in equation (14).

\[ \text{spec}_t = R_t \times v_t. \]  

where $R_t$ is the daily return of Bitcoin at time $t$.

Moreover, investor attention is considered as a demand-side measure. Indeed, Bitcoin (although virtual) could be regarded as an asset whose prices formation and risk-return relationship are mainly driven by the forces of demand and supply. As a result the main question arise is how the two force are determined and interact in crypto-assets markets. In the supply-side, the number of Bitcoin is fixed for every given time span, with a nearly zero contribution to the risk, as the total quantity in the market is fixed. On the contrary, from the demand perspective, crypto-assets market is driven only by expected profits from trading for any

\(^1\) Llorente et al. (2002) detrend turnover using t-200 instead of t-50. However, following Blau (2017), given our data limitations we chose to only use 50days when detrending turnover.

\(^2\) We note that we add a small constant (0.00000255) to volume to account for days without trading volume. This constant is further shown to normalize the distribution of trading volume in Llorente et al. (2002) and Covrig and Ng (2004).
investment horizon. As a result this market is dominated by short-term investors, trend chasers, noise traders and of course speculators. Google Trends counts the searching amount of the key word “Bitcoin” over a period and investigates the popular extent in the steady period. Therefore, the searching frequency of terms related to Bitcoin could be considered as a good measure for investor attention through Google Trends, that express the number of searches for the term “Bitcoin” in a scale ranging from 0 to 100.

Market interoperability could be better depicted by the Bitcoin-implied exchange rate among different markets. We follow the work of Lan, Lu and Tu (2016), so we define the Bitcoin implied exchange rate as in equation (15):

\[ E^{im} = \frac{B_{t}^{RMB}}{B_{t}^{USD}}. \]  

where \( B_{t}^{RMB} \) stands for the market price in Chinese Yuan Renminbi (RMB) and \( B_{t}^{USD} \) the market price in United States dollars (USD). As the open market RMB/USD exchange rate applies, and the transaction is transparent and traceable, then if the market is considered as efficient, the difference between the Bitcoin-implied exchange rate and the open market exchange rate will be negligible. Therefore, we define the market interoperability as in (16):

\[ mai = \frac{E^{im} - E^{op}}{E^{op}}. \]  

where \( E^{op} \) is the open market exchange rate. Hence, if the market is fully communicating, \( mai \) should not be statistically different from zero.

3.2 Markov regime-switching model

If our hypothesis hold, we could notice that the determinants of Bitcoin volatility are regime-dependent. Therefore, we estimate the Markov regime-switching regression Model in this paper (Hamilton 1987). Moreover, the mainly reasons in the application of the Markov regime-
switching regression model are as follow: Firstly, the model needs neither artificially set of thresholds to determine the change of Bitcoin volatility regime, nor its duration. In fact, the Bitcoin volatility regime could be determined by smooth transition among the state variables in different risk regimes. So these parameters can be used to obtain the intensity of different determinants under different regimes. Secondly, the Markov regime-switching regression model reflects the dynamics of the transition among different volatility regimes through state transition variables.

The Markov regime-switching regression model can be written as in (17):

\[
\text{Risk}_t = c(s(t)) + \alpha_1(s(t))\text{Spe} + \alpha_2(s(t))\text{Ia} + \alpha_3(s(t))\text{Mai} + \alpha_4(s(t))\text{Spe} \ast \text{Ia} \ast \text{Mai} + \varepsilon(s(t)).
\]  

(17)

where \( s(t) \) is a first order Markov process, \( \text{Spe} \) represents the speculation variable, \( \text{Ia} \) stands for the investor attention and \( \text{Mai} \) is the market interoperability variable\(^3\). Coefficient \( \alpha_i(s(t)) \) is the intensity of factor \( i \) on state \( s(t) \). Volatility state transition is achieved by the transition probability \( p_{uv} \), namely that the probability from state \( u \) at time \( t-1 \) to state \( v \) at time \( t \), with

\[
p_{uv} = \Pr(S_t = v | S_{t-1} = u). \quad \forall u, v = 1, 2, \cdots, M; \sum_{v=1}^{M} p_{uv} = 1.
\]

To explore the evolution of Bitcoin (CNY) volatility, we use data from January 1, 2013 to September 30, 2017. We used the first 1,434 returns for the estimation of the model parameters and the last 300 observations were used for out-of-sample testing. Especially, we set \( G=10 \), entered the definition of the adaptive model\(^4\). We forecast 1% and 5% 1-day Bitcoin volatilities.

\(^3\) Most of VFAs trading around the world originate from China and the United States markets. Thus, the difference between the market prices of China and United States is the main determinant causing the fluctuation of VFAs return risk as well as the exchange rate between RMB and U.S. dollar.

\(^4\) See Engle and Manganelli (2004). In principle, the parameter \( G \) itself could be estimated; however, this would go against the spirit of this model, which is simplicity. We test different values of \( G \), like 5, 15, 20, and get same result as \( G=10 \).
For our empirical analysis, we pick up data from the following sources. Our data collected from Bitcoin data website (see https://bitcoincharts.com/). In addition the variable for investor attention was retrieved from Google trends (see http://trends.google.com) and the rest of the variables from the State Administration of Foreign Exchange (see http://www.safe.gov.cn/).

4 Forecasting Bitcoin volatility

The results of the forecasts are plotted in Figure 2, and our results for the parameters are reported in Table 1. More analytically, Table 1 shows the estimates and relevant statistics for the four CAViaR specifications. The first striking result is that the coefficient of the autoregressive term ($\beta_2$) is statistically significant in all cases. This indicates that the feature of volatility clustering is relevant also in the tail of the distribution. A second very interesting outcome is the precision of all specifications, as measured by the percentage of the in-sample hits. The results for the 5% show the symmetric absolute value and asymmetric slope and that indirect GARCH models can better describe volatility dynamics. Further, it is interesting to notice the asymmetric slope model. Further, it is clearly noticed that there are differences between the coefficients of the positive and negative part of the lagged returns, and these are always of high significance. This indicates the occurrence of strong asymmetric effects on Bitcoin risk. Thus the asymmetric slope results could be regarded as Bitcoin risk.

Table 1 Estimates and relevant statistics for the four CAViaR specifications

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<tr>
<th>Panel a: 1% VaR</th>
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<tr>
<td>$\beta_1$</td>
<td>0.047*</td>
<td>0.004*</td>
<td>0.0007***</td>
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<td>(0.032)</td>
<td>(0.003)</td>
<td>(0.0004)</td>
<td>(0.006)</td>
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<td>$\beta_2$</td>
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<td>0.891***</td>
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<td>$\beta_3$</td>
<td>0.334***</td>
<td>0.308***</td>
<td>0.825***</td>
</tr>
<tr>
<td></td>
<td>(0.073)</td>
<td>(0.059)</td>
<td>(0.23)</td>
</tr>
<tr>
<td>$\beta_4$</td>
<td>0.42***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.119)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hit in-sample(%)</td>
<td>0.976</td>
<td>0.976</td>
<td>1.046</td>
</tr>
<tr>
<td>Hit out-of-sample(%)</td>
<td>1.333</td>
<td>1.333</td>
<td>2.000</td>
</tr>
<tr>
<td>$DQ_{is}$ (p)</td>
<td>0.920</td>
<td>0.999</td>
<td>0.969</td>
</tr>
<tr>
<td>$DQ_{oos}$ (p)</td>
<td>0.842</td>
<td>0.816</td>
<td>0.194</td>
</tr>
</tbody>
</table>

Panel b: 5% VaR

<table>
<thead>
<tr>
<th></th>
<th>(a)</th>
<th>(b)</th>
<th>(c)</th>
<th>(d)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_1$</td>
<td>0.002***</td>
<td>0.013*</td>
<td>0.0001*</td>
<td>-0.0001***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.009)</td>
<td>(0.0001)</td>
<td>(0.0000)</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>0.855***</td>
<td>0.454**</td>
<td>0.832***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.035)</td>
<td>(0.228)</td>
<td>(0.027)</td>
<td></td>
</tr>
<tr>
<td>$\beta_3$</td>
<td>0.216***</td>
<td>0.516***</td>
<td>0.294</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.075)</td>
<td>(0.202)</td>
<td>(0.622)</td>
<td></td>
</tr>
<tr>
<td>$\beta_4$</td>
<td>1.033***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.067)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hit in-sample (%)</td>
<td>4.951</td>
<td>4.951</td>
<td>4.881</td>
<td>5.718</td>
</tr>
<tr>
<td>Hit out-of-sample(%)</td>
<td>5.000</td>
<td>4.667</td>
<td>6.667</td>
<td>19.000</td>
</tr>
<tr>
<td>$DQ_{is}$ (p)</td>
<td>0.876</td>
<td>0.971</td>
<td>0.626</td>
<td>0.039</td>
</tr>
<tr>
<td>$DQ_{oos}$ (p)</td>
<td>0.388</td>
<td>0.803</td>
<td>0.584</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Notes: Standard errors shown in parentheses; *, ** and *** indicate significance at 1%, 5%, and 0.1% level, respectively. (a) Symmetric absolute value; (b) Asymmetric slope; (c) Indirect GARCH (1,1); (d) Adaptive.
Figure 2 shows the Bitcoin return and 1% and 5% 1-day Bitcoin volatility. In accordance with the results in Table 1, we can clearly verify that Bitcoin volatility shows clustering features (Bariviera, 2017). During the whole sample period, there were two significant and three smaller clusters in the Bitcoin volatility estimation. At the end of 2013, this could be explained due to the increasing popularity of Bitcoin which attracted the attention of institutional investors, resulting an exponential rise of Bitcoin price, as well as its risk. From the regulatory point of view, in December 2013, the Chinese central bank issued the regulatory policy coping with the Bitcoin risk and achieved significant results in decreasing the risk of Bitcoin. After a period of market digestion, Bitcoin once again re-entered the investor's sight in 2017, due to the increasing interest in Blockchain. The rising expectations of blockchain-revolution (the technology that supports Bitcoin), the volatility of Bitcoin price is larger than it in the end of 2013, and its volatility has also increased significantly. The existence of clustering (Urquhart, 2017; Balcilar et al., 2017; Li et al., 2018; Saculsan and Kanamura, 2020), asymmetries (Ante, 2020; Baur and Dimpfl, 2018; Alvarez-Ramirez, Rodriguez and Ibarra-Valdez 2018 and Takaishi, 2018), multifractality (Al-Yahyae, Mensi and Yoon, 2018; Takaishi, 2018; da Silva Filho, Maganini and de Almeida, 2018 and Lahmiri, Bekiros and Salvi, 2018) and jumps (Urquhart, 2017; Chaim and Laurini, 2018) are noticed in several studies.

In our study the adaptive model seems inferior in comparison with its three alternative specifications. Meanwhile, we get some results that cannot be expressed in Table 1. We can clearly notice that Bitcoin volatility is highly correlated with its returns. High and low volatility periods are often associated strongly with the market trend (bull and bear). For example, at the end of 2013, Bitcoin return fluctuated significantly, and Bitcoin volatility also showed a significant increase. As the policy regulates the market, the volatility of Bitcoin return is
significantly reduced, and the Bitcoin volatility is also weakened. At the beginning of 2017, is characterized as a time of entering the “tech mania era”, when expectation for a new technological shock lead to a further explosion of Bitcoin volatility. These volatility shocks tend to reduce the stability of the Bitcoin market and increase investment risk for investors.

Figure 2: 1% and 5% estimated CAViaR plots. (a) Symmetric absolute value; (b) Asymmetric slope; (c) Indirect GARCH (1,1); (d) Adaptive.

5 Empirical results

5.1 Data preprocessing and descriptive statistic

Before estimating the Markov regime-switching Model, the data should be normalized making the speculation, investor attention and market interoperability comparable. In this paper, we apply the Z-score normalization method. Descriptive analysis of the above variables is reported in Table 2, and the series after normalization plot in Figure 3.

More specifically, Table 2 presents descriptive statistics for the variables. We firstly observe that investor attention displays the highest mean (23.24), whereas market
interoperability \( (Mai) \) is among the lowest (0.003). Furthermore, we consider the variation in different variables. The measurement of the variation includes standard deviation (Std. D.), range and coefficient of variation (Coef. var). We find that (i) speculation has the highest Std. D. (380.41), while Risk has the lowest (0.04). (ii) Coef. var, which is meaningful for positive values, shows that Risk has the least variation (0.67), while speculation \( (Spe) \) shows the most (68.05), and (iii) range, which measures the difference between max and min, shows that Risk has the least (0.66), and speculation has the most (10248.39). Above all, consistent with the finding of Gandal (2018), we report that Bitcoin could be regarded as a speculative asset during the sample period. The difference of variation facilitated the model fitting and made it possible to explore the determinants of volatility.

<table>
<thead>
<tr>
<th></th>
<th>Total Number</th>
<th>Mean</th>
<th>Max.</th>
<th>Min.</th>
<th>Std. D.</th>
<th>Range</th>
<th>Coef. var</th>
</tr>
</thead>
<tbody>
<tr>
<td>Risk</td>
<td>1734</td>
<td>0.06</td>
<td>0.68</td>
<td>0.02</td>
<td>0.04</td>
<td>0.66</td>
<td>0.67</td>
</tr>
<tr>
<td>Spe</td>
<td>1734</td>
<td>5.59</td>
<td>3811.36</td>
<td>-6437.03</td>
<td>380.41</td>
<td>10248.39</td>
<td>68.05</td>
</tr>
<tr>
<td>Ia</td>
<td>1734</td>
<td>23.24</td>
<td>144</td>
<td>-5</td>
<td>22.05</td>
<td>149</td>
<td>0.95</td>
</tr>
<tr>
<td>Ma</td>
<td>1155</td>
<td>0.003</td>
<td>0.56</td>
<td>-0.23</td>
<td>0.05</td>
<td>0.79</td>
<td>16.13</td>
</tr>
</tbody>
</table>

Figure 3 presents the correlation coefficients among all independent variables with the dependent, Risk. It could be seen that different determinants exert the heterogeneous features on the volatility. Firstly, the Risk proxy is significantly related to the speculation variable variation. Second, investor attention and Risk have the same trend during the sample period, while in the initiation of Bitcoin, the market microstructure was not well established, and investors’ protection was also insufficient. Investors’ attention easily stimulates the existence of “herd effect” in Bitcoin market, hereby investors begin to follow suit in the market. At this time, due to the speculative manipulation trades, the fluctuation of the Bitcoin returns increased
significantly, the same as risk and market instability. Moreover, the correlation between market interoperability and Risk shows a stage, with a positive trend before 2017, which turned negative after 2017. This mainly caused by the differences in the regulatory regimes of between Bitcoin markets worldwide. Before 2017, the regulatory differences among the global markets for crypto-assets were negligible, leading to a convergence of international investor attention, which explains the same trend between market interoperability and Risk. In 2017, due to the shift of regulatory differences and other restrictions on the market, international investors reduced the transactions in the so-called “non-friendly” markets, resulting a certain impact on the global circulation of Bitcoin which increased volatility. Therefore, under different Bitcoin regimes, speculation, investor attention and market interoperability are heterogeneous.
Figure 3: Time series plots the correlation of speculation, investor attention and market interoperability with Bitcoin volatility. (a) Risk vs Spe; (b) Risk vs Ia; (c) Risk vs Mai.

The next crucial step for our analysis is the determination of the regime number, before the model estimation. In general, the regime number can be determined throughout the evaluation of LogL, AIC and SIC criteria, shown in Table 3.

<table>
<thead>
<tr>
<th>Table 3: The result of regime number choice</th>
</tr>
</thead>
<tbody>
<tr>
<td>regime</td>
</tr>
<tr>
<td>--------</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>3</td>
</tr>
</tbody>
</table>
Table 3 presents the optimal number of regimes for our estimations, using three information criteria to evaluate the goodness-of-fit. When the regime number is set as 2, the value of LogL is -832.89, AIC is 1685.78 and BIC is 1806.82. However, the values of AIC and BIC are 1243.19 and 1424.74 respectively, and LogL is -606.59 when the regime number is 3. According to the selection results of the alternative criteria, we estimate the Markov regime-switching Model with 3 regimes.

5.2 Estimation of Markov regime-switching regression Model

As mentioned in 5.1 section, we estimate the Markov regime-switching regression Model with the regime number equals to 3. The parameters estimation results are reported in Table 4.

In the beginning, we focus on the deviations of the results between Linear and Markov regime-switching Model. F-statistics of the Linear Model (5) is significant at the 5% confidence level. This indicates that the determinants of Risk are mainly speculation, investor attention, market interoperability and their interaction. In addition, the R² of the Linear Model is smaller than in Markov regime-switching Model, showing a better performance in terms of statistical significance. Thus the determinant shows and heterogeneous regime on Risk.

The constant estimation reflects the regime where Bitcoin volatility lies in. In regime 1, the constant is the largest among the three regimes, equal to 1.748, while in regime 3, the value of the constant is -0.483. Thus, we could determine the specific regime according the value of constant. Concretely, we regard regime 1 as the high-risk regime, regime 2 as the medium-risk and regime 3 as the low-risk.

Furthermore, we estimate the coefficients of the different determinants. We notice that different factors have significant heterogeneous under the same regime. For example, under the
low risk regime, investor attention, market interoperability and interaction have a statistically significant impact on the Risk variable with a degree of 0.044, 0.045 and 0.015, respectively. However, speculation shows no significant effect. Under the medium-risk regime, all determinants enhance a significant role, as the entrance of speculators (informed investors) and the interaction term show a negative effect on the returns variation. Their coefficients were estimated at -0.055 and -0.02, respectively. Under this regime, investor attention remains the core determinant factor, whose value was 0.178, as well as the market interoperability with a coefficient of 0.088. Finally, in the high-risk regime, speculation and interaction are not significant, while investor attention and market interoperability have strong positive effects, with their coefficients equal to 1.074 and 0.394, respectively.
Table 4: Parameters Estimation results

<table>
<thead>
<tr>
<th>Model</th>
<th>Linear Model</th>
<th>Markov regime-switching Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) (2) (3) (4) (5)</td>
<td>1 2 3</td>
</tr>
<tr>
<td>$c$</td>
<td>0.012 -0.003 0.107** 0.015 0.123***</td>
<td>1.748*** 0.098** -0.483**</td>
</tr>
<tr>
<td></td>
<td>(0.031) (0.029) (0.033) (0.031) (0.032)</td>
<td>(0.190) (0.035) (0.013)</td>
</tr>
<tr>
<td>$\alpha_1$</td>
<td>-0.028</td>
<td>-0.077**</td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>$\alpha_2$</td>
<td>0.340***</td>
<td>0.378***</td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
<td>(0.028)</td>
</tr>
<tr>
<td>$\alpha_3$</td>
<td>0.197***</td>
<td>0.257</td>
</tr>
<tr>
<td></td>
<td>(0.030)</td>
<td>(0.029)</td>
</tr>
<tr>
<td>$\alpha_4$</td>
<td>-0.009</td>
<td>-0.032***</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.0009 0.106 0.035 0.001 0.17</td>
<td>0.373</td>
</tr>
<tr>
<td>F</td>
<td>1.12 136.8*** 41.62*** 1.30 58.89***</td>
<td>1.623</td>
</tr>
</tbody>
</table>

Total number: 1155

Note: Standard errors shown in parentheses; *, ** and *** indicate significance at 1%, 5%, and 0.1% level, respectively. The number (1), (2), (3), (4) and (5) stands for the different Linear Model with different explanatory variables and 1, 2, 3 presents the regime number in Markov regime-switching Model.
In the low risk regime, investor attention and market interoperability are main determinant factors. For instance, investor attention depicts the level of information sharing among investors from multiple channels and promotes efficiency and investment decision-making process. The investor attention in combination with the increasing information flow, seems to increase trading activity enhancing market volatility. In the medium-risk regime, the larger range of Bitcoin prices seem to attract a greater number of speculators, as it is of more convenience for speculators to obtain the information, rather than noise traders. As large speculative capital enters the BTC market, more investors, including arbitragers, pay attention to Bitcoin. However, the market efficiency and regulatory mechanisms, make this effect useless. Finally, under the high-risk regime, the supervision has increased, creating a collective effect that makes speculation and market interoperability more stabilized. Speculators outflows from Bitcoin market could cause a panic resulting a further increase in volatility.

Furthermore, all of determinants exert heterogeneous features in different regimes. From Table 4, we notice that the speculation and interaction term are “U-shaped” against Risk (the values in low, median and high-risk regimes are -0.016, -0.055 and 0.12, and 0.015, -0.02 and 0.064, respectively). It is interesting that speculation has effect below the medium regime, while interaction term has a more significant role under low- and medium regime, meaning that both market liquidity and hedging seem to impact volatility. Under low-risk regime, the stability and effectiveness in the Bitcoin market also seem to benefit from speculation. However, the interaction focuses on the Bitcoin price differences. With the increase of Bitcoin volatility, the regulatory lag provides an opportunity for excess profits and arbitrage opportunities, which attracts more speculators. The excess profits lead to the expansion of the so-called “herd effect”
in the Bitcoin market, which feeds increasing volatility. Under the high-risk regime, policy makers could effectively limit speculation and interaction.

The determinant factors of investor attention on Risk shows a positive linear trend. Under the low-risk regime, the impact of the investor attention on Bitcoin risk is 0.044, while under the medium-risk regime, the impact on Bitcoin risk is 0.178, while the one under high-risk regime is 1.074. Investors now focus on the expected return of Bitcoin and policy and herd effect in Bitcoin market attract attention of investors. Under low-risk regime, policy does not refer to Bitcoin market, so this provides some channels for investors to earn expected return. Thus investor attention increases volatility. Under the medium risk regime, a large number of new investors enter the market. Thus, the role of investor attention is higher, than it in the lower risk regime, market efficiency shows a significant improvement because of the supervision mechanisms. Now it is easier for both investors and speculators to gain the expected return. Furthermore, investors' trading frequency has been increased, which in turn has reduced market stability and increased market risk.

Besides, the market interoperability shows linear effect on Risk (The values in low, median and high-risk regimes are 0.045, 0.088 and 0.394, respectively). Market interoperability mainly refers to the competitive interaction between different Bitcoin markets. As volatility lower remains, this attracts diverse investors in Bitcoin markets. Their transactions promote complex trading, which has positive effect on Bitcoin volatility. Under the medium risk regime, market interoperability enhances the Bitcoin volatility because of the increasing number of transactions and under the high-risk regime, more arbitrage opportunities rise. Therefore, market interoperability has a positive and significant impact on Risk. In summary, the hypotheses H1, up to H5 are valid, with differentiations under the different regimes.
Following we analyze and discuss the regime feature of Bitcoin volatility over the sample period. The duration of different regimes presented in Figure 4 and the transition probability report is given in Table 5.

Figure 4 shows the volatility regime. As mentioned above we defined Regime 3 as the low-risk regime, Regime 2 as the medium-risk and Regime 1 as the high-risk. Our two major notices are the following: (1) Bitcoin volatility mainly aggregate in medium-risk regime while low-risk regime occurs less frequently, and (2) when Bitcoin volatility is relatively flat, the risk factor switches between high and medium-risk regime. This indicates that expected return is a key factor on Bitcoin volatility. Due to the lag of information dissemination, investors do not have enough information on Bitcoin, and the expected return on Bitcoin is lower during its first years of trading. As information sharing increases, the expect return increases gradually. The increasing expectations leads new investors to enter the market. The explosion of market activity seems to have an increased Bitcoin market uncertainty, which in turn causes the higher volatility.

Meanwhile, the combined effect of governments and markets has led to a shift in Bitcoin volatility between high and medium regime. Bitcoin market activity has attracted the attention of speculators. Speculators change the market capital structure with large amount capital support, hereby increased the uncertainty of the market and reduced the regulatory efficiency of the Bitcoin market, thus increased the Bitcoin volatility. However, policies reduce the market effect of speculative trading. Therefore, speculative trading shifts the Bitcoin volatility between high and medium regime. The same result can be seen in Table 5.
<table>
<thead>
<tr>
<th>regime</th>
<th>low</th>
<th>medium</th>
<th>high</th>
</tr>
</thead>
<tbody>
<tr>
<td>low</td>
<td>0.678</td>
<td>0.295</td>
<td>0.027</td>
</tr>
<tr>
<td>medium</td>
<td>0.077</td>
<td>0.768</td>
<td>0.155</td>
</tr>
<tr>
<td>high</td>
<td>0.002</td>
<td>0.143</td>
<td>0.855</td>
</tr>
</tbody>
</table>
Figure 4: Bitcoin volatility regime during the sample period. Regime 1 is high-risk regime. Regime 2 is medium-risk regime and Regime 3 is low-risk regime.

Table 5 shows the transition probability of Bitcoin volatility between two regimes. As it can be seen from the matrix, Bitcoin volatility has a higher probability maintaining the current regime. Specifically, the probability maintaining a high-risk regime is
highest (0.855), followed by the probability maintaining a medium risk regime is 0.768 and the probability maintaining a low regime is least (0.678). This shows that high-risk regime admits strong stability. Under the high-risk regime, the collective effect of market and government make the market efficiency is higher than it in other regimes. High market efficiency can better adjust the liquidity, capital structure and hedging changes in the Bitcoin market caused by speculation and investor attention. Therefore, high-risk regime could be more stability.

Moreover, it is interesting to note the transition probability between different regimes. As it can be seen from Table 5, the transition probability from low to medium risk regime is greater than the one from low to high risk regime, which is 0.295 and 0.027, respectively. In contrast, the transition probability from high to medium risk regime (0.143) is also greater than the one from high to low risk is 0.002. This indicates that, it is difficult to occur the regime jumping (rising from low to high regime) in Bitcoin volatility, and the policy has a strong supervision over the Bitcoin volatility.

In combination with the results of Figure 4, we can find that the low-to-high-regime conversion of Bitcoin volatility during the sample period is mainly concentrated in the technical reform period. The first occurred at the end of 2013 and followed with a crash in Bitcoin price. At this time, the People's Bank of China issued a policy to shift the Bitcoin volatility from the high-risk regime to the low-risk regime. Due to the market's ability to absorb policies, Bitcoin volatility is shifting between low and medium-risk regime. The second, more pronounced, low-to-high transition occurred in early 2017. Meanwhile, the global emphasis on blockchain technology leads to further increases in investor expectations and reduce in market stability and the Bitcoin volatility is significant increased. Therefore, it is necessary to use and regulate the Bitcoin technology and transactions.
6 Conclusions and policy implication

Bitcoin is the first and most well-recognized crypto-asset, that has attracted investors interest in the recently established market for virtual financial assets. The present paper, aimed to use the CAViaR method in order to estimate and forecast Bitcoin’s VaR. We provide evidence on its main features asymmetric behavior, cluster effect, and it is significantly related to its volatility. In addition, the paper explore the heterogeneous feature of the main determinants of Bitcoin volatility via using a Markov regime-switching model.

Our conclusions specifically show that Bitcoin volatility is clearly determined by speculation, investor attention, market interoperability and their interaction. Furthermore, we verify that the impact of the determinants show significant heterogeneous behavior in three different volatility regimes. More analytically, our results provide evidence that the speculation and interaction on Bitcoin volatility was “U-shaped” for the examined timespan, whereas investor attention and market interoperability follow a linear trend. Further, investor attention remains a major determinant, while speculation factor is insignificant under the low- and high-risk regime, as well as the common interaction term did in the high-risk regime.

In addition, it seems that different determinant factors have a significant heterogeneous feature, both under the same regime and the transitions between two volatility regimes as well. Under the low risk regime, investor attention, market interoperability and interaction enhance a significant role on BTC volatility. Under the medium-risk regime, speculators began to work on it. Under the high-risk regime, the investor attention and market interoperability play significant roles on volatility forecasting. In addition, the transition probability matrix shows that the transitions between two regimes exert heterogeneous property.
Based on our results it seems that both institutional and individual investors should increase their awareness on the existing information set and emphasize on their investment decision-making ability, considering the risk involved. Investors could also benefit from volume-based strategies and timing strategies in different regimes. As alternative investments, such as virtual assets become mainstream in the finance field, regulators should impose official standardized processes for information flow and provide guidelines on the content, aiming to increase investors’ protection. Therefore, authorities should establish official information criteria and guarantee the information flow through channels, in order to guarantee the quality of existing information set for investors benefit. In addition, probably transaction thresholds should be set, to monitor and control large-volume transactions in this market, for the prevention of opportunities for money laundering (Auer and Claessens, 2018) and possible market manipulation or inside trading practices. The implementation of such mechanisms could possibly increase market efficiency and contribute to the stability of the market.

This paper is not without limitation. On the one hand, we could ignore the nonlinear effect of factors, such as investor attention and speculation, on Bitcoin risk. This allows investors to make short investment to max their profit. Thus, we would further study the nonlinear effect of factors on Bitcoin risk by added nonlinear item such as threshold or quadratic component. On the other hand, the role of factors on the connectedness between Bitcoin risks could be further explored with development of internet finance.
Acknowledgements:

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References


