

Intraday regime switching volatility dynamics of bitcoin liquidity

Régimen intradiario cambiando la dinámica de volatilidad de la liquidez de bitcoin

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Abstract

Technological developments are followed in the form of speed and new products in the large finance ecosystem. Particularly, we can easily observe the increasing importance of both new products and speed in the cryptocurrency markets. Examining the liquidity in cryptocurrency markets, which are open 24 hours a day, 7 days a week, draws attention as an important issue. Liquidity, in simple terms, refers to the ease of converting a financial instrument into cash. Bid-ask spread of a financial instrument is also considered as a measure of liquidity. This study employs Markov switching GARCH (MSGARCH) models to investigate the intraday volatility of the liquidity of Bitcoin under low volatile and high volatile regime periods. The study analyses the 5 minutes' intraday bid-ask spread by different types of MSGARCH models with different numbers of regimes. The analysed period 01.01.2019 – 06.29.2021 contains 52,548 observations. The first results of the study provide evidence that low and high volatility periods can be explained by different models such as MS EGARCH, MS TGARCH, and MS GJRGARCH. Secondly, the two-regime MSGARCH and MS GJR GARCH models are the best models for explaining low and high volatility periods of intraday Bitcoin liquidity.

Keywords: Liquidity, bitcoin, volatility, Markov switching.

Resumen

Los avances tecnológicos y los nuevos productos avanzan de forma rápida en el gran ecosistema financiero. En particular, podemos observar fácilmente la creciente importancia tanto de los nuevos productos como de la velocidad en los mercados de criptomonedas. Examinar la liquidez en los mercados de criptomonedas, que están abiertos las 24 horas del día, los 7 días de la semana, llama la atención como un tema importante. La liquidez, en términos simples, se refiere a la facilidad para convertir un instrumento financiero en efectivo. El diferencial entre oferta y demanda de un instrumento financiero también se considera una medida de liquidez. Este estudio emplea los modelos Markov Switching GARCH (MSGARCH) para investigar la volatilidad intradía de la liquidez de bitcoin en períodos de régimen de baja y alta volatilidad. El diferencial de oferta y demanda intradía de 5 minutos se analiza mediante diferentes tipos de modelos MSGARCH con diferentes números de regímenes. El período analizado del 01.01.2019 al 29.06.2021 contiene 52 548 observaciones. Los primeros resultados del estudio proporcionan evidencia de que los períodos de alta y baja volatilidad pueden explicarse mediante diferentes modelos como MS EGARCH, MS TGARCH y MS GJRGARCH. En segundo lugar, los modelos de dos regímenes MSGARCH y MS GJR GARCH son los mejores modelos para explicar los períodos de baja y alta volatilidad de la liquidez intradía de bitcoin.

Palabras clave: liquidez, bitcoin, volatilidad, cambio de Markov

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■ Introduction

As technology continues to rapidly develop, the finance ecosystem has seen an increase in both the speed of transactions and the introduction of new products. In the world of cryptocurrency, these trends are particularly pronounced, with the markets operating 24/7 and a constant flow of new digital assets being created. One important factor in understanding these markets is liquidity, which refers to the ease with which a financial instrument can be converted to cash. Liquidity is a crucial aspect of any financial market, and the cryptocurrency market is no exception (Fang et al., 2009; Ghabri et al., 2021; Takaishi & Adachi, 2020). Bitcoin, as the largest and most widely traded cryptocurrency, is often used as a benchmark for measuring liquidity in the broader crypto market (Hu et al., 2019). Especially since 2017, the extreme volatility and speculative price bubbles in cryptocurrencies have become a research area for scholars. Although the blockchain system possesses reliable, accessible, transparent, and immutable features, Bitcoin (BTC) does not possess traits like handling risks in investment portfolios or providing a safe haven for investors (Stavroyianis & Babalos, 2019), and continues to maintain its position as the cryptocurrency market with the highest trading volume. In the context of Bitcoin, liquidity refers to the ease with which investors can buy or sell Bitcoin in exchange for other currencies or assets. High liquidity means that there is a large volume of Bitcoin available for purchase or sale, which helps to ensure that investors can execute trades quickly and at a fair price. One key measure of liquidity is the bid-ask spread, which is the difference between the highest price that a buyer is willing to pay for the asset (the bid) and the lowest price that a seller is willing to accept (the ask). The bid-ask spread reflects the market's perception of the supply and demand at any given time. A narrow bid-ask spread indicates high liquidity, while a wide spread suggests lower liquidity. Trading volume, average daily trading volume, and market depth are the other common measures of liquidity used for financial markets (Pagano, 1989; Erwin & Miller, 1998; Chordia et al., 2001;

Lesmond, 2005) Firstly, low spread means there is less difference between how much buyers are willing to pay and how much sellers want. Further, bid-ask spread is often preferred because it reflects the cost of executing trades in the market. While a wide spread means high transaction costs, a low range means low costs and makes the market more attractive for investors. In efficient markets, bid-ask spreads tend to be lower because there is more competition among buyers and sellers, causing to narrower spreads. Therefore, bid-ask spreads can provide insights into market efficiency and the effectiveness of price discovery mechanisms.

The liquidity of an asset can be affected by a range of factors, including market volatility, trading volume, and regulatory changes (Roll, 1984; Koski & Michaely, 2000; Le & Gregoriou, 2020). Understanding the liquidity dynamics of the Bitcoin market is essential for investors looking to enter or exit positions quickly and at a fair price. Although the liquidity and volatility of cryptocurrencies (Caporale & Zekokh, 2019; Panagiotidis et al., 2022; Pichl & Kaizoji, 2017; Chaim & Laurini, 2018; Takaishi & Adachi, 2020; Bartoletti & Zunino, 2019; Hasan et al., 2022) are widely studied topics, there is limited research on the volatility of the liquidity of cryptocurrencies. Investors are subject to both the risk associated with the magnitude of liquidity and the fluctuations in liquidity levels (Leirvik, 2022). The volatility of the liquidity provides information on the efficiency of cryptocurrency markets whose importance is increasing and many investors are looking for speculation and arbitrage opportunities (Hansen et al., 2024; Leirvik, 2022).

The dynamics of cryptocurrency trading is influenced by many factors such as trading costs, the interconnection of crypto liquidity, and broader market liquidity (Hasan et al., 2022). Moreover, research in this area can help develop better risk management strategies for reducing the impact of liquidity shocks on market stability, also providing insights into how efficiently prices adjust to new information. As regulators increasingly focus on understanding and regulating cryptocurrency markets, volatility in liquidity can raise concerns about market integrity,

investor protection and systemic risks. While the use of cryptocurrencies as a money laundering tool and the resulting crime and difficulties in law enforcement remain on the agenda for public authorities (Christopher, 2014), predictions for the future of markets emphasise that cryptocurrencies will have an important place in payment systems. This makes the issue an important research area for policy makers. Ultimately, this research extends the body of literature on cryptocurrency liquidity by delving deeper.

In this article, we examine the liquidity of Bitcoin, the largest and most well-known cryptocurrency, using a Markov switching GARCH model. Financial markets often exhibit periods of high volatility followed by periods that are relatively low. These different regimes can be identified by MS-GARCH models, thus providing a more accurate representation of financial markets. The flexibility allows researchers to capture complex patterns. Specifically, this study aims to identify different regimes of volatility of bitcoin liquidity and analyse how the liquidity of Bitcoin behaves under these different volatility regimes. By analysing bid-ask spread data from January 2019 to June 2021, we identify different regimes of volatility and find that the liquidity of Bitcoin can be explained by different models depending on the level of volatility present. These findings shed light on the complexities of the cryptocurrency market and provide insights into how investors can better understand and navigate this rapidly changing landscape. Additionally, this study aims to contribute to the literature on cryptocurrency liquidity, providing valuable information for regulators, finance professionals, and policy makers.

■ Literature Review

The liquidity and volatility of cryptocurrencies are extensively researched topics, however there is limited research specifically focused on the volatility of the liquidity of cryptocurrencies. Cryptocurrencies are relatively new to financial markets. Studies on volatility and liquidity have primarily focused on the stock market, resulting in old and extensive literature. Traditionally, high

and low prices have been used to proxy volatility, such as in Garman and Klass' (1980), Parkinson's (1980), and Beckers' (1983) methods. Garman and Klass (1980) find demonstrations of efficiency factors which are at least eight times better than the classical estimators. More recently, Corwin and Schultz (2012) developed a new method for estimating the bid-ask spread of a stock using its daily high and low prices. The authors found that the variance component of the high-low ratio is proportional to the return interval, but the spread component is not. Therefore, they were able to derive a spread estimator as a function of high-low ratios over 1-day and 2-day intervals, which is easy to calculate and can be applied in various research areas. In 2017, Fong et al. developed a new estimator called FHT that simplifies existing LOT measures. In 2009 Holden, in collaboration with Goyenko, and Trzcinka, introduced the effective tick measure based on the concept of price clustering (EffTick). Holden's measure (2009), the high-low spread estimator, is considered computationally efficient, making it an ideal choice for analysing large samples (Le & Gregoriou, 2020). This means that the estimator does not require a significant amount of computer time to calculate, which is particularly advantageous when dealing with large datasets. As a result, the high-low spread estimator is a useful tool for researchers who need to process large amounts of data quickly and efficiently.

Due to the limited number of studies directly examining the liquidity of cryptocurrencies, the following section attempts to present significant findings under three headings: volatility on cryptocurrency markets, liquidity on cryptocurrency markets, and volatility of liquidity on cryptocurrency markets.

■ Volatility of Cryptocurrency Markets

In recent times, there has been an unprecedented surge in research dedicated to exploring various dimensions of cryptocurrencies. Dyhrberg (2016a) investigates the financial asset characteristics of BTC using GARCH models. According to the created models, BTC exhibits several similar features to gold and the dollar in terms of hedging risk and serving as a medium of

exchange. When examining the volatility of BTC, it can be accepted that it changes over time and remains valid in the long term. Examining the daily return series of BTC and the S&P 500 index, Baek and Elbeck (2015) state that the BTC market has 26 times more volatility compared to the S&P 500, and also characterise BTC as speculative.

One notable area of focus is the examination of cryptocurrencies as financial assets, with Corbet et al. (2019) making significant strides in this domain. They delve into the intricacies of the role of cryptocurrency as a financial asset, shedding light on its unique characteristics and behaviour in the market. Additionally, Chu et al. (2019) have conducted a comprehensive investigation into the adaptive market hypothesis, focusing on the two largest cryptocurrencies. Their research uncovers compelling evidence that supports the notion of time-varying market efficiency. This finding has far-reaching implications, providing a deeper understanding of how cryptocurrency markets adapt and evolve over time. There is very extensive literature on the volatility of cryptocurrency markets, where price changes are very high compared to other financial markets (Dyhrberg, 2016b; Frascaroli & Pinto, 2016). The research, conducted by Katsiampa et al. (2019), uncovers the presence of an asymmetric volatility relationship in cryptocurrency markets. However, to facilitate a direct comparison between cryptocurrency and traditional stock markets, this study does not consider the possible asymmetric connection between liquidity volatility and expected stock returns. The findings provide valuable insights into the distinct characteristics of cryptocurrency markets but highlight the importance of further research to explore and understand the comparative behaviours of these two financial domains. Hansen et al. (2024) studied the volatility of the cryptocurrencies market from another perspective. They find that periodicity is important for the interpretation of changes in real-time measures of volatility and volume.

■ Liquidity on Cryptocurrency Markets

In two studies, Kim (2017) and Dyhrberg et al. (2018) have both concluded that the low transac-

tion costs associated with Bitcoin make it well-suited for retail trading. This is because the low transaction costs allow for smaller trades, which is particularly attractive for retail investors who do not typically make large trades. On the other hand, Loi (2018) conducted a study that compared the liquidity of Bitcoin with equities across different exchanges using several low-frequency liquidity proxies. The findings showed that liquidity varied between exchanges but was generally lower for Bitcoin when compared to equities. This means that it may be more difficult to buy and sell Bitcoin quickly and at a fair price due to lower levels of liquidity, particularly in comparison to more established traditional assets such as equities.

Brauneis et al. (2021) compare different measures of liquidity in cryptocurrency markets using transactions-based measures and benchmark measures derived from high-frequency order book data. The study considers four benchmark measures: the quoted and effective spread, the price impact, and the cost of a roundtrip trade. It evaluates the performance of the transactions-based measures across three dimensions. The findings suggest that no estimator performs well across all dimensions, but the Corwin and Schultz (2012) and Abdi and Rinaldo (2017) estimators best capture the time series variation in liquidity. The Amihud (2002) illiquidity ratio and the Kyle and Obizhaeva (2016) estimator perform best in the cross-sectional analysis and when estimating the level of execution costs.

Scharnowski's (2021) research demonstrates that bitcoin liquidity exhibits time-varying behaviour and reacts differently to upward and downward market movements. Specifically, liquidity tends to decrease on days characterised by negative returns and, to some extent, after days with particularly extreme returns. These findings shed light on the asymmetric nature of liquidity dynamics in the bitcoin market. In another study, Yue et al. (2021) contribute to the understanding of cryptocurrency liquidity by revealing its relative independence from other financial markets, such as equities and currencies. Notably, their study indicates that spread estimates in cryp-

tocurrencies show a positive correlation with measures of cryptocurrency volatility and trading activity. This highlights the significance of considering volatility and trading patterns when assessing liquidity in the cryptocurrency realm.

Thiery et al. (2023) conducted a study to examine the impact of the Russia-Ukraine conflict on cryptocurrency liquidity, specifically Bitcoin and Ethereum. They found that the war had a significant but temporary effect, with liquidity levels increasing in the first two days and then returning to pre-war levels. Interestingly, the response of BTC and ETH liquidity was not uniform, showing a decline after the event despite an initial surge in pre-event windows. In the medium term, spreads in BTC and ETH markets were not notably associated with the war event. However, higher liquidity in BTC was linked to increased trading activities and uncertainty triggered by the conflict.

Volatility of the Liquidity on the Cryptocurrencies Market

While there are studies examining the relationship between volatility and liquidity in the literature (Bedowska et al., 2021, Corbet et al., 2022), there is also one study directly investigating the volatility of liquidity. Said study examines the relationship between the volatility of liquidity and returns. Presenting evidence of a positive relationship between expected returns and the volatility of liquidity, Leirvik (2022) examines the idiosyncratic volatility of market liquidity and its effect on the returns of the top five cryptocurrencies by market capitalisation. The findings indicate that the correlation between liquidity volatility and returns is generally positive, but it varies significantly over time.

Methodology

A wide range of evaluating techniques with low or high-frequency data are used for modelling or forecasting the volatility in financial markets and commodity markets. Andersen and Bollerslev's (1998) study can be considered as a breakthrough in the sense that they develop a well-known volatility estimator. As a result of the

given study, volatility almost becomes an observable variable, straightforwardly modelled with standard time-series techniques.

Many researchers use GARCH models to generate volatility forecasts. Klaassen's (2002) study generalises the GSRCH model by distinguishing two regimes with different volatility levels to obtain more flexibility regarding volatility persistence. The resulting Markov regime-switching GARCH model improves on existing variants, for instance by making multi-period-ahead volatility forecasting a convenient recursive procedure (Klaassen, 2002). Based on the empirical results of this study it appears that the model resolves the problem with the high single-regime GARCH forecasts. It also yields significantly better out-of-sample volatility forecasts.

To achieve the desired results, our study utilised several types of Markov regime switching GARCH (MS-GARCH) models (Klaassen, 1999; Kim, 1993; Dueker, 1997) such as the threshold GARCH (TGARCH, Zakoian, 1994), the Glosten-Jagannathan-Runkle GARCH (GJR-GARCH, Glosten et al., 1993), and the exponential generalised autoregressive conditional heteroscedastic (EGARCH; Nelson, 1991). Firstly, Engle (1982) developed the autoregressive conditional heteroscedasticity model (ARCH) to estimate variances for financial assets. Bollerslev (1986) generalised this model as the generalised autoregressive conditional heteroskedasticity model (GARCH). GARCH-class models describe the features of financial time series beyond future volatility clusters (e.g., extreme plausibility and fat tails). In the GARCH models developed, the variance in error terms is affected both by their past values and the values of their conditional variance:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 \quad (1)$$

The main structure of MS-GARCH models, which analyse financial markets in terms of low volatility and high volatility, was created by Klaassen (1999). The studies from Kim (1993), Cai (1994), Hamilton and Susmel (1994), and Due-

ker (1997) also developed the constraints in MS-GARCH models.

In Markov regime switching (MRS) models the market is not directly observable, the time series variable can be observed, and the regime of the economy (s_t) can be obtained through probabilities (Hamilton, 1989). If the last state is known, the following state s_{t+1} can be estimated based on the probability of regime-switching (Bildirici et al., 2010). The MRS model has a time series process based on an unobservable regime variable (Krolzig, 2000). The regime-generating process is an ergodic Markov chain (Krolzig, 2000) where $p_{ij} = \Pr(s_{t+1} = j | s_t = i)$; $\sum_{j=1}^m P_{ij} = 1$; $i, j = \{1, \dots, m\}$, and s_t follows an ergodic M -state Markov process with an irreducible transition matrix:

$$P = \begin{bmatrix} p_{11} & \dots & p_{1m} \\ \dots & \dots & \dots \\ p_{m1} & \dots & p_{mm} \end{bmatrix} \quad (2)$$

A standard MS-GARCH model has a conditional mean, a conditional variance, a regime process, and a conditional distribution.

$$r_t = \mu_t^{(i)} + \varepsilon_t = \delta^{(i)} + \varepsilon_t \quad (3)$$

In the formula above, $i = 1, 2$, $\varepsilon_t = \eta_t \sqrt{h_t}$ and η_t is the zero mean unit variance process. Knowing h_{t-1} is the regime independent mean of the past conditional variance, the conditional variance of GARCH(1,1) r_t can be expressed as:

MS-EGARCH (Ardia et al., 2019):

$$\ln(h_t^{(i)}) = \alpha_0^{(i)} + \alpha_1^{(i)} (|\varepsilon_{t-1}| - E[|\varepsilon_{t-1}|]) + \alpha_2^{(i)} \varepsilon_{t-1} + \beta_1^{(i)} \ln(h_{t-1}) \quad (4)$$

MS-GJR-GARCH (Ardia et al., 2019):

$$h_t^{(i)} = \alpha_0^{(i)} + \alpha_1^{(i)} \varepsilon_{t-1}^2 + \alpha_2^{(i)} \varepsilon_{t-1}^2 I\{\varepsilon_{t-1} < 0\} + \beta_1^{(i)} h_{t-1} \quad (5)$$

The MSGARCH models may be estimated with the normal distribution or the skewed version of the normal. Fernández and Steel (1998) introduce skewness into any unimodal standardised distribution; via the additional parameter $\xi > 0$; if $\xi = 1$ the distribution turns out to be symmetric. Trottier and Ardia (2016) derive the moments of the standardised Fernandez-Steel skewed dis-

tributions which are needed in the estimation of the EGARCH, GJR-GARCH, and TGARCH models.

Results

The first results of the study provide evidence that low and high volatility periods can be explained by different models such as MS EGARCH, MS TGARCH, and MS GJR-GARCH. Table 1 and Table 2 show the results of 8 models that fit the normal distribution, where we can describe the transitions of Bitcoin between low-volatility and high-volatility periods. As seen from the alpha and beta parameters, the sum of these values is higher in some regimes and lower in others. In 2-regime models (Model 1, 3, 5, and 7), regime 1 explains periods of low volatility in Bitcoin intraday returns, and periods with the high volatility of Bitcoin returns are represented by regime 2. In 3-regime models, it is difficult to decide which is the high volatility regime when the coefficients are examined. Results showed close coefficients. The results show that the 2-regime models are more successful and useful in distinguishing between low and high volatility regimes.

Based on the AIC and log likelihood statistics seen in Table 2, MS GARCH(2) (Model 1) and MS-GJR-GARCH(2) (Model 5) models appear to be the most successful models among the alternatives.

The second source of volatility persistence, the persistence of regimes, is given by switching probabilities by probabilities of staying in regime 1 and regime 2, respectively. It is important to demonstrate successful separation of regimes in MRS models. Although AIC log likelihood statistics helped us choose the most successful econometric models, if the probability of switching between regimes is very high and the probability of staying in the same regime is low, the regimes are not well separated. Models with a high probability of staying in the same regime have formulated the regimes more accurately. According to the results in Table 2, the probability of Bitcoin returns staying in a low volatility regime (p_{11}) is higher than 0.96 for models 1, 5, 6, and 7. In the related models, switching probability from a low volatility regime

Table 1. MS GARCH Models

		Model 1: MS GARCH (2) n.	Model 2 : MS GARCH (3) n.	Model 3: MS EGARCH (2) n.	Model 4: MS EGARCH (3) n.	Model 5: MS GJR GARCH (2) n.	Model 6: MS GJR GARCH (3) n.	Model 7: MS TGARCH (2) n.	Model 8: MS TGARCH (3) n.
Regime 1	Alpha 0	0.0005 (0.0000)	0.0000 (0.0000)	-1.9571 (0.0000)	1.5491 (0.0000)	0.0009 (0.0000)	0.0012 (0.0000)	0.0004 (0.0000)	0.0071 (0.0000)
	Alpha 1	0.1045 (0.0000)	0.0126 (0.0000)	2.0158 (0.0000)	3.3113 (0.0000)	0.1361 (0.0000)	0.5982 (0.0000)	0.0291 (0.0000)	0.2543 (0.0000)
	Alpha 2	0.0000 (0.0000)	0.0000 (0.0000)	0.8097 (0.0000)	-3.0064 (0.0000)	0.0865 (0.0000)	0.0047 (0.0000)	0.0095 (0.0000)	0.0076 (0.0000)
	Beta	0.7332 (0.0000)	0.9871 (0.0000)	0.4480 (0.0000)	0.8460 (0.0000)	0.5777 (0.0000)	0.3992 (0.0000)	0.9699 (0.0000)	0.7298 (0.0000)
	Xi								
Regime 2	Alpha 0	1.5028 (0.0000)	0.0000 (0.0000)	-1.5257 (0.0000)	1.5491 (0.0000)	0.8943 (0.0000)	0.0093 (0.0000)	18.2455 (0.0000)	0.0194 (0.0000)
	Alpha 1	0.0000 (0.0000)	0.0126 (0.0000)	1.7689 (0.0000)	3.3113 (0.0000)	0.0000 (0.0000)	0.0012 (0.0000)	0.0397 (0.0000)	0.1893 (0.0000)
	Alpha 2	0.0000 (0.0000)	0.0000 (0.0000)	0.9073 (0.0000)	-3.0064 (0.0000)	0.0003 (0.0000)	0.1024 (0.0000)	0.0064 (0.0000)	0.0081 (0.0000)
	Beta	0.0054 (0.0000)	0.9871 (0.0000)	0.1545 (0.1138)	0.8460 (0.0000)	0.1054 (0.0000)	0.9475 (0.0000)	0.9621 (0.0000)	0.7957 (0.0000)
	Xi								
Regime 3	Alpha 0		0.0009 (0.0000)		1.9302 (0.0000)		0.0514 (0.0000)		0.0196 (0.0000)
	Alpha 1		0.0043 (0.0000)		3.2242 (0.0000)		0.0011 (0.0000)		0.1886 (0.0000)
	Alpha 2		0.0000 (0.0000)		-2.7932 (0.0000)		0.0225 (0.0000)		0.0081 (0.0000)
	Beta		0.9956 (0.0000)		0.8102 (0.0000)		0.9874 (0.0000)		0.7963 (0.0000)
	Xi								

Source: Prepared by the author

to high volatility is lower than 0.04 (Models 1, 5, 6, and 7). Table 2 shows that the probability of switching from periods of high volatility to periods of low volatility for Model 1 (p_{21} : 0.8399), Model 2 (p_{21} : 0.9819), Model 5 (p_{21} : 0.9816), Model 6 (p_{21} : 0.9998), Model 7 (p_{21} : 0.7156) are expected to be higher than the probability of transition from low to high volatility.

Conclusion

The financial industry is currently undergoing a rapid wave of technological advancements, giving rise to the emergence of innovative products and accelerated services. This phenomenon is particularly pronounced in the realm of cryptocurrency markets, which operate ceaselessly around the clock. The ease of converting a finan-

Table 2. Regime Probabilities

		Model 1: MS GARCH (2) n.	Model 2 : MS GARCH (3) n.	Model 3: MS EGARCH (2) n.	Model 4: MS EGARCH (3) n.	Model 5: MS GJR GARCH (2) n.	Model 6: MS GJR GARCH (3) n.	Model 7: MS TGARCH (2) n.	Model 8: MS TGARCH (3) n.
Transition Possibilities	P11	0.9699	0.0180	0.5153	0.3364	0.9780	0.9797	0.9932	0.3279
	P12	0.0301	0.9819	0.4847	0.3471	0.0220	0.0169	0.0068	0.3582
	P13		0.0000		0.3165		0.0034		0.3139
	P21	0.8399	0.9819	0.5035	0.3471	0.9816	0.9998	0.7156	0.3241
	P22	0.1601	0.0180	0.4965	0.3364	0.0184	0.0002	0.2844	0.3517
	P23		0.2088		0.3365		0.0000		0.3241
	P31		0.0000		0.3346		0.9998		0.3139
	P32		0.0000		0.3346		0.0000		0.3582
	P33		0.5824		0.3307		0.0002		0.3279
Stable Properties	Regime 1	0.9654	0.5000	0.5095	0.3395	0.9781	0.9801	0.9906	0.3221
	Regime 2	0.0346	0.5000	0.4905	0.3395	0.0219	0.0166	0.0094	0.3559
	Regime 3		0.0000		0.3210		0.0033		0.3221
Information on Criteria	AIC	-127335.5526	-110979.3265	-56528.0073	-103219.9038	-128013.5138	-124788.1247	-124546.4152	-74202.0215
	Log likelihood	63675.7763	55504.6632	28274.0037	51627.9519	64016.7569	62412.0624	62283.2076	37119.0108

Source: Prepared by the author

cial instrument into cash, known as liquidity, is an important issue when analysing these markets.

The liquidity of financial markets involves examining the bid-ask spread of a financial instrument, a metric indicative of liquidity levels. Various factors such as market volatility, trading volume and regulatory changes can affect the

liquidity of an asset. For investors who want to buy or sell Bitcoin quickly and at a reasonable price, understanding the liquidity dynamics of the Bitcoin market is crucial.

While there is considerable research on the liquidity and volatility of cryptocurrencies, there is still a lack of investigation into the volatility

of cryptocurrency liquidity. This study aims to bridge this gap by employing a range of Markov switching GARCH models to scrutinise the intra-day volatility of Bitcoin liquidity during periods characterised by both low and high volatility.

The analyses focus on bid-ask spread data at 5-minute intervals, employing a range of MSGARCH models with varying numbers of regimes. The findings suggest that different models such as MS EGARCH, MS TGARCH, and MS GJRGARCH can explain low and high volatility periods. It has been concluded that among the models constructed with 2 and 3 regimes, the two-regime MSGARCH and MS GJR GARCH models are the best models for explaining low and high volatility periods of Bitcoin liquidity.

This study provides important findings for investors, markets, professionals and regulators. As regulators increasingly focus on understanding and regulating cryptocurrency markets, volatility in liquidity raises concerns about market integrity, investor protection and systemic risks. Research findings are also valuable for policymakers as they reveal the importance of the issue.

Volatile liquidity may indicate periods of inefficiency. Where prices deviate from their fundamental values due to liquidity shocks, the fundamental value of cryptocurrencies is also a controversial topic. Analysing the volatility of liquidity helps policymakers and market participants identify potential sources of instability. Studying how liquidity fluctuates over time can help researchers gain a better understanding of the underlying mechanism in Bitcoin markets. Understanding liquidity dynamics is also crucial for designing trading strategies in this high-volatility market.

Moreover, the different types of MS-GARCH models present a strong framework for modelling and analysing financial time series data, particularly environments characterised by regime-switching behaviour. MS-GARCH models improve the accuracy of volatility forecasts compared to traditional GARCH models. Accurate volatility forecasts done by MS-GARCH models are essential for estimating value at risk (VaR) and other risk metrics for risk management purposes.

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