**Asymmetric volatility in the cryptocurrency market: new evidence from models with structural breaks**

**Abstract**

Previous literature shows that major cryptocurrencies exhibit inverse asymmetric volatility: positive shocks increase price volatility more than negative ones. In this study, we revisit the asymmetric volatility dynamics of major cryptocurrencies using asymmetric GARCH models that incorporate endogenously detected structural breaks. Our results show that, after incorporating structural breaks, volatility persistence decreases, and asymmetric volatility increases for all cryptocurrencies in this study. Thus, prior research that ignores structural breaks underestimates the impact of unexpected news on price volatility in cryptocurrency markets. We also present an important economic implication of our results: ignoring structural breaks adversely impacts the hedging strategies, derivatives valuations, and risk exposure of investors in cryptocurrency markets.

**Keywords:** Cryptocurrencies,Asymmetric volatility, Volatility persistence, Structural breaks.

**JEL Codes:** G10, G11, G12, G14

1. **Introduction**

Understanding the volatility behavior of cryptocurrencies is important because it affects the risk exposure of investors and other financial market participants. Cryptocurrencies are inherently volatile assets, and recent evidence shows that volatility in cryptocurrency markets is transmitted to other financial markets and the overall economy (Uzonwanne, 2021). The valuation of many derivative securities also depends on underlying volatility behavior in cryptocurrency markets. Therefore, understanding the volatility dynamics of cryptocurrencies is important for investment, hedging strategies, derivative valuation, and public and private policy-making in financial markets. The recent rise in the popularity of cryptocurrencies has led to an increase in the volume of literature concerned with analyzing the volatility properties of popular cryptocurrencies and the similarities between price volatility in cryptocurrencies and other financial assets (Ardia et al., 2019; Abakah et al., 2020; Shen et al., 2020).

In this study, our goal is to examine the asymmetric volatility dynamics of major cryptocurrencies by using the asymmetric GARCH models that incorporate endogenously-detected structural breaks. In the literature, we find strong evidence of asymmetric behavior: for example, the way that negative news impacts conditional volatility more than positive news in the equity market (see Black, 1976; Christie, 1982; Bekaert and Wu, 2000, for example) and energy sector (Ewing and Malik, 2017). The authors of several recent studies have attempted to understand the asymmetric volatility dynamics of major cryptocurrencies by using asymmetric GARCH models and reported an inverted asymmetric behavior. In other words, positive news impacts conditional volatility more than negative news (see Bouri, Azzi, and Dyhrberg, 2017; Baur and Dimpfl, 2018; Cheikh, Zaied, and Chevallier, 2020). However, none of these studies considered incorporating endogenously-deducted structural breaks to examine the asymmetric behavior of popular cryptocurrencies. According to Ewing and Malik (2017), studies that unintentionally ignore structural breaks may underestimate the impact of unanticipated news on the volatility-generating process of the underlying asset. In this study, we fill the gap in the literature by estimating the asymmetric volatility behavior for popular cryptocurrencies by incorporating endogenously-detected structural breaks into asymmetric GARCH models. In doing so, we correctly estimate the impact of unexpected news on the cryptocurrency volatility-generating process.

We examine the asymmetric volatility behavior of five popular cryptocurrencies: Bitcoin, Ethereum, Dogecoin, Ripple (XRP), and Monero. The modified iterative sums of squares (ICSS) algorithm of Inclan and Tiao (1994) is employed to endogenously deduct the structural breaks in the unconditional variance of cryptocurrencies. We incorporate the detected structural breaks into asymmetric GARCH models to more accurately model the impact of unexpected news on the volatility of cryptocurrencies. There are some interesting results. First, we find that volatility persistence in cryptocurrencies decreases after incorporating structural breaks into asymmetric GARCH models. More importantly, our results indicate that, after accounting for structural breaks in asymmetric GARCH models, the asymmetric behavior of all the cryptocurrencies we consider increases, as indicated by an increase in the value of the asymmetric term. Our results indicate that to understand how new information affects price volatility in cryptocurrency markets, it is important to include both asymmetric effects and structural breaks in GARCH models.

The remainder of the paper is organized as follows. In section 2, we provide a brief review of related literature. In section 3, we describe the data. In section 4, we discuss the empirical models used. In section 5, we present the empirical results. In section 6, we present some economic implications of our study, and section 7 concludes the paper.

1. **Literature Review**

Volatility in cryptocurrency markets has important implications for the risk exposure of investors in financial markets, and the volatility dynamics of cryptocurrencies are gaining increasing attention from scholars. Uzonwanne (2021) studies the return and volatility spillover between Bitcoin and several major stock markets and finds a unidirectional and bidirectional return and volatility spillover between these pairs. In a similar study, Cao and Xie (2022) examine asymmetric volatility transmission between the Chinese financial and cryptocurrency markets. The authors find that the cryptocurrency market dominated by Bitcoin, Ethereum, and Ripple significantly impacts the Chinese financial market. Exploring the dynamic volatility connectedness between major cryptocurrencies and the market for thermal coal futures in China, Pham, Nguyen, and Do (2022) find that China’s thermal coal futures significantly depend on volatility in cryptocurrency markets. Dyhrberg (2016) attempts to investigate the effectiveness of Bitcoin as a hedge against movements in the FTSE index and the US dollar and finds that it is a good hedge for the FTSE index but only a good hedge for the US dollar in the short term. Conon and McGee (2020) examine the safe haven properties of Bitcoin during the COVID-19 pandemic and find that it is not a suitable safe haven against movements in the S&P 500.[[1]](#footnote-1)

The ARCH and GARCH models of Engle (1982) and Bollerslev (1986) are normally utilized in financial time series literature to determine time-varying volatility. A general assumption with GARCH models is that the unconditional variance of the underlying asset returns is constant, and volatility is generated by a stable GARCH process. However, due to political, economic, and social events, financial markets are prone to sudden changes in volatility (also known as structural breaks). These sudden changes in the unconditional variance of asset returns create structural breaks in the GARCH process. Lamoureux and Lastrapes (1990) find that volatility persistence is overestimated when they apply a standard GARCH model to a series where there are structural breaks in the variance of the return series. With the help of theoretical and empirical exercises, Mikosch and Starica (2004) report that not incorporating structural breaks within a GARCH model also overestimates the volatility persistence. Therefore, if structural breaks are present in the unconditional variance of a given asset, these breakpoints should be properly incorporated into the GARCH model to accurately examine the volatility dynamics of the underlying asset.

Some studies incorporate structural breaks into GARCH models to study volatility in cryptocurrency markets. Bouri et al. (2019) uncovered evidence of mean reversion after incorporating structural breaks to study the volatility persistence of Bitcoin. The evidence of mean reversion was lacking when structural breaks were not incorporated into the underlying models. Abakah et al. (2020) also explore the volatility persistence of 12 major cryptocurrencies by considering the possibility of structural breaks and find that the degree of apparent volatility persistence in the cryptocurrency market decreases if the structural breaks are accounted for correctly. In a similar study, Mensi, Al-Yahyaee, and Kang (2019) examine the interplay of structural breaks and dual memory levels of Bitcoin and Ethereum by utilizing GARCH family models. The authors find that apparent volatility persistence decreases after accounting for structural breaks, and the model that accurately incorporates structural breaks provides superior forecasting performance. Shen, Urquhart, and Wang (2020) also find evidence that heterogeneous autoregressive (HAR) models that incorporate structural breaks provide superior forecasting compared to other models without structural breaks. However, none of these studies have considered analyzing the asymmetric dynamics of the cryptocurrency market by considering the possibility of structural breaks.

Surprisingly, we find only a few studies examining asymmetric volatility in cryptocurrency markets. Bouri, Azzi, and Dyhrberg (2017) study the Bitcoin return-volatility relation around the 2013 crash using the GJR-GARCH and Exponential-GARCH models. For the entire period under study (pre- and post-crash) and during the post-crash period, the authors find no asymmetric behavior for Bitcoin. However, for the pre-crash period, the authors find significant inverse asymmetric volatility for Bitcoin and suggest that, before the 2013 crash, Bitcoin exhibited safe haven properties similar to gold. Baur and Dimpfl (2018) also examine asymmetric volatility dynamics for several cryptocurrencies using GJR-GARCH and quantile-based asymmetric models. In general, the authors find evidence of inverse asymmetric behavior for major cryptocurrencies. However, the authors note that Bitcoin and Ethereum exhibit positive asymmetric behavior similar to equities. The authors attribute the inverted asymmetric behavior of many cryptocurrencies (except for Bitcoin and Ethereum) to the herding behavior of uninformed investors. Cheikh, Zaied, and Chevallier (2020) further explore the asymmetric volatility dynamics of Bitcoin, Ethereum, Ripple (XRP), and Litecoin by utilizing a battery of symmetric and asymmetric GARCH models. The authors provide evidence of inverse asymmetric volatility[[2]](#footnote-2) for all cryptocurrencies except Ethereum and highlight the safe haven properties of major cryptocurrencies.

Interestingly, we do not find any study in the literature that explores the asymmetric volatility dynamics for cryptocurrency markets by considering GARCH models that account for structural breaks. This study fills the gap in the literature by studying the asymmetric volatility of major cryptocurrencies by accurately accounting for structural breaks within the framework of popular asymmetric GARCH models. First, we contribute to the existing literature on cryptocurrencies that explores the volatility dynamics, especially the asymmetric volatility of major cryptocurrencies. The results of this study enable us to estimate the real impact of positive and negative news on the volatility dynamics of cryptocurrency markets. Second, in the current stressful environment for cryptocurrency markets, this study makes a timely contribution to the debate on whether major cryptocurrencies can be considered a hedge or safe haven for conventional asset classes.

1. **Empirical Methodology**

**3.1 GARCH model**

To study the volatility persistence of cryptocurrencies, we use the benchmark GARCH(1,1) model, defined as

$R\_{t} = μ+ ρR\_{t-1}+ε\_{t}$ (1)

$h\_{t} = ω+ α ε\_{t-1}^{2}+βh\_{t-1}$ (2)

where $R\_{t}$ represents the cryptocurrency return at time *t* and $ε\_{t}$ is normally distributed with a mean equal to zero. In equation 2, the conditional variance ($h\_{t}$) depends on the average volatility level ($ω$) and last period’s news ($ε\_{t-1}^{2}$) and variance ($h\_{t-1}$). For a given shock, the sum of $α $and $β$ measures volatility persistence.

**3.2 GJR-GARCH model**

To examine the asymmetric behavior, we utilize the GJR-GARCH model given by Glosten et al. (1993), which is defined as

$R\_{t} = μ+ ρR\_{t-1}+ε\_{t}$ (3)

$h\_{t} = ω+ α ε\_{t-1}^{2}+γε\_{t-1}^{2}d\_{t-1}+βh\_{t-1}$ (4)

where the ($ε\_{t-1}^{2}d\_{t-1}$) is the asymmetric component and the parameter $d\_{t}$ takes the value of 1 if $ε\_{t}$ < 0 (bad news) and 0 otherwise. In this model, $α$ represents the impact of good news (positive error) and $α+ γ$ represents the impact of bad news. More importantly, the impact of news on volatility is asymmetric if and only if $γ$ is statistically significant and different from zero. In the GJR-GARCH model, the volatility persistence is given by $α+\left(\frac{1}{2}\right)γ+β$.

**3.3 EGARCH model**

To further examine the asymmetric behavior of volatility, we also utilize the EGARCH model given by Nelson (1991), which is defined as

$R\_{t} = μ+ ρR\_{t-1}+ε\_{t}$ (5)

$log⁡(h\_{t}) = ω+ α\left| ε\_{t-1}\right|/\sqrt{h\_{t-1}}+γε\_{t-1}/\sqrt{h\_{t-1}}+βlog⁡(h\_{t-1})$ (6)

where the value of α represents the size impact of news. A statistically significant value of α indicates that the magnitude of news or shocks has an impact on the volatility-generating process. The coefficient γ represents the sign effect and, in a similar way to the GJR-GARCH model, the impact of news on volatility is asymmetric if and only if $γ$ is statistically significant and different from zero. Good news has an impact of $α+ γ$ and bad news has an impact of $α- γ.$ Finally, the volatility persistence for a given shock for the EGARCH model is given by β.

**3.4 Detecting and incorporating structural breaks**

In this study, we use the Inclan and Tiao (1994) modified iterative cumulative sums of squares (ICSS) algorithm for testing multiple breaks in the unconditional variance of the returns on major cryptocurrency at the 5% significance level.[[3]](#footnote-3) By following Aggarwal et al. (1999) and Ewing and Malik (2010), we incorporate structural breaks in the GARCH model as

$R\_{t} = μ+ ρR\_{t-1}+ε\_{t}$ (7)

$h\_{t} = ω+d\_{1}D\_{1}+…+d\_{n}D\_{n}+αε\_{t-1}^{2}+βh\_{t-1}$ (8)

where $D\_{1}+…+D\_{n}$ are the dummy variables that take the value of 1 when the breakpoint in the variance is detected and zero elsewhere. We incorporate structural breaks into asymmetric GARCH models in a similar way.

1. **Data**

We obtained daily data for the following cryptocurrencies from CoinMarketCap.com: Bitcoin, Ethereum, Dogecoin, Ripple (XPR), and Monero. The sample period selected for this study starts from the date when these cryptocurrencies began to be displayed on CoinMarketCap.com and ends on April 30, 2022. We selected these cryptocurrencies for the following reasons: 1) Many recent studies have used these cryptocurrencies for analysis (see Baur and Dimpfl, 2018; Abakah et al., 2020; Cao and Xie, 2022, for example); 2) All selected cryptocurrencies have a market capitalization that is greater than the average market capitalization of the cryptocurrency market on April 30, 2022; 3) To ensure that the selected cryptocurrencies are well representative of the cryptocurrency market, the selected series were within the top 20 cryptocurrencies by market capitalization as of April 30, 2022. Consistent with earlier studies, we use the returns for the selected cryptocurrencies to make the data stationary.

Figure 1 shows the price evolution of all cryptocurrencies included in this study. Table 1 provides the descriptive statistics for the cryptocurrencies utilized in this study. All cryptocurrencies exhibit positive average returns and high standard deviation, which can be attributed to the highly-volatile nature of the crypto asset class. All series display high kurtosis except for Bitcoin, and all other cryptocurrencies are positively skewed. We use the Jarque-Bera test to determine whether the series are normally distributed, and we reject the normality assumption at a 1% significance level. Finally, the last row of Table 1 shows the number of observations available for all cryptocurrencies in this study. We find that Bitcoin has the highest number of daily observations and Ethereum has the lowest.

1. **Empirical results**

In this section, we discuss the results from a symmetric GARCH(1,1) model with and without structural breaks to examine volatility persistence in cryptocurrencies, followed by an analysis of asymmetric volatility using asymmetric GARCH models.

**5.1. GARCH(1,1) and volatility persistence in cryptocurrencies**

Although the objective of this study is to examine the asymmetric volatility behavior of cryptocurrencies under structural breaks, we begin our analysis with a symmetric GARCH(1,1) with and without incorporating structural breaks and reconcile the results of this exercise with existing literature on the prices of other asset classes and commodities such as stocks, crude oil, and currency exchange rates. We employed the modified iterative cumulative sums of squares (ICSS) algorithm to identify the structural breaks in returns on cryptocurrencies. The detected breakpoints are presented in Table 2. The modified ICSS algorithm identified 7 or 8 breakpoints for the cryptocurrencies in our sample, which implies that these currencies are highly volatile.

In Table 3, we provide the results of the GARCH(1,1) model for all cryptocurrencies in this study. To examine the effect of structural breaks on the volatility dynamics of cryptocurrencies, we incorporate the identified structural breaks into the unconditional variance of the model as described in equation 8. The overall results in Table 3 show that when we incorporate the structural breaks in the model, the volatility persistence and the half-life of the shocks are lower than when structural breaks are ignored. For example, in panel 3.A. for Bitcoin, we find that when the structural breaks are ignored, the volatility persistence (α+β) is 0.969, and the half-life of the shock is 22.52 days. However, if structural breaks are accounted for in the model, the volatility persistence and half-life of the shock decline substantially, to 0.803 and 3.15 days, respectively. We also find that the log-likelihood statistic increases if the structural breaks are incorporated, which shows that incorporating the breakpoints improves the model. Moreover, the reduction in skewness, kurtosis, and Jarque-Bera statistics also indicate that the model that accounts for breakpoints is a better fit. We find similar results for almost all the cryptocurrencies in this study, as displayed in panels 3.B. to 3.F. of Table 3. The results of this analysis are consistent with the results of similar studies for cryptocurrencies (Abakah et al., 2020), stock market indices (Hood and Malik, 2018; Baig et al., 2022), oil prices (Ewing and Malik, 2017), and exchange rates (Anjum and Malik, 2020).

**5.2. Asymmetric GARCH models and asymmetric volatility dynamics in cryptocurrencies**

After establishing that incorporating structural breaks in GARCH(1,1) model changes the volatility dynamics (i.e., decreases volatility persistence and the half-life of shocks) for all cryptocurrencies in this study, we turn our attention to examining the asymmetric volatility dynamics of cryptocurrencies using asymmetric GARCH models that incorporate structural breaks. To do so, we utilize GJR-GARCH and EGARCH models. As we stressed in section 3, the asymmetric term (γ) is our variable of interest, and a statistically significant value of γ means that a cryptocurrency exhibits asymmetric volatility behavior. We provide the results of this analysis in Tables 4 to 8. In general, we find that, for GJR-GARCH and EGARCH models, the coefficient of the asymmetric term is statistically significant for all cryptocurrencies in our sample except for Ethereum.[[4]](#footnote-4) The result implies that these cryptocurrencies exhibit asymmetric volatility behavior, which indicates that the impact of good and bad news on volatility is significantly different. More importantly, when we incorporate structural breaks into asymmetric GARCH models using the dummy variables discussed in subsection 3.5, we find that the asymmetric term (γ) increases significantly. For example, the results of the model for Bitcoin without (with) structural breaks are provided in Panel A (B) of Table 4. In the GJR-GARCH model, we see that the asymmetric term (γ) is 0.0376 when the breakpoints are ignored, but increases to 0.1083 when the breakpoints are correctly accounted for: a three-fold increase. Similarly, for the EGARCH model, the asymmetric term (γ) increases from 0.0310 to 0.0475 when structural breaks are incorporated, ignoring the negative sign that shows that bad news impacts volatility more than good news.[[5]](#footnote-5) Our results suggest that the asymmetric impact of news on the volatility-generating process is larger when structural breaks are correctly incorporated into asymmetric GARCH models.

The results of the asymmetric analysis for Ethereum are given in Table 5. As discussed earlier, the asymmetric term (γ) is insignificant for Ethereum when structural breaks are not incorporated in the asymmetric GARCH models. These results are consistent with the results we find in previous studies (Baur and Dimpfl, 2018; Cheikh, Zaied, and Chevallier, 2020, for example). As we incorporate structural breaks in asymmetric GARCH models, we find that the asymmetric term (γ) increases but is significant only for the EGARCH model and remains insignificant for the GJR-GARCH model. Cheikh, Zaied, and Chevallier (2020) argue that Ethereum is a relatively new cryptocurrency, and the short period since its introduction might not be sufficient to clearly exhibit asymmetric volatility behavior. However, the results for Ethereum do indicate that asymmetric behavior increases after accounting for the breakpoints. Similar to Bitcoin, other cryptocurrencies in this study (i.e., Dogecoin, Ripple (XRP), and Monero) exhibit strong asymmetric volatility behaviors measured by the GJR-GARCH and EGARCH models (see Tables 6 – 8). For Dogecoin, in Table 6, we report that the coefficient γ for GJR-GARCH (EGARCH) is 0.0436 (0.0622), and the value of the coefficient increases to 0.1411 (0.1040) after incorporating breaks in asymmetric GARCH models. Likewise, in Table 7 for Ripple (XRP), we find that the asymmetric term (γ) not only increases after incorporating structural breaks but also becomes statistically more significant. Finally, in Table 8, Monero exhibits the same asymmetric behaviors as other cryptocurrencies, and the asymmetric term (γ) increases when structural breaks are accounted for. This evidence further suggests that previous studies, which ignored breakpoints when estimating the asymmetric volatility dynamics for cryptocurrencies, may have underestimated the actual impact of news on the volatility-generating process (Ewing and Malik, 2017).

The following observations further support the importance of taking structural breaks into consideration. Similarly to the GARCH(1,1) analysis, the volatility persistence for GJR-GARCH and EGARCH models decreases as we consider the structural breaks. The results for the half-life of shocks suggest that their impact within the models dissipates more quickly when structural breaks are properly accounted for than when we ignore structural breaks. In Table 4, we find that the volatility persistence (half-life of shocks) for the GJR-GARCH model decreases from 0.968 (21.31) days to 0.848 (4.22) days. We find consistent results for all cryptocurrencies in this study. We also find the likelihood ratio (LR) statistic supports the importance of considering structural breaks. The LR statistic is calculated as $LR=2\left[L\left(θ\_{1}\right)- L\left(θ\_{0}\right)\right]$, where $L\left(θ\_{1}\right)$ and $L\left(θ\_{0}\right)$ are the maximum log-likelihood statistics obtained from the asymmetric GARCH model with and without incorporating structural breaks, respectively. For asymmetric GARCH models and all cryptocurrencies, we reject the null hypothesis (H0) of no change at a 1% significance level. Also, standardized residuals of both asymmetric GARCH models have skewness and kurtosis for all cryptocurrencies but skewness and kurtosis decrease as we account for structural breaks in these models. Finally, we employed the Jarque-Bera test to investigate whether the standardized residuals are normally distributed. The results generally show that for all cryptocurrencies the standardized residuals are not normally distributed, but they become relatively closer to normal distribution once structural breaks are accounted for.

1. **Economic implications**

The results of this study suggest that incorporating structural breaks significantly alters the underlying asymmetric volatility dynamics of cryptocurrencies, which has valuable economic implications. Anderson et al. (2006) provide evidence that the volatility forecast estimated by the asymmetric GARCH models depends considerably on the asymmetric term (γ), which determines how good and bad news impacts volatility. Our results indicate that the value of the asymmetric term changes significantly after incorporating structural breaks. In other words, after announcements of major good or bad news, forecasted market volatility produced by the asymmetric GARCH models will differ dramatically depending on whether structural breaks are accounted for. Furthermore, we find several studies that employ Value-at-Risk to estimate downside risk in cryptocurrencies (see, Stavroyiannis, 2018; Ardia et al., 2019, among others). Value-at-Risk forecasts depend on a volatility-generating process, which in turn depends on whether the structural breaks are incorporated into the model. Therefore, the Value-at-Risk forecast is indirectly impacted by the treatment of structural breaks: ignoring structural breaks will produce erroneous forecasts.

We find mixed evidence in the existing literature on whether cryptocurrencies exhibit hedging and safe haven abilities. For example, Dyhrberg (2016) and Cheikh et al. (2020) support this hypothesis, while Eisl et al. (2015), Bouri et al. (2017), Cai et al. (2022), and Iqbal et al. (2022) reveal Bitcoin as a weak hedge and safe haven against conventional commodities and suggest that it is a more suitable diversifier. By using various asymmetric GARCH models for major cryptocurrencies, Cheikh et al. (2020) reveal inverse asymmetric volatility behavior and support the safe haven and hedging properties of digital currencies. They conclude that cryptocurrencies exhibit asymmetric volatility behavior because the coefficient of the asymmetric term in asymmetric GJR-GARCH models is negative. Baur and Dimpfl (2018) attribute the inverse asymmetric behavior in cryptocurrencies to herding behavior by uninformed noise traders. In this study, the coefficient of the asymmetric term (γ) for the two largest cryptocurrencies, Bitcoin and Ethereum, is positive (negative) for the GJR-GARCH (EGARCH) model, negating the evidence of inverse asymmetric volatility behavior. However, for Dogecoin, Ripple, and Monero, we also find inverse asymmetric behavior as the asymmetric term (γ) is negative (positive) for the GJR-GARCH (EGARCH) model. Our results are consistent with those of Baur and Dimpfl (2018), who also find that Bitcoin and Ethereum do not show evidence of inverse asymmetric volatility behavior, while the other cryptocurrencies do. Therefore, in line with Baur and Dimpfl (2018), we carefully conclude that, unlike other cryptocurrencies, Bitcoin and Ethereum do not exhibit inverse asymmetric volatility behavior; therefore, they cannot be used as hedging or safe haven assets. The contrarian behavior of Bitcoin and Ethereum can be attributed to the following factors. Bitcoin and Ethereum are the largest cryptocurrencies, with almost 40% and 20% market cap, respectively. Bitcoin and Ethereum are the only cryptocurrencies on which futures contracts are traded, which may increase their market efficiency (Blau and Whitby, 2019). Unlike other cryptocurrencies, Bitcoin and Ethereum are not subject to herding behavior and are not dominated by uninformed investors (Baur and Dimpfl, 2018).

Stein (1987) provides a theoretical framework in which introducing derivative contracts such as options and futures destabilizes the prices of the underlying assets. Blau and Whitby (2019) provide empirical evidence that, after the introduction of Bitcoin futures in 2018, Bitcoin volatility increased significantly. The pricing of derivative contacts depends not only on the estimated volatility forecast but also on how persistent the volatility is over time (Duan, 1995). We use the GJR-GARCH specification for Bitcoin and construct a news impact curve in Figure 2. Figure 2 shows that after significant (good or bad) news in the market, a difference in the forecasted volatility produced by two models (with and without the breakpoints) will lead to a considerable difference in the option pricing. Our results provide important implications for derivative contract pricing for Bitcoin and other cryptocurrencies, especially given the recent turbulence in cryptocurrency markets.

1. **Conclusion**

In this study, we endogenously detect structural breaks in the returns of major cryptocurrencies by using the modified ICSS algorithm and incorporate these breakpoints into various symmetric and asymmetric GARCH models to examine the volatility persistence and asymmetric volatility dynamics of Bitcoin, Ethereum, Dogecoin, Ripple (XRP), and Monero. Interestingly, we find that volatility persistence decreases when we incorporate structural breaks into our models, and the actual impact of unexpected news increases for all cryptocurrencies in our study. We argue that previous studies, which examine asymmetric volatility behavior in cryptocurrency markets without taking structural breaks into account, have underestimated the actual impact of unexpected news. Since the valuation of derivative securities and the hedging capabilities of cryptocurrencies also depend on the underlying volatility dynamics, we argue that structural breaks should be considered to accurately evaluate the volatility dynamics of cryptocurrencies. This study also makes a timely contribution to the understanding of investors and market participants, as financial markets experience unprecedented volatility due to the rising interest rate environment and adverse geopolitical events. Like those of conventional asset classes, cryptocurrency market returns have plummeted, and investors are looking for hedging strategies to cover their tail risks. Our study highlights the methods that can accurately capture the volatility dynamics of cryptocurrency markets so that investors can navigate these stressful market conditions.

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**Table 1**

**Descriptive Statistics**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Bitcoin(btc) | Ethereum (eth) | Dogecoin(doge) | Ripple(xrp) | Monero(xmr) |
| Mean  | 0.001917 | 0.003198 | 0.001030 | 0.001297 | 0.001518 |
| Std. Dev. | 0.037546 | 0.054181 | 0.061472 | 0.058676 | 0.058082 |
| Maximum  | 0.115945 | 0.173440 | 0.241771 | 0.240984 | 0.177092 |
| Minimum  | -0.121197 | -0.163096 | -0.189006 | -0.180906 | -0.162481 |
| Skewness  | -0.145358 | 0.152748 | 0.768958 | 0.736085 | 0.126094 |
| Kurtosis  | 5.050624 | 4.725627 | 6.822885 | 7.086718 | 4.186702 |
| Jarque-Bera | 587.1358(0.00) | 313.7659(0.00) | 2150.754(0.00) | 2500.082(0.00) | 177.1752(0.00) |
| Observations | 3285 | 2452 | 3040 | 3180 | 2889 |

**Notes:** Descriptive statistics for all cryptocurrencies in our sample. Bitcoin has the highest number of daily observations while Ethereum has the lowest number of daily observations. The Jarque-Bera test rejects the normality hypothesis for all cryptocurrencies in this study.

**Table 2**

**Structural breaks using ICSS algorithms**

|  |  |  |
| --- | --- | --- |
| **Series**  | **No. of breaks** | **Break dates** |
| Bitcoin (btc) | 8 | 11/4/2013; 12/19/2013; 4/17/2014; 5/7/2017; 2/6/2018; 6/17/2020; 12/15/2020; 6/27/2021. |
| Ethereum (eth) | 8 | 11/23/2016; 1/21/2017; 4/26/2017; 9/23/2017;2/14/2018; 7/18/2019; 1/11/2021; 7/23/2021. |
| Dogecoin (doge) | 7 | 10/6/2014; 1/28/2015; 3/23/2017; 2/6/2018;8/29/2018; 12/19/2020; 5/24/2021.  |
| Ripple (xrp) | 8 | 12/19/2013; 1/15/2015; 3/22/2017; 12/11/2017;4/29/2018; 6/13/2020, 11/20/2020; 9/23/2021.  |
| Monero (xmr) | 7 | 12/22/2014; 8/5/2015; 8/21/2016; 3/14/2018;6/25/2019; 1/2/2020; 3/24/2020. |

**Notes:** We endogenously detect structural breaks by using a modified ICSS algorithm. The results show that all cryptocurrencies are very volatile.

**Table 3**

**Estimation results for symmetric GARCH(1,1) model**

|  |
| --- |
| **3.A. Bitcoin (btc)** |
| Model | ω | α | β | α+β | Half-life (days) | Log likelihood | Skewness | Kurtosis | Jarque-Bera |
| Breaks Ignored | 7.05E-05(0.00) | 0.1262(0.00) | 0.8435(0.00) | 0.969 | 22.52 | 6125.376 | -0.9218 | 15.326 | 21257.5(0.00) |
| Breaks accounted for | 0.0001(0.00) | 0.1131(0.00) | 0.6899(0.00) | 0.803 | 3.15 | 6134.484 | -0.6984 | 11.256 | 9594.5(0.00) |
| **3.B. Ethereum (eth)** |
| Model | ω | α | β | α+β | Half-life (days) | Log likelihood | Skewness | Kurtosis | Jarque-Bera |
| Breaks Ignored | 0.0002(0.00) | 0.1561(0.00) | 0.7793(0.00) | 0.935 | 10.38 | 3697.089 | -0.3401 | 8.613 | 3265.646(0.00) |
| Breaks accounted for | 0.0002(0.00) | 0.1601(0.00) | 0.7499(0.00) | 0.910 | 7.35 | 3717.264 | -0.3962 | 8.738 | 3427.254(0.00) |
| **3.C. Dogecoin (doge)** |
| Model | ω | α | β | α+β | Half-life (days) | Log likelihood | Skewness | Kurtosis | Jarque-Bera |
| Breaks Ignored | 0.0001(0.00) | 0.1764(0.00) | 0.8093(0.00) | 0.985 | 48.12 | 4729.147 | 0.9554 | 9.051 | 5099.8(0.00) |
| Breaks accounted for | 0.0013(0.00) | 0.2119(0.00) | 0.6360(0.00) | 0.847 | 4.20 | 4827.078 | 0.7952 | 8.374 | 3977.7(0.00) |
| **3.D. Ripple (xrp)**  |
| Model | ω | α | β | α+β | Half-life (days) | Log likelihood | Skewness | Kurtosis | Jarque-Bera |
| Breaks Ignored | 0.0003(0.00) | 0.2915(0.00) | 0.6442(0.00) | 0.935 | 10.42 | 4872.360 | 0.6643 | 11.051 | 8821.5(0.00) |
| Breaks accounted for | 0.0041(0.00) | 0.2875(0.00) | 0.3900(0.00) | 0.677 | 1.78 | 4993.877 | 0.7337 | 10.671 | 8080.9(0.00) |
| **3.F. Monero (xmr)** |
| Model | ω | α | β | α+β | Half-life (days) | Log likelihood | Skewness | Kurtosis | Jarque-Bera |
| Breaks Ignored | 0.0001(0.00) | 0.0977(0.00) | 0.8521(0.00) | 0.949 | 13.45 | 4690.968 | 0.0503 | 2.929 | 1.8161(0.40) |
| Breaks accounted for | 0.0003(0.00) | 0.0974(0.00) | 0.8254(0.00) | 0.922 | 8.63 | 4698.539 | 0.0268 | 2.916 | 1.1881(0.55) |

**Notes:** Volatility persistence is calculated as (α + β). We calculate the half-life of the shock by using the following expression: (α+β)j = ½. We find p-values given in the parenthesis by using the methodology from Bollerslev and Wooldridge (1992). We also use standard residuals from the estimated models (with and without structural breaks) to find the values of Skewness, Kurtosis, and Jarque-Bera statistics. Based on the Jarque-Bera test, we reject the null hypothesis of normality at a 1% significance level for all cryptocurrencies except Monero.

**Table 4**

**Asymmetric volatility estimation results for Bitcoin (btc)**

|  |  |
| --- | --- |
| **Panel A: Estimation without structural breaks**  | **Panel B: Estimation incorporating structural breaks** |
|  | **GJR-GARCH** | **EGARCH** |  | **GJR-GARCH** | **EGARCH** |
| ω | 7.25E-05(0.00) | -0.5616(0.00) | ω | 5.48E-05(0.00) | -0.9304(0.00) |
| α | 0.1094(0.00) | 0.2510(0.00) | α | 0.0629(0.00) | 0.2354(0.00) |
| γ | 0.0376(0.00) | -0.0310(0.00) | γ | 0.1083(0.00) | -0.0475(0.00) |
| β | 0.8403(0.00) | 0.9399(0.00) | β | 0.7315(0.00) | 0.8825(0.00) |
| Volatility persistence  | 0.968 | 0.939 | Volatility persistence  | 0.848 | 0.882 |
| Half-life (days) | 21.31 | 9.55 | Half-life (days) | 4.22 | 5.42 |
| Log-likelihood | 6128.323 | 6139.458 | Log-likelihood | 6139.727 | 6210.963 |
| Skewness | -0.8135 | -0.7786 | Skewness | -0.6455 | -0.7764 |
| Kurtosis | 14.237 | 15.265 | Kurtosis | 11.415 | 13.501 |
| Jarque-Bera test | 18261.14(0.00) | 20918.30(0.00) | Jarque-Bera test | 9919.435(0.00) | 15429.24(0.00) |

**Notes:** We find the p-values given in the parentheses by using the methodology from Bollerslev and Wooldridge (1992). We also use standard residuals from the estimated models (with and without structural breaks) to find the values of Skewness, Kurtosis, and Jarque-Bera statistics. Based on the Jarque-Bera test, we reject the null hypothesis of normality at a 1% significance level.

**Table 5**

**Asymmetric volatility estimation results for Ethereum (eth)**

|  |  |
| --- | --- |
| **Panel A: Estimation without structural breaks** | **Panel B: Estimation incorporating structural breaks** |
|  | **GJR-GARCH** | **EGARCH** |  | **GJR-GARCH** | **EGARCH** |
| ω | 0.0002(0.00) | -0.6630(0.00) | ω | 0.0002(0.00) | -0.8162(0.00) |
| α | 0.1540(0.00) | 0.2792(0.00) | α | 0.1525(0.00) | 0.2869(0.00) |
| γ | 0.0069(0.56) | -0.0009(0.98) | γ | 0.0228(0.13) | -0.0160(0.09) |
| β | 0.7776(0.00) | 0.9203(0.00) | β | 0.7427(0.00) | 0.8943(0.00) |
| Volatility persistence | 0.935 | 0.920 | Volatility persistence | 0.906 | 0.894 |
| Half-life (days) | 10.31 | 8.31 | Half-life (days) | 7.06 | 5.94 |
| Log-likelihood | 3697.135 | 3694.179 | Log-likelihood | 3717.638 | 3712.058 |
| Skewness | -0.3291 | -0.3613 | Skewness | -0.3691 | -0.3602 |
| Kurtosis | 8.558 | 9.417 | Kurtosis | 8.536 | 9.511 |
| Jarque-Bera test | 3200.06(0.00) | 4259.16(0.00) | Jarque-Bera test | 3185.59(0.00) | 4407.11(0.00) |

**Notes:** We find the p-values given in the parentheses by using the methodology from Bollerslev and Wooldridge (1992). We also use standard residuals from the estimated models (with and without structural breaks) to find the values of Skewness, Kurtosis, and Jarque-Bera statistics. Based on the Jarque-Bera test, we reject the null hypothesis of normality at a 1% significance level.

**Table 6**

**Asymmetric volatility estimation results for Dogecoin (doge)**

|  |  |
| --- | --- |
| **Panel A: Estimation without structural breaks** | **Panel B: Estimation incorporating structural breaks** |
|  | **GJR-GARCH** | **EGARCH** |  | **GJR-GARCH** | **EGARCH** |
| ω | 0.0001(0.00) | -0.5756(0.00) | ω | 0.0014(0.00) | -1.1630(0.00) |
| α | 0.1921(0.00) | 0.3117(0.00) | α | 0.2650(0.00) | 0.3442(0.00) |
| γ | -0.0436(0.00) | 0.0622(0.00) | γ | -0.1411(0.00) | 0.1040(0.00) |
| β | 0.8127(0.00) | 0.9388(0.00) | β | 0.6401(0.00) | 0.8112(0.00) |
| Volatility persistence | 0.983 | 0.938 | Volatility persistence | 0.834 | 0.811 |
| Half-life (days) | 40.42 | 9.55 | Half-life (days) | 3.83 | 3.28 |
| Log-likelihood | 4731.471 | 4733.950 | Log-likelihood | 4837.530 | 4836.513 |
| Skewness | 0.9167 | 0.9743 | Skewness | 0.6998 | 0.6955 |
| Kurtosis | 9.040 | 9.462 | Kurtosis | 8.228 | 8.230 |
| Jarque-Bera test | 5045.44(0.00) | 5769.23(0.00) | Jarque-Bera test | 3709.73(0.00) | 3709.27(0.00) |

**Notes:** We find the p-values given in the parentheses by using the methodology from Bollerslev and Wooldridge (1992). We also use standard residuals from the estimated models (with and without structural breaks) to find the values of Skewness, Kurtosis, and Jarque-Bera statistics. Based on the Jarque-Bera test, we reject the null hypothesis of normality at a 1% significance level.

**Table 7**

**Asymmetric volatility estimation results for Ripple (XRP)**

|  |  |
| --- | --- |
| **Panel A: Estimation without structural breaks** | **Panel B: Estimation incorporating structural breaks** |
|  | **GJR-GARCH** | **EGARCH** |  | **GJR-GARCH** | **EGARCH** |
| ω | 0.0004(0.00) | -1.4760(0.00) | ω | 0.0042(0.00) | -2.2936(0.00) |
| α | 0.3898(0.00) | 0.4934(0.00) | α | 0.4071(0.00) | 0.4902(0.00) |
| γ | -0.1574(0.09) | 0.0936(0.06) | γ | -0.2160(0.01) | 0.1116(0.02) |
| β | 0.6104(0.00) | 0.8060(0.00) | β | 0.3619(0.00) | 0.5697(0.00) |
| Volatility persistence | 0.921 | 0.806 | Volatility persistence | 0.661 | 0.569 |
| Half-life (days) | 8.47 | 3.21 | Half-life (days) | 1.67 | 1.23 |
| Log-likelihood | 4880.924 | 4866.828 | Log-likelihood | 5003.780 | 5003.380 |
| Skewness | 0.5282 | 0.7065 | Skewness | 0.6438 | 0.6575 |
| Kurtosis | 10.534 | 11.831 | Kurtosis | 10.387 | 10.607 |
| Jarque-Bera test | 7667.38(0.00) | 10594.70(0.00) | Jarque-Bera test | 7448.74(0.00) | 7895.26(0.00) |

**Notes:** We find the p-values given in the parentheses by using the methodology from Bollerslev and Wooldridge (1992). We also use standard residuals from the estimated models (with and without structural breaks) to find the values of Skewness, Kurtosis, and Jarque-Bera statistics. Based on the Jarque-Bera test, we reject the null hypothesis of normality at a 1% significance level.

**Table 8**

**Asymmetric volatility estimation results for Monero (xmr)**

|  |  |
| --- | --- |
| **Panel A: Estimation without structural breaks** | **Panel B: Estimation incorporating structural breaks** |
|  | **GJR-GARCH** | **EGARCH** |  | **GJR-GARCH** | **EGARCH** |
| ω | 0.0001(0.00) | -0.4568(0.00) | ω | 0.0003(0.00) | -0.5671(0.00) |
| α | 0.1117(0.00) | 0.1666(0.00) | α | 0.1146(0.00) | 0.1643(0.00) |
| γ | -0.0398(0.04) | 0.0243(0.04) | γ | -0.0440(0.05) | 0.0277(0.05) |
| β | 0.8628(0.00) | 0.9465(0.00) | β | 0.8377(0.00) | 0.9211(0.00) |
| Volatility persistence | 0.954 | 0.946 | Volatility persistence | 0.930 | 0.921 |
| Half-life (days) | 14.92 | 12.60 | Half-life (days) | 9.59 | 8.44 |
| Log-likelihood | 4693.826 | 4687.820 | Log-likelihood | 4701.186 | 4698.338 |
| Skewness | 0.0352 | 0.0367 | Skewness | 0.0172 | 0.0133 |
| Kurtosis | 2.941 | 2.965 | Kurtosis | 2.927 | 2.937 |
| Jarque-Bera test | 1.009(0.06) | 0.795(0.05) | Jarque-Bera test | 0.775(0.05) | 0.553(0.05) |

**Notes:** We find the p-values given in the parentheses by using the methodology from Bollerslev and Wooldridge (1992). We also use standard residuals from the estimated models (with and without structural breaks) to find the values of Skewness, Kurtosis, and Jarque-Bera statistics. Based on the Jarque-Bera test, we reject the null hypothesis of normality at a 1% significance level.

**Figure 1**

**Daily cryptocurrency prices**



**Notes:** The longest series of data is available for Bitcoin (May 1, 2013 – April 30, 2022) and the shortest series of data was available for Ethereum (August 15, 2015 – April 30, 2022). Source: https://coinmarketcap.com/

**Figure 2**

**News impact curve**

**Notes:** The solid line represents the GJR-GARCH model for Bitcoin, ignoring breakpoints. The dotted line corresponds to the GJR-GARCH model that accounts for breakpoints. The x-axis shows whether the shock is positive or negative. The y-axis represents the impact of any given shock on the volatility of Bitcoin. More details about the construction of these curves are discussed in Engle and Ng (1993).

1. As per Bouri et al. (2016), an asset is considered a hedge if it is negatively correlated with another asset on average; a safe haven is an asset that is, during a time of crisis, negatively correlated with another asset. [↑](#footnote-ref-1)
2. Inverse or inverted asymmetric behavior means that positive news or shocks increase the volatility more than negative news or shocks. The opposite is true for equity investments in general. [↑](#footnote-ref-2)
3. The modified ICSS algorithm is a popular methodology to detect the structural breaks in unconditional variance. It has been previously employed by Shen et al. (2020) for Bitcoin, Baig et al. (2022) for Islamic market indices, Anjum and Malik (2020) for the U.S. dollar exchange rate, Ewing et al. (2019) for oil prices, and Hood and Malik (2018) for stock market returns. [↑](#footnote-ref-3)
4. Apart from Bitcoin, Ethereum, Dogecoin, Ripple (XRP), and Monero, we also conducted the same analysis for Binance, Dash, NEM, and Stellar and found a statistically significant asymmetric term (γ). Results are available upon request. [↑](#footnote-ref-4)
5. More discussion on signs of the asymmetric term (γ) is presented in section 6. [↑](#footnote-ref-5)