Bitcoin, Gold, Oil Implied Volatility Spillover to Stock Market: Evidence from an Asymmetric Quantile Regression Model

Submission ID: 1570978865

Abstract—**This paper investigates the implied volatility spillovers of three commodities (bitcoin, gold and oil) onto the stock market (VIX) to determine if bitcoin behaves differently from other commodities in terms of its effect on stock market behaviour. To capture any asymmetry in terms of the change in implied volatility of these commodity markets, we apply a time-lagged asymmetric quantile regression (QR), a non-linear and heterogeneity-consistent model. Through the data analysis with daily implied volatility data from January 2019 to November 2023, we find an asymmetric relation: impacts of positive changes in gold and oil implied volatility on changes in VIX are stronger than impacts of negative changes, particularly at upper quantiles. This finding supports the intuition that the increase in volatility has a stronger spillover effect than an equivalent magnitude decrease in volatility. We also confirm that gold and oil have tail risk in contrast to bitcoin. We further find that bitcoin volatility change has almost no effect on change in VIX, implying that turbulence in the bitcoin market does not affect the stock market. Taken together, these results can support policy makers and market participants by informing them that bitcoin differs in nature to traditional commodities and works as an effective diversification tool.**

Keywords—**bitcoin, gold, oil, stock, implied volatility, asymmetric QR**

I. Introduction

Bitcoin is frequently referred to as "digital gold" [38], [14] due to its potential as a hedging and safe-haven tool against financial turmoil [23], [12]. In view of this, numerous papers have studied the relationship between bitcoin and other assets (e.g. [4], [15], [28], [39]). Particularly, the nexus among bitcoin and strategic commodities, such as gold and crude oil is intensively investigated [13], [27], [26], [35].

When examining the nexus among assets, spillovers in higher-order moments is one of the crucial elements to consider [25] and therefore *volatility*, the second moment of asset price is often examined. With respect to bitcoin price spillover to commodity volatility, [36] showed that bitcoin exhibits net-positive volatility spillovers to precious metals. [19] concluded through dummy variable GARCH model [5], [43] and quantile regression (QR) [30] that bitcoin outperforms gold and commodities in hedging implied crude oil volatility index (OVX). [44] used multivariate GARCH to reveal the bidirectional volatility spillover between the bitcoin market and the gold markets. Furthermore, [25] studied the spillovers in higher-order moments for bitcoin, gold and crude oil to highlight the need to capture the linkages across these markets by leveraging higher-order moments.

However, compared to the great deal of discussion surrounding the effect of bitcoin price returns or volatility on returns in other markets [41], [37], [31], [32], the study on the inter-volatility relationship is relatively limited. Furthermore, little quantitative analysis has been undertaken on the effect of bitcoin price behaviour on stock market volatility [34], particularly in the realm of implied volatility. Additionally, there is a paucity of papers examining the implied volatility relationships in comparison with other commodities [26].

To fill this research gap, this paper investigates the spillovers of implied volatility of three commodities – bitcoin, gold and oil – onto the stock market to examine if the implied volatility of bitcoin has a particular effect to that of stock (VIX) in comparison with traditional assets. We apply a time-lagged asymmetric quantile regression (QR) [30], which has been previously employed to a similar end in the context of returns and volatility linkage of oil and stock markets [45]. The choice of this method comes firstly from the analogy of *asymmetrical* responses of volatility to return shocks [9], [10], [7]. Particularly, stock markets are shown to have the negatively asymmetric return-volatility nexus, implying that negative return shocks (bad news) have more effect on volatility than positive return shocks (good news) (e.g. [18], [2], [6], [33]). We aim to test whether the inter-implied volatility relation also exhibits asymmetric behaviours similar to those found in the return-volatility studies. Secondly, QR provides a *heterogeneity*-consistent model, which captures multimodal and fat-tailed distributions. This feature contributes to detecting investors' heterogeneous views on asset payoffs, hence the investors' different responses to a similar market shock [40].

By applying a time-lagged asymmetric quantile regression (QR) to implied volatility data for bitcoin (BitVol), gold (GVZ), oil (OVX) and stock (VIX) markets between January 2019 and November 2023, we find the presence of asymmetric relationship – positive changes in the implied volatility of gold and oil have greater effects on changes in VIX than negative changes, especially in higher quantiles. This is consistent with the general theory that investors are more observant on downside than upside risk. We also confirm that bitcoin volatility change has almost no effect on the VIX change or even slightly reduces the VIX change, implying that the stock market is unaffected by fluctuation in the bitcoin market. Furthermore, we certify the tail risk, which derives from investor heterogeneity, while it does not appear in bitcoin. In all, our results capture the cross-market linkages of implied volatility and suggests that bitcoin behaves differently from gold and oil to act as a hedging tool – providing insights which help market participants in assessing market risks.

II. Preliminaries

A. Implied Volatility Index

In finance, *volatility* measures the level of price variation or fluctuation in a commodity. High volatility denotes higher risk and greater reward, while low volatility shows less risk but low options' premium.

Volatility can be expressed mainly in two ways – *historical volatility* and *implied volatility*. Historical volatility assesses the price fluctuation of an underlying security and is calculated by past data. Implied volatility, in contrast, provides market's view of expected future price fluctuations of an underlying security. Implied volatility is the more prevalent metric compared to historical volatility due to its forward-looking nature.

There have been a lot of volatility-related indices devised, particularly for 30-day implied volatility. For bitcoin, gold, oil, stock markets, *BitVol*, *GVZ*, *OVX* and *VIX* provide the relevant 30-day implied volatility indices, respectively. These indices have been calculated by the Chicago Board Options Exchange (CBOE) – aside from BitVol, produced by *T3 Index* – which uses strike prices of tradable bitcoin options and employs a similar methodology to the VIX Index.

B. Quantile Regression (QR)

Quantile regression (QR) [30] constructs linear models for predicting specified quantiles of a dependent variable. The model is helpful when analysing data that are non-normally distributed and hence have non-linear interactions with independent variables, as the model captures relationships between variables that lie outside of the mean.

Mathematically, QR model imposes different weights to positive and negative residuals and minimises this sum of the weighted absolute residuals, thus obtaining as the solution the conditional function for different quantiles [29]. The asymmetrically weighted sum is:

$$\min_{\xi \in \mathbb{R}} \sum \rho_\tau (y_i - \xi(x_i, \beta)), \tag{1}$$

where $\rho_\tau(\cdot)$ denotes the asymmetric absolute value function, which provides the τth sample quantile as a solution. $\xi(\cdot)$ gives the parametric function. Eq. (1) is further expressed as:

$$\min_{\xi \in \mathbb{R}} \left[\sum_{i:y_i \geq \xi} \tau |y_i - \xi(x_i, \beta)| + \sum_{i:y_i < \xi} (1-\tau)|y_i - \xi(x_i, \beta)| \right] \tag{2}$$

The advantage of using QR model is that it captures the changing distribution at various quantiles. Additionally, the model provides robust estimates when the error terms are either skewed, leptokurtic or with any omitted variables [20]. Furthermore, it captures investors' heterogeneous responses to market turmoil and thus showing multimodal and fat-tailed distributions in variables [40]. This model provides an in-depth analysis through yielding accurate estimation of coefficients and capturing important relationships, particularly in extreme tail cases [8] and thus been employed in numerous studies to avoid producing biased estimates [3], [11], [46], [16].

III. Data and Methodology

We investigate the relationship between implied volatility of three commodities (bitcoin, gold and oil) and stock market (VIX) through quantile regression (QR) [30], a heterogeneity-consistent model. In order to assess the asymmetric and the time-lagged effect, we further incorporate the positive and negative factors as well as the lagged components, as was once employed in the study on oil–stock volatility relationship [45]. Using the stock implied volatility change (ΔVix) as the objective variable and changes in implied volatility of bitcoin (ΔBitvol), gold (ΔGvz), oil (ΔOvx) as explanatory variables, we reduce this to finding the significant explanatory variables. Through comparing with other assets, i.e. gold and oil, we aim to find if bitcoin exhibits unique features regarding its effect on stock markets.

A. Methodology

Following previous analysis which study the asymmetric return–volatility relationships in equity markets [3], [42] and in oil market [45], we apply a time-lagged asymmetric quantile regression (QR) to investigate the asymmetric relations in terms of the change in implied volatility. To capture this asymmetry, our model frames the negative and positive changes in explanatory variables. For example, the asymmetric effect of bitcoin is expressed as:

$$BC_t^- = \min(BC_t, 0) \tag{3}$$

$$BC_t^+ = \max(BC_t, 0) \tag{4}$$

where BC_t is the first difference of the bitcoin implied volatility index ($\Delta Bitvol$) at time t. We can then provide the following form of the time-lagged asymmetric QR:

$$\begin{aligned} SC_t^\tau &= \alpha^\tau + \sum_{i=0}^{T} \beta_i^\tau BC_{t-i}^- + \sum_{i=0}^{T} \gamma_i^\tau BC_{t-i}^+ + \sum_{i=0}^{T} \delta_i^\tau GD_{t-i}^- \\ &+ \sum_{i=0}^{T} \theta_i^\tau GD_{t-i}^+ + \sum_{i=0}^{T} \lambda_i^\tau CO_{t-i}^- + \sum_{i=0}^{T} \phi_i^\tau CO_{t-i}^+ + \epsilon_t^\tau \end{aligned} \tag{5}$$

where we define BC_t, GD_t, CO_t, and SC_t as change in implied volatility at time t of bitcoin, gold, oil, and stock, respectively. α^τ denotes the intercept of the respective quantile. β_i^τ and γ_i^τ represent the τ-quantile coefficients for negative and positive change in bitcoin implied volatility, respectively. Similarly, δ_i^τ and θ_i^τ, as well as λ_i^τ and ϕ_i^τ are the coefficients for negative and positive change in the implied volatility of gold and oil. ϵ is the residual regression term.

We first run Eq. (5) to populate the coefficients estimation results to observe the effects the three explanatory variables have on dependent variable, the change in VIX. We further plot the asymmetric coefficients for negative and positive changes in implied volatility for each asset across different quantiles (τ = 0.1 to 0.9) to investigate if there is asymmetrical responses of VIX change to volatility change of each asset. We further test the existence of tail risk for each three asset.

B. Data

The data used in this study consists of implied volatility index series for bitcoin (BitVol), gold (GVZ), crude oil (OVX) and stock market (VIX) from 8th January 2019 to 30th November 2023. We obtained daily closing data for BitVol from *T3 Index* and GVZ, OVX and VIX from *Bloomberg*, resulting in 1220 observations for each series. Fig. 1 charts the evolution of each implied volatility index series for the period of this study. We observe several spikes in all assets, while we also confirm an extreme spike in oil during COVID-19. In order to capture the interlinkage between the change in implied volatility of each asset, we computed the first difference of each series.

Table I presents descriptive statistics and unit root test results of the changes in the implied volatility index for bitcoin, gold, oil and stock markets that are employed in our investigation. The mean values show bitcoin achieves the highest magnitude of implied volatility change of -0.0185, followed by stock and oil. Regarding the maximum and minimum of implied volatility change, oil has the most significant values of 130.220 and -90.610, respectively, followed by bitcoin. The

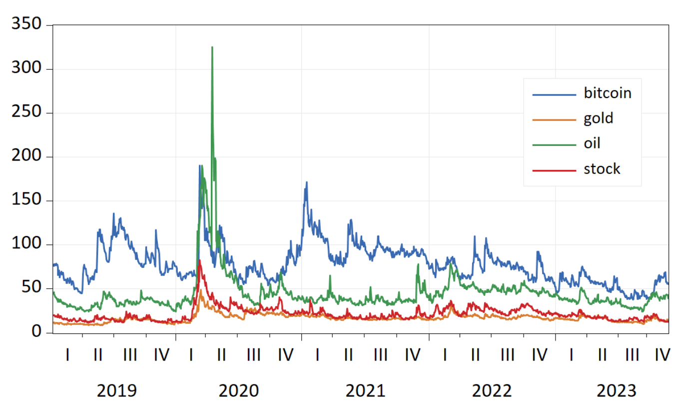

Fig. 1: Implied volatility index of bitcoin, gold, oil and stock markets

TABLE I: Descriptive Statistics for the Changes in Implied Volatility Index of Bitcoin, Gold, Crude Oil and Stock markets

	ΔBitvol	**ΔGvz**	**ΔOvx**	**ΔVix**
Mean	-0.0185	0.0025	-0.0055	-0.0062
Median	-0.3900	-0.0700	-0.2400	-0.1800
Maximum	57.530	7.250	130.220	24.860
Minimum	-36.240	-9.500	-90.610	-17.640
Std Dev.	5.7141	1.0638	7.2711	2.1751
Skewness	2.1894	0.2768	3.9891	2.4789
Kurtosis	25.0916	15.5902	154.8920	32.7276
No. Obs	1219	1219	1219	1219
ADF	-36.947***	-35.831***	-14.516***	-44.656***

ADF test: The null hypothesis is that the series has a unit root.
***Statistically significant at the 1% level. (1% critical value: -5.719131)

standard deviation for oil and bitcoin implied volatility change is again larger than those of gold and stock, indicating their volatile nature. While the implied volatility change shows a positive skew to the right in all markets, oil exhibits the heaviest skewness. On kurtosis, the change in implied volatility is extremely leptokurtic when compared to the normal distribution (with heavier tails) for all assets. Lastly, results from Augmented Dickey–Fuller (ADF) unit root test [22] indicate that all the series are stationary.

IV. Results

We estimate Eq. (5), a time-lagged asymmetric quantile regression (QR), to analyse the relationship between the implied volatility of bitcoin, gold, oil and stock. Table II reports the coefficients for our QR-based model and OLS. The results contain 9 quantile regressions (τ = 0.1–0.9). Regarding the time-lagged effect, we only report till $t-1$ results, as further lags do not present significant coefficients. Fig. 2 charts the estimated slope coefficients of contemporaneous terms at each quantile, for bitcoin, gold and oil.

Looking at the coefficients of contemporaneous terms (e.g. BC_t^-, BC_t^+) in Table II, we observe that contemporaneous implied volatility change have greater absolute values and are more significant, in comparison to those of lagged terms. This suggests the dominant explanatory power of contemporaneous terms when estimating changes in implied volatility, while lagged terms have limited effect. This contradicts previous research which shows the long-term lagged effect in the first-moment series for bitcoin, gold and oil [32].

In terms of the bitcoin implied volatility change, the coefficients of contemporaneous terms are mostly insignificant across the majority of quantiles, implying no effect of bitcoin volatility change on the VIX change. Negative bitcoin volatility change (BC_t^-) is significant only at the lower quantiles (τ = 0.2, 0.3), suggesting that bitcoin volatility reduces the stock volatility when a change in VIX is small, that is, when a stock market is expected to be less volatile. On the other hand, there is no positive contemporaneous effect (BC_t^+), while the effect of lagged positive bitcoin volatility change (BC_{t-1}^+) is observed throughout the lower quantiles (τ = 0.1–0.5) with negative significance. Taken the results from negative and positive terms together, the outcome suggests the ability of bitcoin to reduce the stock volatility at lower quantiles: when the VIX change is small, bitcoin volatility changes lower the VIX change through the t and $t-1$ effects. This suggests that turbulence in the bitcoin market does not affect the stock market, even reduces the expected volatility of the stock market, confirming bitcoin's nature as a good hedging tool. The finding is in line with the previous study that suggest the low correlation between bitcoin and traditional assets, implying a potential of bitcoin as a hedging tool [17], [21].

The empirical evidence from gold provides prominent results. The coefficients of contemporaneous terms (GD_t^-, GD_t^+) are statistically significant at most quantiles. Negative change in gold volatility (GD_t^-) reduces the stock volatility throughout the quantiles in high magnitude, suggested by the positively significant coefficients ranging from 0.454 (τ = 0.9) to 0.914 (τ = 0.1). Meanwhile, Fig. 2 demonstrates the downward trend of the coefficient for GD_t^-, implying that when the VIX change is large (upper quantile), that is, when the stock market is too volatile, then the effect of gold to reduce the stock volatility decreases. On the other hand, positive volatility change of gold (GD_t^+) increases the VIX change only at upper quantiles (τ = 0.4–0.9), suggesting that when VIX change is large, the effect of positive change in gold volatility onto stock volatility change becomes significant. The monotonous increase of the coefficients for GD_t^+ observed in Fig. 2 further shows that when the stock market is volatile (upper quantile), the effect of gold volatility change to stock volatility is enhanced. Taking these results from negative and positive volatility changes together, we can conclude the existence of tail risk at higher quantiles.

Furthermore, when significant, absolute values of the coefficient are larger for positive gold volatility change than that of negative change, particularly at upper quantiles (τ = 0.7–0.9). This implies that when the stock market is volatile, positive change in gold volatility leads to a higher VIX change than that of negative change. One possible explanation of this asymmetric relation can be that an increase in VIX is linked with unfavourable trends before a market turmoil [24], leading to investors focusing more on downward than upward movements, resulting in the effect from downside movements being dominant.

Fig. 2 also suggests that coefficients of GD_t^+ monotonously increase while those of GD_t^- steadily decrease, implying that positive change in gold implied volatility, i.e., the increase in gold implied volatility has more significant positive impacts on changes in stock implied volatility at upper quantiles. We confirm from the comparison with the OLS that OLS underestimates the negative effect across all quantiles, while it undervalues positive effects in upper quantiles (τ = 0.8, 0.9). These suggest that the asymmetric effect in the inter-volatility nexus is more prominent at upper quantiles. This could be because of investor heterogeneity, which forms various clusters of investors who react differently to rise and fall in implied volatility. For instance, during periods of significant market volatility, pessimistic investors concentrated near the left tail of the distribution tend to overestimate risk while underestimate profits [45].

Regarding oil, contemporaneous negative (CO_t^-) and positive (CO_t^+) oil volatility change both enhance the change in VIX, only at some parts of the upper quantiles (τ = 0.6–0.8), considering the negative coefficient of CO_t^-. Like in the gold case, when there is a large change in volatility, increase in the oil volatility positively affects the change in stock volatility, leading to a more volatile stock market. It is worth noting that the lagged term is negatively significant for CO_{t-1}^+ at upper quantiles. Accordingly, the oil market exhibits tail risk, consistent with previous findings [1]. Similarly to gold, when significant, the coefficients' absolute values are greater for positive changes in oil volatility than for negative ones at the upper quantiles, implying asymmetric inter-volatility relations in the market. Lastly, a possible explanation for oil not being fully significant is that the sectoral effect is not considered in the model, while oil volatility

TABLE II: Parameter Estimates for Eq. (5) – Dependent Variable: Change in Stock Implied Volatility (ΔVix_t)

	Bitcoin				**Gold**				**Crude Oil**			
τ	BC_t^-	BC_{t-1}^-	BC_t^+	BC_{t-1}^+	GD_t^-	GD_{t-1}^-	GD_t^+	GD_{t-1}^+	CO_t^-	CO_{t-1}^-	CO_t^+	CO_{t-1}^+
0.1	0.054*	0.020	-0.009	-0.047***	0.914***	0.141	0.066	-0.423*	0.088*	0.086	0.071***	-0.114***
	(0.06)	(0.20)	(0.59)	(0.01)	(0.00)	(0.30)	(0.63)	(0.08)	(0.07)	(0.21)	(0.00)	(0.00)
0.2	0.055***	0.020*	-0.007	-0.033**	0.851***	0.208*	0.200	-0.254*	0.071	0.091	0.068***	-0.074
	(0.01)	(0.09)	(0.70)	(0.04)	(0.00)	(0.07)	(0.12)	(0.05)	(0.40)	(0.12)	(0.00)	(0.20)
0.3	0.057***	0.033**	-0.008	-0.040***	0.889***	0.133	0.200	-0.171	0.071	-0.011	0.078	-0.045
	(0.01)	(0.04)	(0.68)	(0.00)	(0.00)	(0.39)	(0.10)	(0.28)	(0.59)	(0.73)	(0.14)	(0.26)
0.4	0.030	0.039**	0.001	-0.050***	0.745***	0.082	0.380**	-0.034	0.031	-0.003	0.074	-0.047
	(0.25)	(0.05)	(0.98)	(0.00)	(0.00)	(0.49)	(0.03)	(0.73)	(0.59)	(0.95)	(0.19)	(0.27)
0.5	0.020	0.032*	0.011	-0.050***	0.669***	0.180	0.474***	-0.023	-0.001	0.002	0.099	-0.070
	(0.29)	(0.08)	(0.26)	(0.00)	(0.00)	(0.12)	(0.00)	(0.74)	(0.99)	(0.95)	(0.15)	(0.16)
0.6	0.014	0.025	0.005	-0.016	0.696***	0.127	0.544***	0.005	-0.027**	0.012	0.153	-0.057***
	(0.44)	(0.22)	(0.62)	(0.63)	(0.00)	(0.27)	(0.01)	(0.95)	(0.02)	(0.16)	(0.20)	(0.00)
0.7	0.019	0.030	0.016	-0.003	0.654***	0.040	0.764***	0.116	-0.012	0.009	0.150***	-0.049
	(0.28)	(0.14)	(0.63)	(0.86)	(0.00)	(0.78)	(0.00)	(0.40)	(0.88)	(0.73)	(0.00)	(0.52)
0.8	-0.002	-0.002	0.054	-0.006	0.653***	0.027	1.107***	0.149	-0.021***	-0.014**	0.238***	-0.061***
	(0.93)	(0.96)	(0.37)	(0.69)	(0.00)	(0.86)	(0.00)	(0.12)	(0.01)	(0.02)	(0.00)	(0.00)
0.9	-0.036	-0.002	0.110	0.047	0.454***	0.102	1.774***	0.213	-0.009	-0.004	0.277	-0.063***
	(0.48)	(0.95)	(0.13)	(0.26)	(0.00)	(0.59)	(0.00)	(0.35)	(0.31)	(0.86)	(0.39)	(0.00)
OLS	0.061***	0.025	0.002	0.012	0.812***	-0.034	0.493***	0.167*	-0.001	0.012	0.110***	-0.068***
	(0.00)	(0.20)	(0.87)	(0.45)	(0.00)	(0.73)	(0.00)	(0.08)	(0.92)	(0.37)	(0.00)	(0.00)

***, **, * : statistically significant at the 1%, 5%, and 10% levels, respectively. p-values are displayed in parentheses.

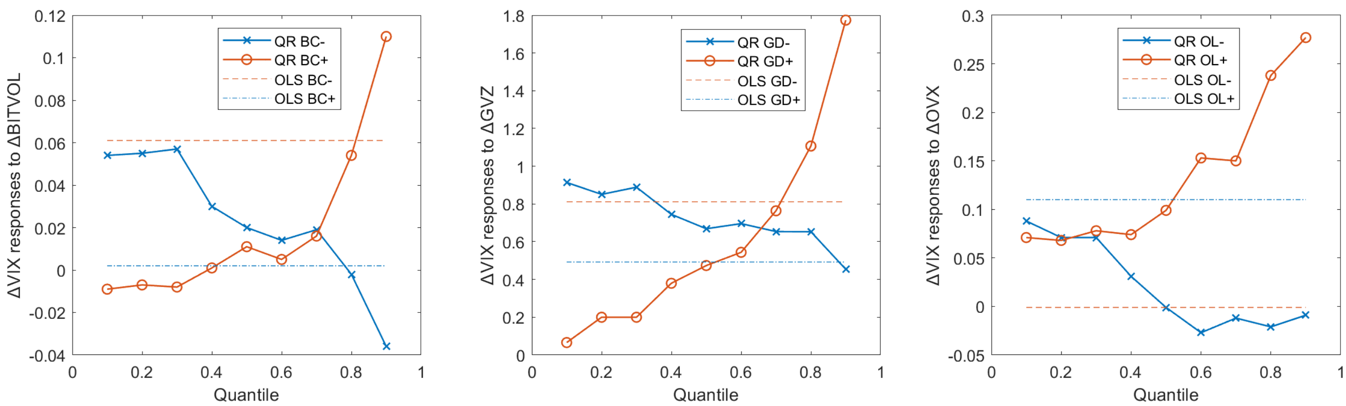

Fig. 2: Asymmetric contemporaneous responses of changes in VIX to changes in implied volatility of bitcoin, gold, and oil

would have a prominent impact on a particular sector, such as to transport industry.

Our findings revealed cross-market linkages of implied volatility, a crucial index when managing risks. Taking linkages among several assets via higher moments through appropriate model is crucial as otherwise, market participants fail to capture the asymmetric inter-volatility relation and investor heterogeneity that have important implications for risk management decisions. Although our results suggested the bitcoin's less influence to stock markets, our analysis does not negate the necessity to monitor the risk of bitcoin to the financial system, given that tail risk and asymmetric response are observed in strategic commodities that are regarded as hedges (crude oil) and safe havens (gold) – as bitcoin markets mature, the likelihood of bitcoin affecting the financial stability might be augmented.

V. Conclusion

While the linkages between bitcoin and financial variables are heavily studied, little has been documented on bitcoin implied volatility spillovers onto stock markets, particularly by comparing with gold and crude oil. In this paper, we investigated the response of VIX change to changes in bitcoin, gold, and oil implied volatility index through applying a time-lagged asymmetric quantile regression (QR), in order to incorporate asymmetric and diverse response of markets. Using daily data for the period January 2019 to November 2023, we found that contemporaneous changes in implied volatility of the three assets are dominant factors of changes in VIX. We also confirmed the presence of asymmetric relationship, that is, response of VIX change to positive changes in gold and oil implied volatility are greater than impacts of negative changes, at upper quantiles in particular. This is unsurprising as investors are more attentive on downside than upside risk. We also found that bitcoin volatility change has almost no effect on VIX change or even slightly reduces it, implying that turmoil in the bitcoin market has little effect on the stock market. Furthermore, we certified the tail risk, which derives from investor heterogeneity, in gold and oil, while it was not captured in bitcoin. Our results with the asymmetric QR model contributed to capturing the cross-market linkages of implied volatility, whereby suggesting that bitcoin behaves differently from gold and oil and that bitcoin can be a useful hedging instrument.

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