Proceedings of Business and Economic Studies, 2025, Volume 8, Issue 3
http://ojs.bbwpublisher.com/index.php/PBES
Online ISSN: 2209-265X
Print ISSN: 2209-2641

Short-Term Spillover Effects in High-order Moments of Stocks, Foreign Currency Exchange and Bitcoin with Intraday Data

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Abstract: This paper employs Granger causality analysis and the generalized impulse response function (GIRF) to study the higher-order moment spillover effects among Bitcoin, stock markets, and foreign exchange markets in the U.S. Using intraday high-frequency data, the research focuses on the interactions across higher-order moments, including volatility, jumps, skewness, and kurtosis. The results reveal significant bidirectional spillover effects between Bitcoin and traditional financial assets, particularly in terms of volatility and jump behavior, indicating that the cryptocurrency market has become a crucial component of global financial risk transmission. This study provides new theoretical perspectives and policy recommendations for global asset allocation, market regulation, and risk management, underscoring the importance of proactive management measures in addressing the complex risk interactions between cryptocurrencies and traditional financial markets.

Keywords: Higher-order moments; Intraday data; Spillover effects; Bitcoin; Risk management

Online publication: July 14, 2025

1. Introduction

The cryptocurrency market has experienced rapid growth, with Bitcoin reaching a market capitalization of over $2 trillion in 2023. This growth has led to the increasing integration of cryptocurrencies into the global financial system, with Bitcoin playing a key role. Bitcoin's unique characteristics, such as its limited supply and high volatility, have drawn significant attention from both investors and researchers. As Bitcoin continues to mature, its interactions with traditional financial assets like stocks and foreign exchange have become increasingly complex. Understanding how Bitcoin's price movements transmit risk across these markets, particularly in times of economic uncertainty, is essential.

Bitcoin's price behavior, which often shows high volatility and fat-tailed distributions, suggests that it may play a significant role in the transmission of financial risks. This study explores Bitcoin's spillover effects, particularly how its higher-order moments affect traditional assets like stocks and exchange rates. Given Bitcoin's 24/7 unrestricted trading and high sensitivity to external shocks, this study uses high-frequency 5-minute intraday data to analyze short-term spillover effects.

The primary objective of this study is to examine the spillover effects of Bitcoin's higher-order moments—volatility, jumps, skewness, and kurtosis—on traditional financial assets in the U.S. market. By using a vector autoregression (VAR) model and Granger causality tests, alongside generalized impulse response functions (GIRF), the study investigates the dynamics of these spillovers and their implications for financial risk transmission.

The empirical results show that in the U.S. market, significant bidirectional spillover exists between Bitcoin and traditional financial assets, particularly in higher-order moments. Bitcoin not only absorbs risk but also transmits it to other markets, particularly during extreme market events. These findings underline the growing importance of Bitcoin's role in financial markets, particularly during times of market instability.

2. Related studies

Many studies have explored intraday spillover effects in traditional asset markets and cryptocurrency markets. Mensi *et al.* examined the intraday volatility spillover between oil, gold, and stock markets during the COVID-19 pandemic, finding significant spillovers from oil and gold to stocks during the crisis [1]. Shakeel *et al.* investigated intraday volatility spillovers among exchange rates, gold, and crude oil, using a DCC-GARCH model, and found stronger spillover effects from gold and oil to exchange rates in high-frequency data [2].

Mensi *et al.* analyzed intraday volatility spillovers between Bitcoin and other cryptocurrencies, revealing complex interactions, particularly in higher-order moments, using high-frequency data and multiscale analysis [3]. Esparcia *et al.* explored high-frequency volatility and connectedness in the cryptocurrency market after the FTX collapse, noting a sharp increase in market volatility following financial events [4].

The volatility spillovers between Bitcoin and traditional financial markets have garnered significant academic interest, especially given the rapid development of the Bitcoin market. Mensi *et al.* used high-frequency asymmetric volatility models to study spillovers between Bitcoin and major precious metals, such as gold and silver, revealing significant connections, particularly during financial market turbulence [5]. GKillas *et al.* examined higher-order moment spillovers between crude oil, gold, and Bitcoin, highlighting intricate transmission effects in terms of volatility, skewness, and kurtosis, with intensifying spillovers during market turbulence [6].

Using high-frequency data, Zhang *et al.* demonstrated dynamic spillover effects between stock and foreign exchange markets in emerging markets, indicating that market sentiment and policy changes can rapidly impact asset price volatility [7]. Bouri *et al.* explored spillover effects between Bitcoin and traditional assets using a VAR-DCC-GARCH model, noting that Bitcoin's volatility is influenced not only by its own supply and demand but also significantly by fluctuations in other financial assets [8]. Kang *et al.* further confirmed the importance of high-frequency data in revealing dynamic spillover effects between foreign exchange and stock markets, emphasizing the impact of high-frequency trading on market volatility [9].

In this context, the stock market is typically viewed as the risk taker, while the foreign exchange market acts as the risk provider, reflecting macroeconomic changes and policy dynamics that subsequently affect stock market performance. Future research will focus on incorporating Bitcoin into this model and examining how it influences the original spillover behaviors, using high-frequency intraday data to capture more nuanced effects in realized volatility, skewness, kurtosis, and jumps.

3. Methodology

This study examines spillover effects on realized distribution moments, including realized volatility, jumps, realized skewness, and realized kurtosis, among Bitcoin, stock, and exchange rate markets. It starts with an overview of the intraday data, detailing the adjustments and methodology used to compute daily realized moment estimators.

Daily returns were derived using intraday 5-minute data for three assets to capture daily fluctuations. The dataset covers 1,805 calendar days from January 1, 2020, to August 31, 2024. High-frequency intraday data for Bitcoin was sourced from Binance, reflecting activity in several liquid Bitcoin markets. For stock market volatility, we used the S&P 500, CSI 300, and Nikkei 225 indices, representing the U.S., China, and Japan, respectively. The S&P 500 data was obtained from Bloomberg, CSI 300 from iFinD, and the Nikkei 225 from Wenhua Financial. The exchange rates analyzed include EURUSD, USDCNY, and USDJPY, with 5-minute data provided by UBS.

Daily returns for each price series are calculated using the logarithmic difference between consecutive prices. Specifically, the daily return for the *t-th* observation on the t-th day is given by:

$$r_{t,i} = \log(P_{t,i}) - \log(P_{t,i-1}) \tag{1}$$

where $r_{t,i}$ denotes the daily returns, and $P_{t,i}$ is the price for the *i-th* observation on day t, with i ranging from 1 to T.

For each day t, the daily realized volatility RV_t. was calculated using all intraday returns from the dataset. This RV_t serves as an estimator of the second realized moment, reflecting the dispersion risk associated with the price process and measuring the average deviation of observed returns from the mean return. The calculation method for RV_t for each day t is described as follows:

$$RV_t = \sum_{i=1}^{T} r_{t,i}^2 \tag{2}$$

Jumps are detected by analyzing the realized volatility through the method suggested by Duong *et al*. This detection process relies on choosing a jump-robust realized volatility estimator. Here, the threshold bi-power variation ($TBPV_t$) estimator is utilized, following the approach of Corsi *et al.*, to maintain robustness in the presence of jumps. The jump statistic ($ZJ_t^{(TBPV)}$) is formulated as follows:

$$ZJ_t^{(TBPV)} = \sqrt{T}\frac{(RV_t - TBPV_t)RV_t^{-1}}{\left[\left(\xi_1^{-4} + 2\xi_1^{-2} - 5\right)max\{1, TQ_t TBPV_t^{-2}\}\right]^{1/2}} \tag{3}$$

In this context, TQ_t denotes the realized tri-power quarticity, which is computed using the following formula:

$$TQ_t = T\xi_{4/3}^{-3}\sum_{i=1}^{T} \left|r_{t,i}\right|^{4/3}\left|r_{t,i+1}\right|^{4/3}\left|r_{t,i+2}\right|^{4/3} \tag{4}$$

which converges in probability to the integrated quarticity. To estimate the jump-free volatility, the threshold bi-power variation ($TBPV_t$) is employed, as defined by the following formula:

$$TBPV_t = \sum_{i=2}^{T} \left|r_{t,i-1}\right|\left|r_{t,i}\right| I_{\left\{\left|r_{t,i-1}\right|^2 \le \theta_{i-1}\right\}} I_{\left\{\left|r_{t,i}\right|^2 \le \theta_i\right\}} \tag{5}$$

In this context, $I_{\{\cdot\}}$ denotes the indicator function, with $r_{t,i}$ representing the daily return series and t indicating time at a daily frequency. A jump is deemed statistically significant when $ZJ_t^{(TBPV)}$ exceeds the critical value from the standard Gaussian distribution. Therefore, the jump component of daily realized volatility is defined accordingly. Here, $I_{\{\cdot\}}$ functions as an indicator to determine whether $ZJ_t^{(TBPV)}$ exceeds a specified critical threshold ϕ_α from the Gaussian distribution at a chosen significance level.

$$J_t = |RV_t - TBPV_t| I_{\left\{ZJ_t^{(TBPV)} > \phi_\alpha\right\}} \tag{6}$$

Realized skewness (RS_t) measures asymmetry risk and indicates potential crash risk by assessing the conditional skewness of daily returns. The daily realized skewness is calculated as follows and normalized by dividing by $RV_t^{3/2}$.

$$RS_t = \frac{\sqrt{T}\sum_{i=1}^{T} r_{t,i}^3}{RV_t^{3/2}} \tag{7}$$

The calculation of intraday realized kurtosis RV_t is described in Equation 8. This metric measures kurtosis risk in a univariate price process, indicating the thickness of the tails around the mean. To normalize the measurement, it is divided by RV_t^2.

$$RK_t = \frac{T\sum_{i=1}^{T} r_{t,i}^4}{RV_t^2} \tag{8}$$

Next, Granger causality tests are performed within a four-variable vector autoregressive (VAR) framework to assess the directional relationships between the four markets being analyzed. A k-dimensional VAR model can be generally expressed as follows:

$$Y_t = \nu + A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + \varepsilon_t \qquad (9$$

where Y_t represents a $K\times1$ vector of variables, ν denotes the $K\times1$ intercept vector, is the $K\times K$ coefficient matrix, and ε_t refers to the $K\times1$ error term vector.

After verifying stationarity and cointegration using the ADF unit root test and Johansen test, we conducted the Granger causality analysis and generated Generalized Impulse Response Function (GIRF) plots. The model's lag order was selected based on AIC and BIC. However, a very low lag order (e.g., lag of 1) can cause a rapid decline in GIRF responses, limiting the capture of dynamic interactions. In such cases, we prefer the lag order determined by the LR test.

The analysis of the Generalized Impulse Response Function (GIRF) provides insights into the causal relationships among Bitcoin, stocks, and exchange rates. Specifically, the GIRF measures the system's response to a one-standard-deviation shock in the *j-th* variable at time *t*, as observed at time *t+h*. This response is calculated using the formula:

$$\widehat{\psi}_j(h) = \sigma_{jj}^{-1/2} \prod_h \sum_{\varepsilon} e_j\,, h = 0,1,2,\cdots \tag{10}$$

Here, $\sum_\varepsilon = \{\sigma_{ij}\}$ represents the $K\times K$ variance-covariance matrix related to the error term ε_t, where ε_j is a $K\times1$ vector with the *j-th* element set to 1 and all other elements set to zero, applicable for $i,j = 1,2,...K$. The term Π_i refers to a $K\times K$ coefficient matrix, obtained from the infinite moving average form of the previous equation.

Additionally, the matrix Π_i can be derived recursively using the formula for Π_0, which is equivalent to I_K, denoting a K-dimensional identity matrix.

$$\prod_i = \begin{cases} \sum_{j=1}^{i} \prod_{i-j} A_j \,, i = 1,2,\cdots p \\ \sum_{j=1}^{p} \prod_i - jA_j \,, i > p \end{cases} \tag{11}$$

4. Empirical results

Using the methodology from Section 3, Granger causality tests and GIRF analyses are performed. The results for the realized moment estimators of Bitcoin, the S&P 500 index (S&P500), and the EURUSD exchange rate are presented in tables, with p-values noted in parentheses. Each panel shows dependent variables on the vertical axis and explanatory variables on the horizontal axis, while accompanying graphs illustrate response trajectories over 10 lag periods following an external shock.

Table 1 outlines spillover effects among the three assets using daily data to assess Granger causality between realized volatility (RV), jump statistics (ZJ), realized skewness (RS), and realized kurtosis (RK), with each panel corresponding to a different moment indicator.

Table 1. VAR Granger causality tests among intraday realized estimators of Bitcoin and US markets

Variables	Bitcoin	S&P500	EURUSD	All
Panel A: realized volatility				
Bitcoin	-	145.53***	34.03***	177.82**
	-	[0.000]	[0.000]	[0.000]
S&P500	221.91***	-	13.7	250.53***
	[0.000]	-	[0.133]	[0.000]
EURUSD	59.886***	55.848***	-	141.91***
	[0.000]	[0.000]	-	[0.000]
Panel B: jumps				
Bitcoin	-	18.23***	2.3212	26.534***
	-	[0.000]	[0.508]	[0.000
S&P500	172.52***	-	9.3846**	188.55***
	[0.000]	-	[0.025]	[0.000]
EURUSD	11.624***	62.817***	-	72.031***
	[0.009]	[0.000]	-	[0.000]
Panel C: realized skewness				
Bitcoin	-	1.8734	0.8090	2.5402
	-	[0.171]	[0.368]	[0.281]
S&P500	0.5862	-	0.3005	0.7871
	[0.444]	-	[0.584]	[0.675

Table 1 (Continued)

Variables	Bitcoin	S&P500	EURUSD	All
EURUSD	0.0078	6.498**	-	6.7463**
	[0.930]	[0.011]	-	[0.034]
Panel D: realized kurtosis				
Bitcoin	-	3.9583	2.4771	6.9003
	-	[0.555]	[0.780]	[0.735]
S&P500	9.7007*	-	3.7375	13.672
	[0.084]	-	[0.588]	[0.188]
EURUSD	2.0131	2.9425	-	5.1055
	[0.847]	[0.709]	-	[0.884]

In Panel A, significant bidirectional Granger causality is found between the RVs of Bitcoin and S&P500, indicating mutual volatility transmission. Bitcoin's RV significantly influences EURUSD's RV and vice versa. EURUSD also impacts S&P500's RV, though the reverse effect is not significant, highlighting EURUSD's critical role in overall market volatility transmission.

In Panel B, the spillover effects of jump statistics (ZJ) show significant bidirectional causality between Bitcoin's and S&P500's ZJ. EURUSD also has bidirectional causality with S&P500 and is a Granger cause of Bitcoin's ZJ, highlighting the exchange rate market's role in jump behavior transmission.

Panel C examines realized skewness (RS), revealing that EURUSD's RS significantly influences S&P500's RS, while Bitcoin's RS does not significantly impact other markets. Changes in EURUSD's skewness have a more pronounced effect on the stock market.

In Panel D, S&P500's realized kurtosis (RK) significantly influences Bitcoin's RK, but Bitcoin's and EURUSD's RKs do not significantly affect other markets, indicating the stock market's stronger influence on extreme risk events.

Overall, significant bidirectional causality exists between Bitcoin and S&P500 in both RV and ZJ dimensions, while EURUSD has a notable spillover effect on both in the ZJ dimension. The markets interact differently across higher-order moment dimensions, reflecting complex relationships in the transmission of volatility, jumps, and asymmetry risks.

Figure 1 to **Figure 4** illustrate the dynamic interactions among Bitcoin, the S&P500, and the EURUSD exchange rate through generalized impulse response analysis over 10 lag periods. Each subplot shows lag periods on the horizontal axis and response magnitudes on the vertical axis, with a shaded gray area indicating the 95% confidence interval.

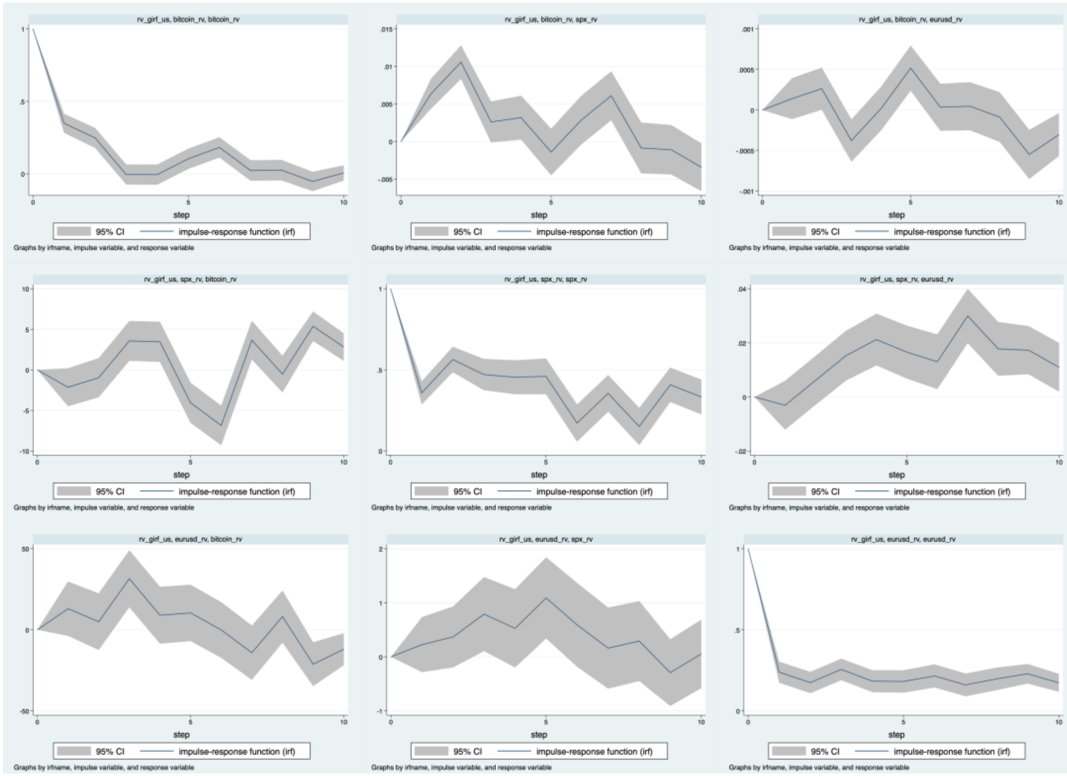

Figure 1. GIRF for a shock to Bitcoin, US stock, and USDJPY (Panel A: Realized volatility)

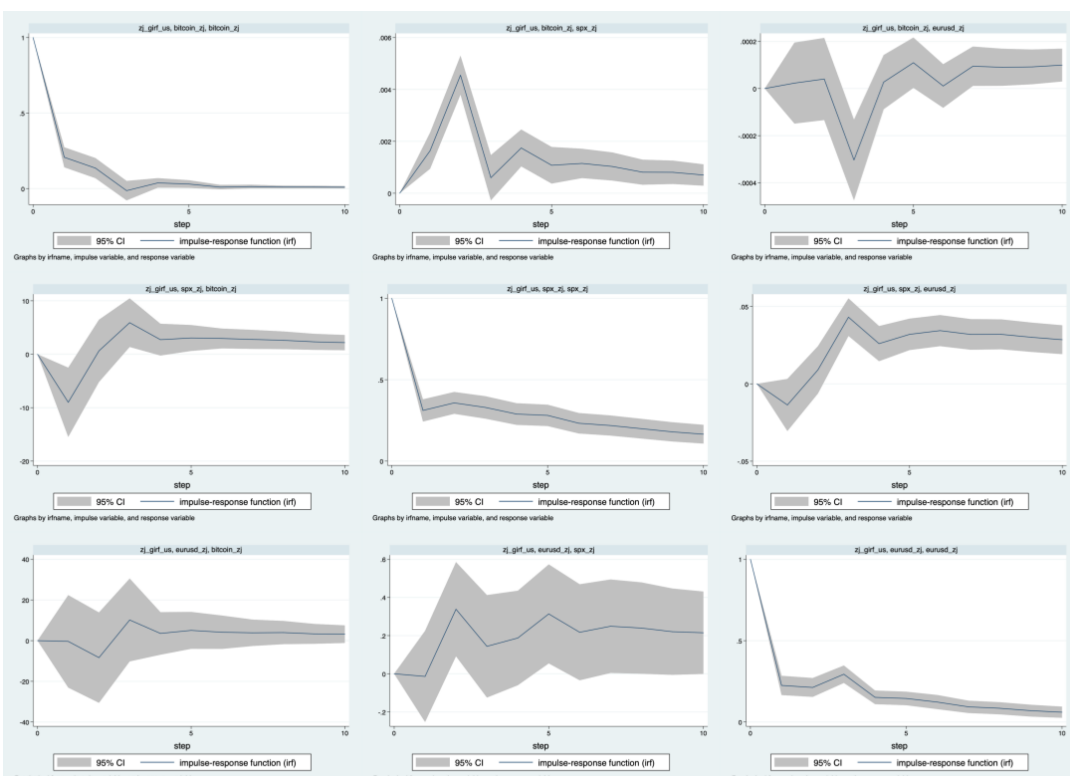

Figure 2. GIRF for a shock to Bitcoin, US stock, and USDJPY (Panel B: Jump)

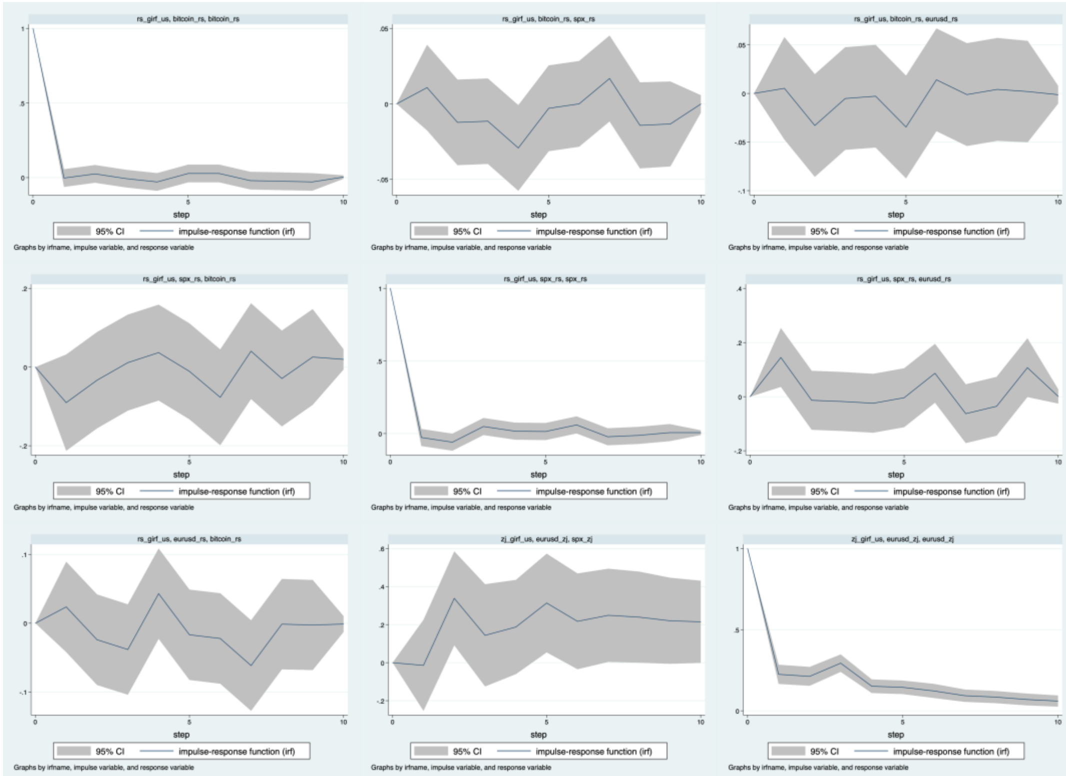

Figure 3. GIRF for a shock to Bitcoin, US stock, and USDJPY (Panel C: realized skewness)

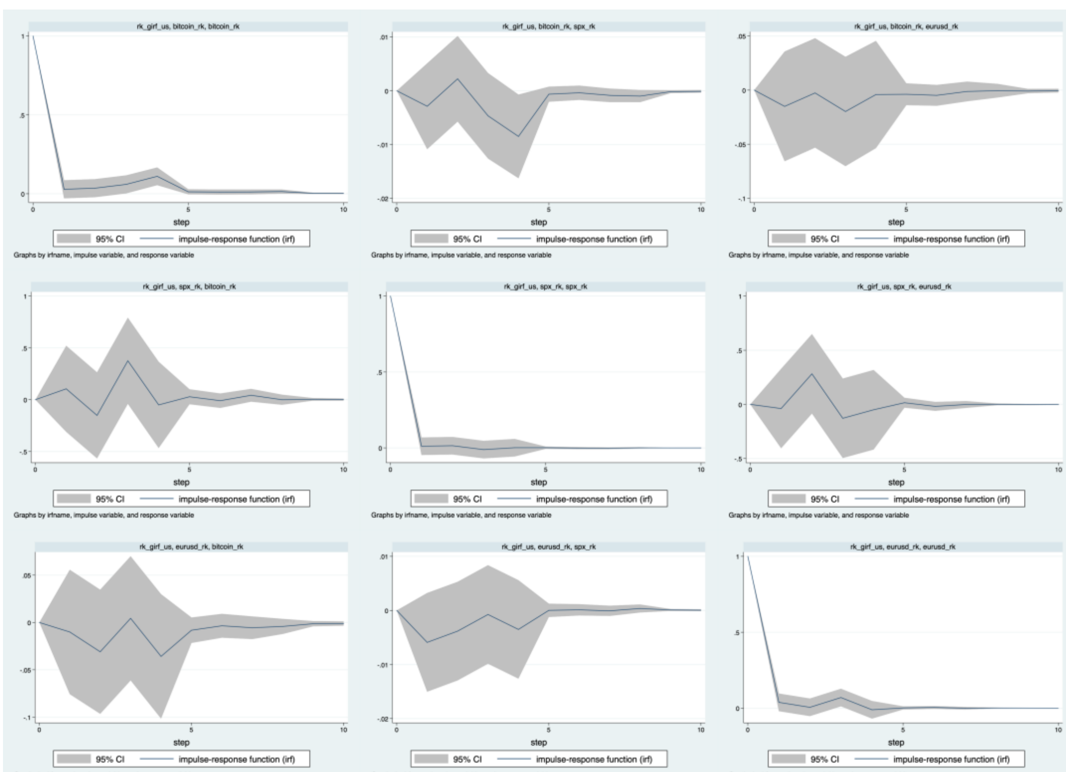

Figure 4. GIRF for a shock to Bitcoin, US stock, and USDJPY (Panel D: Realized kurtosis)

In Panel A, Bitcoin initially reacts positively to its own shocks, with the effect diminishing over time. It positively influences the S&P500 at first, but this shifts to a negative influence as lag periods increase. Bitcoin's response to EURUSD shocks is weak, indicating less transmission to the foreign exchange market compared to the stock market.

The S&P500 exhibits significant responses to shocks from both Bitcoin and itself, showing strong self-feedback. Its response to EURUSD shocks is small but notable. Conversely, EURUSD has limited influence on the other markets, resulting in minor volatility spillovers to Bitcoin, though it demonstrates persistence in responding to its own shocks, suggesting stronger volatility transmission within the foreign exchange market.

In Panel B, Bitcoin, S&P500, and EURUSD each show significant initial responses to their own jump shocks, stabilizing over several lag periods. The S&P500 demonstrates a strong positive response to Bitcoin's jump shocks, indicating that volatility in Bitcoin significantly affects the U.S. stock market. In contrast, EURUSD exhibits a negative response to Bitcoin's jump shocks, with a rapid initial decline that stabilizes over time. When Bitcoin experiences shocks from the S&P500, it sharply decreases, showing significant negative feedback before returning to positive values. The influence of EURUSD on S&P500's jumps is relatively weak, with some initial fluctuations. Bitcoin's response to EURUSD shocks is minimal, while S&P500 shows a positive response that persists over several lag periods, suggesting clearer transmission of jump behaviors from the foreign exchange market to the stock market.

Panel C shows that Bitcoin's skewness shocks significantly affect the skewness of both the S&P500 and EURUSD, with notable fluctuations around zero over the lag period. This indicates the U.S. stock market and exchange rates are sensitive to changes in Bitcoin's skewness. In contrast, Bitcoin and S&P500 exhibit relatively mild responses to skewness shocks from EURUSD, with only minor initial fluctuations. Each market displays a significant initial response to its own skewness shocks, highlighting stronger internal transmission within each market.

Panel D shows that the S&P500 and EURUSD exhibit volatility in response to shocks in Bitcoin's daily realized kurtosis (RK), with EURUSD experiencing noticeable initial fluctuations that diminish over time. Both Bitcoin and EURUSD have significant positive initial responses to shocks in the S&P500's RK, but these responses quickly decline. In contrast, both Bitcoin and the S&P500 initially react negatively to shocks from EURUSD's kurtosis before stabilizing. Each variable's kurtosis experiences a sharp initial decline upon its own shocks, followed by stabilization, indicating strong internal stability in kurtosis within each market.

5. Conclusion

This paper employs Granger causality and generalized impulse response function (GIRF) analyses to investigate spillover effects among Bitcoin, stock markets, and foreign exchange markets in the U.S. across various higher-order moment dimensions (volatility, jumps, skewness, and kurtosis).

Significant bidirectional spillover exists between Bitcoin and the S&P 500 regarding volatility and jumps, indicating strong risk transmission between cryptocurrency and traditional stock markets. EURUSD significantly impacts both Bitcoin and the S&P 500 in these dimensions, with its skewness also affecting the S&P 500, highlighting the foreign exchange market's critical role in volatility transmission. In the kurtosis dimension, the S&P 500's influence is more pronounced, especially during extreme risk events, where it exerts a stronger impact on Bitcoin.

Both intraday and monthly analyses show significant spillover effects, indicating a tightening connection between Bitcoin and traditional financial markets. Intraday data captures higher-frequency fluctuations and immediate market reactions, while monthly data reflects longer-term trends, resulting in smoother manifestations of volatility transmission. The monthly analysis demonstrates greater predictive power regarding the persistence of market responses to shocks. Additionally, daily data allows for sharper detection of immediate fluctuations, revealing that exchange rate skewness significantly impacts Bitcoin, while S&P 500 kurtosis emerges as a new contributor to Bitcoin's risk.

In summary, this study provides insights into risk transmission mechanisms between Bitcoin, stock markets, and foreign exchange markets, particularly concerning higher-order moment spillover effects in intraday data. It offers valuable theoretical support and policy recommendations for future global asset allocation, market regulation, and risk management.

Disclosure statement

The author declares no conflict of interest.

References

[1] Mensi W, Kang SH, Vo XV, 2022, COVID-19 Pandemic's Impact on Intraday Volatility Spillover Between Oil, Gold, and Stock Markets. Economic Analysis and Policy, 82: 449–479.

[2] Shakeel M, Rabbani MR, Hawaldar IT, Chhabra V, Zaidi FK, 2023, Is There an Intraday Volatility Spillover Between Exchange Rate, Gold, and Crude Oil? Journal of Open Innovation: Technology, Market, and Complexity, 9: 100094.

[3] Mensi W, Vo XV, Kang SH, 2024, Spillovers and Multiscale Relationships Among Cryptocurrencies: A Portfolio Implication Using High-Frequency Data. Economic Analysis and Policy, 82: 449–479.

[4] Esparcia C, Escribano A, Jareño F, 2024, Assessing the Crypto Market Stability After the FTX Collapse: A Study of High Frequency Volatility and Connectedness. International Review of Financial Analysis, 94: 103287.

[5] Mensi W, Sensoy A, Kang SH, 2019, High-Frequency Asymmetric Volatility Connectedness Between Bitcoin and Major Precious Metals Markets. The North American Journal of Economics and Finance, 50: 101031.

[6] Gkillas K, Bouri E, Gupta R, et al., 2020, Spillovers in Higher-Order Moments of Crude Oil, Gold, and Bitcoin. The Quarterly Review of Economics and Finance, 75: 176–187.

[7] Zhang Z, Wang Y, 2021, Dynamic Spillover Effects Between Stock and Currency Markets: Evidence from the Emerging Market. International Review of Financial Analysis, 76: 101710.

[8] Bouri E, Gupta R, Roubaud D, 2017, The Return and Volatility Spillovers Between Bitcoin and Traditional Assets: Evidence from a VAR-DCC-GARCH Model. Finance Research Letters, 20: 225–233.

[9] Kang W, Yoon S, 2020, Dynamic Spillover Effects Between Stock and Currency Markets: Evidence from High-Frequency Data. Journal of International Financial Markets, Institutions & Money, 67: 101196.

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