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Higher-order moment nexus between the US Dollar, crude oil, gold, and bitcoin

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ABSTRACT

This paper explores the relationships between the US dollar, crude oil, gold, and bitcoin by taking into account the higher-moment linkages. Specifically, we construct robust estimators for the realized volatility, realized skewness, realized kurtosis, and jump, and study the causalities between the estimators through the Granger causality test. A generalized impulse response analysis identified by our quad-variate VAR specification is further implemented to uncover the lead-lag spillover effect across the variables of interest. We utilize high-frequency data for the chosen assets from January 3, 2016, to June 23, 2022, and observe various patterns of cross-market interconnection related to higher-order moments. These findings suggest that systematic risk factors must be considered while jointly modeling market linkages. Practical implications for investors and market regulators are also discussed.

1. Introduction

Over the past decades, market spillover has constantly been a subject of keen interest in the financial area, given that it is of great importance for both researchers and investors in terms of market stability, risk management, and asset allocation. The majority of existing studies focus mainly on return and volatility spillover, overlooking the interactions in higher distribution moments (Warshaw, 2020). In addition to the ordinary first and second distribution moments, higher-order moments represented by skewness and kurtosis reveal some additional types of risk sources such as asymmetry and extremity, which should not be ignored in modeling price movement and market dependence (Aretz and Arisoy, 2023; Engle and Mistry, 2014). Moreover, as volatility often presents discontinuous dynamics characterized by jump behavior, prior studies highlight the role of jumps in asset pricing and volatility modelling (Dutta et al., 2022; Xu, Bouri and Cepni, 2022). The fluctuation and its spillover effect of some strategic assets such as the US dollar, crude oil and gold are especially crucial because they are not only related to the performance of the global financial market, but also relevant to many economic activities (Georgiadis and Schumann, 2021). Accordingly, it is meaningful to study the cross-market risk propagation among these assets from a full perspective by taking into account higher-moment factors.

The above problems are also relevant to bitcoin. As a leading cryptocurrency, bitcoin is widely recognized as a novel category of investment assets and payment tools, which has been controversial since its birth. The emergence of bitcoin has enriched the capital market structure and provided investors with more investment opportunities. On the other hand, bitcoin has raised widespread criticism for its high level of volatility and speculation (Gronwald, 2019). Moreover, the market positioning of bitcoin is ambiguous,

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and understanding of its price determination mechanism still falls short, which disturbs the supervision of bitcoin in practice (Fletcher, Larkin and Corbet, 2021). Despite this controversy, the bitcoin market is still expanding, and increasing attention has been paid to the relationship of bitcoin with conventional assets (Ahmed, 2021; Palazzi, Júnior and Klotzle, 2021). In particular, the interaction between bitcoin and strategic commodities is investigated (Urom et al., 2020; Okorie and Lin, 2020), based on some observations and inferences that bitcoin is a hybrid asset and is affected by oil and gold prices. However, volatility is latent: hence, scholars have proposed the use of a realized estimator of volatility relying on high frequency interval data for volatility modeling and forecasting, as it has been shown to be a consistent estimate of actual volatility (Gallo and Otranto, 2015). Furthermore, volatility often features discontinuous variation, termed as jump behavior, and extant studies highlight the significance of jumps in fitting high frequency financial data (Dungey et al., 2018). Lastly, in addition to the first and the second moments, higher distribution moments of the price process and the related risk spillover effect need further investigation, given that these moment factors possess some important information on the underlying price dynamics.

Against this background, this study furthers the extant research by investigating the spillovers of higher-order moments of the return distributions across the US dollar, bitcoin, oil, and gold markets. To be specific, we first construct robust realized estimators for realized volatility, realized skewness, and realized kurtosis using high frequency intraday data. Then, the Granger causality test is implemented to describe the lead-lag relations of the realized estimators. We proceed to the generalized impulse response analyses identified by our quad-variate VAR structure to uncover the contemporaneous and lagged spillover effect among the variables of interest. We also take into account the discontinuous component of volatility, characterized as jumps, to distinguish jump events from the continuous volatility process. Our work is a natural extension of related studies such as the works of Khalfaoui, Jabeur and Dogan (2022), and Jiang et al. (2022). However, by employing intraday data, we are able to capture more intraday patterns of price dynamics and higher-order moment risk features. Moreover, we use realized volatility as the proxy for practical volatility, as realized estimators have been extensively proven to be superior in high-frequency modeling.

The empirical findings show various patterns of interaction among the four markets through higher-moment channels, in which the most prominent is the relationship between bitcoin and gold. The bitcoin and gold markets are significantly linked through the channels of realized volatility, realized skewness, realized kurtosis, and jumps, suggesting that a spillover effect between the two markets not only exists in volatility risk, but also in asymmetric and extreme risks. We also find that the US dollar is the common driver of volatility risk for the other three markets.

The rest of the paper is organized as follows: Section 2 illustrates the theoretical background and reviews the related studies. Section 3 introduces our employed methodology. Section 4 displays the empirical findings. Section 5 discusses the results and the insights for management. The last section concludes the work.

2. Theoretical background and related studies

Price movement and risk spillovers across strategic financial assets, such as the US dollar, crude oil, and gold, has always been a key issue in financial economics, since it is of great importance for asset allocation, risk management, and asset pricing. As is well known, the US dollar is the most commonly converted currency in the world and is regularly used as a benchmark in the Forex market. As the dominant global reserve currency, it is held by nearly every central bank in the world. Additionally, the dollar is used as the standard currency in the commodity market, and thus has a direct impact on commodity prices (Grossmann and Kim, 2022; Ayres, Hevia and Nicolini, 2020). Crude oil is a strategic resource for each country because it is the upstream raw material of many industrial products. Crude oil is the input of some economic activities, and an oil market shock not only affects petroleum markets but also capital markets such as the foreign exchange market (Ivan, Banti and Kellard, 2022). On the other hand, crude oil is also prominent for its financial attributes. Financial derivatives based on crude oil prices are widely used by worldwide investors for hedging and speculation (Guo, Long and Luo, 2022; Li, 2018). Accordingly, the volatility of the crude oil market will significantly influence the stability of the international financial market. Gold has long been viewed as a global currency, a commodity, and an investment. In contrast to oil, gold is less associated with macroeconomic activities, and the underlying driving factor of the market is quite different. Since gold is weakly correlated with many other conventional assets, it is generally considered as a hedge to counter the adverse movement of various asset classes (Younis, Shah and Yousaf, 2023; Ansari and Sensarma, 2019). The performance of gold is particularly impressive during market crises. Previous studies validate the excellent performance of gold during several crisis periods, such as the 2007 global financial crisis and the 2020 pandemic crisis (Choudhry, Hassan and Shabi, 2015).

In recent years, cryptocurrency, represented by bitcoin, has attracted increasing attention from both academics and investors. Bitcoin is widely regarded as a new means of value storage and payment, which accommodates the attributes of currency, commodity, and investment goods (Elsayed, Gozgor and Lau, 2020; Kajtazi and Moro, 2019). Despite the strict regulatory measures issued by many countries, bitcoin transactions are still growing exponentially, reaching more than $32 trillion by the end of 2021. The emergence of bitcoin has brought vast shocks and challenges to the traditional financial market, and has also raised considerable controversy and criticism. The doubts about this new category of digital assets mainly lie in three aspects. First, the status of bitcoin in economics and finance is ambiguous. Whether it should be viewed as a commodity, an investment asset, or an alternative to standard currency is still debatable. The identity of bitcoin is vital because it determines the role of bitcoin in the economic system and how the government should regulate it. In any case, bitcoin is a highly risky asset with a trading market that fluctuates dramatically and frequently. Indeed, the value of this currency has seen wild price swings during its short existence. Due to the high volume of buying and selling on exchanges, it is highly sensitive to any newsworthy events.[1] Moreover, Bitcoin is criticized for consuming a tremendous amount of electrical energy and computing power during its mining process, which leads to a waste of national resources.[2] Consequently, the ecological destruction and carbon emissions associated with Bitcoin undermine global sustainable development efforts (Jiang et al., 2021). Although debatable, the promises and attractiveness of bitcoin mean that it plays an increasingly important role in the financial market.

The literature on financial market linkages is abundant and prominent, and many empirical models have been developed regarding the return and volatility spillovers across different categories of assets (Golitsis, Gkasis and Bellos, 2022; Elsayed, Gozgor and Yarovaya, 2022; Lin et al., 2021). We mainly focus on and briefly review the bitcoin-related literature on market linkages, given the scope of this study. As regards the relations between bitcoin and the currency market, Yang, Wang and Gao (2022) examine the hedging of bitcoin against six currencies before and during the recent Covid-19 crisis, concluding that bitcoin is an effective hedging tool for currency market risk in both stable and turbulent periods. Kwon (2020) focuses on the tail dependency between bitcoin and US dollar returns. Using the CAVaR model, the author indicates that the tail of dollar return appears to be related to the risk premium on bitcoin return. However, a contrasting result is reported by Ji et al. (2018), who apply the DAG model to investigate the contemporaneous causalities between bitcoin and some other assets, including the dollar, concluding that bitcoin is isolated instead of coupling with these assets.

The relation between bitcoin and commodities has been extensively studied in the past, with most of these studies showing evidence that the two categories of assets are closely linked through multiple channels (Khalfaoui, Jabeur and Dogan, 2022; Semeyutin, Gozgor and Lau, 2021; Al-Yahyaee et al., 2019; Beneki et al., 2019). Bouri et al. (2018) use a DCC-GARCH model to examine spillover effects between bitcoin and strategic commodities under different market conditions, finding that the bitcoin market is closely related to commodity markets via return and volatility channels. Bouoiyour and Selmi (2015) show a long-term cointegration between bitcoin and gold prices. Corbet et al. (2018) employ network analysis to investigate market spillovers between bitcoin and a variety of energy sectors, indicating the presence of spillover in both time and frequency domains. Huang, Duan, and Urquhart (2023) particularly focus on the effect of the Covid-19 event on the interdependence between bitcoin and commodities by taking into account two subsamples, taken before and during the onset of the pandemic, and finding that the dependence is significantly enhanced and expanded after the onset of the crisis. Quite similar results are presented by Katsiampa, Yarovaya and Zięba (2022) and Guo, Lu, and Wei (2021), although the former apply a machine learning approach, while the latter construct a spillover index in a financial network framework. Although limited, a few studies extend the examination of market spillovers to higher-order moment representations. For instance, Gkillas et al. (2022) study the lead-lag relationship between bitcoin and strategic commodities through the causality test with higher-order moment, emphasizing the importance of incorporating these higher-order systematic factors when modeling connectedness across these markets.

As a lot of evidence indicates, market integration is highly dependent on market conditions. This means that significant shifts in the underlying relationships between financial markets or assets can occur due to structural breaks. Structural breaks are often associated with the onset of financial crises. Guhathakurta et al. (2020) demonstrate that gold serves as the main transmitter of shocks to oil and other commodities when considering spillover networks that account for structural breaks. Zhang et al. (2022) conduct research on cross-market contagion related to jump behavior and find significant changes in jump correlations before and after the occurrence of Covid-19. Nazlioglu et al. (2022) provide support for financial market integration by incorporating heavy tails, structural shifts, and nonlinearity into their analysis.

Against the status of a relatively scant literature on market linkage related to higher-order moments, the present work explores the relationships among the US dollar, bitcoin, oil, and gold from three perspectives, namely higher-order moment estimators relying on high-frequency data, causality between higher-moment estimators, and cross-market spillovers among the variables. To the best of our knowledge, our study is among the first to examine the possible higher-moment information spillovers between bitcoin and strategic assets, while considering the recent market turbulent period induced by the Covid-19 crisis. Such analysis is meaningful for both policy-makers and investors in order to avoid any misguided assumptions with respect to the casual interaction among these markets.

3. Methodology

3.1. Realized higher-moment estimators

We assume that the logarithm price of a financial asset takes a standard jump-diffusion pricing process, described as

$$dp(t) = \mu(t)dt + \sigma(t)dW(t) + \kappa(t)dq(t) \tag{1}$$

in which $p(t)$ denotes the log price at time t, and $\mu(t)$ is the drift term with a continuous and locally bounded variation sample path, $\sigma(t)$ denotes the volatility process, which is strictly positive, and $W(t)$ represents the independent standard Brownian motion. $q(t)$ refers to a Poisson counting process with a random jump size $\kappa(t)$ and intensity $\lambda(t)$. $q(t)$ is equal to 1 if there is a jump event at time t

[1] According to the Consumer Financial Protection Bureau (CFPB), the price of bitcoin fell by 61% in a single day in 2013, while the one-day price drop record in 2014 was as big as 80%.

[2] According to the statistics of the International Energy Agency (IEA), bitcoin "mining" consumed about 50 to 70 megawatt hours in 2020, roughly equivalent to the consumption of a country as large as Switzerland.

and 0 otherwise.

Next, we compute the nonparametric daily realized volatility RV_t using intraday squared returns to observe the continuous sample path for asset prices as

$$RV_{t+1}(\Delta) \equiv \sum_{j=1}^{1/\Delta} r_{t+j\Delta,\Delta}^2 \tag{2}$$

In accordance with the theory of quadratic variation, RV_t converges uniformly in probability to a quadratic variation as $\Delta \to 0$. Therefore, it provides a consistent estimation of total variation in a nonparametric paradigm when suitable scaling is implemented.

In the presence of a jump event, we use the realized bi-power variation (BV) estimator proposed by Barndorff-Nielsen and Shephard (2004) to separate the discrete jump component from the consistent total variation as

$$BV_{t+1}(\Delta) \equiv \mu_1^{-2} \sum_{j=2}^{1/\Delta} |r_{t+j\Delta,\Delta}||r_{t+(j-1)\Delta,\Delta}| \to \int_{t-1}^{t} \delta^2(s)ds, \mu_1 = \sqrt{2/\pi} \tag{3}$$

when $\Delta \to 0$, the difference between RV and BV measures the discontinuous component of the sample variance. We can use the Z statistic proposed by Huang and Tauchen (2005) to characterize statistically significant jump events. The jump statistic Z is defined as

$$Z_{t+1}(\Delta) \equiv \frac{[RV_t(\Delta) - BV_t(\Delta)]RV_t(\Delta)^{-1}}{\left[(\mu_1^{-4} + 2\mu_1^{-2} - 5)\max\left\{1, TQ_t(\Delta)BV_t(\Delta)^{-2}\right\}\right]^{1/2}} \tag{4}$$

in which $TQ_{t+1}(\Delta) \equiv \Delta^{-1}\mu_{\frac{4}{3}}^{-3}\sum_{j=3}^{1/\Delta}|r_{t+j\Delta,\Delta}|^{4/3}|r_{t+(j-1)\Delta,\Delta}|^{4/3}|r_{t+(j-2)\Delta,\Delta}|^{4/3}, \mu_{\frac{4}{3}} \equiv 2^{\frac{2}{3}}\Gamma\left(\frac{7}{6}\right)\cdot\Gamma\left(\frac{1}{2}\right)^{-1}$.

Given the significance level of 1 - α, we define the discrete jump component in daily frequency as

$$J_{t+1,\alpha}(\Delta) = I[Z_{t+1}(\Delta)\rangle\phi_\alpha] \times [RV_{t+1}(\Delta) - BV_{t+1}(\Delta)] \tag{5}$$

where $I(\cdot)$ is the indicator function, and ϕ_α stands for a Gaussian distribution.

The second moment RV comprises both a continuous component and a discontinuous component, characterized as jumps, while the third and fourth moments of the return distribution are merely decided by jump parameters. Specifically, the third realized moment RS calculates the conditional skewness of returns to reveal the tail risk in the price process. A negative RS suggests that the daily return is left-skewed distributed to the mean value, implying a higher probability of price crash risk, whereas a positive RS is usually preferred by rational investors because this price pattern indicates a greater upside potential. The realized skewness RS is constructed based on intraday returns as

$$RS_t = \frac{\sqrt{T}\sum_{i=1}^{T} r_{t,i}^3}{RV_t^{3/2}} \tag{6}$$

We construct the fourth realized moment estimator to reflect the extreme deviations risk of the return distribution as

$$RK_t = \frac{T\sum_{i=1}^{T} r_{t,i}^4}{RV_t^2} \tag{7}$$

RK_t is the daily realized kurtosis, which is equal to three in the case of normal distribution. An excess RK_t indicates a leptokurtic distribution, implying that the probability of extreme value occurrence is significantly greater than that of a normal distribution.

3.2. Spillover effect

To investigate the spillovers across the higher-moment estimators for US dollar, crude oil, gold, and bitcoin, we employ the Granger causality test combined with the Wald tests within a VAR framework. In a standard form, a k-dimensional VAR representation can be expressed as

$$Y_t = \upsilon + A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + \varepsilon_t \tag{8}$$

where Y_t is a $K \times 1$ vector of response variables, υ is a $K \times 1$ vector encapsulating the deterministic components of the specification, A_i represents the coefficient matrices of size $K \times K$, and ε_t is the vector of structural residuals. For the estimation of the VAR model, we apply ordinary least squares to produce estimates which are robust to both heteroskedasticity and autocorrelation.

Then, we proceed to the Granger causality test to examine whether the values of a specific variable have explanatory power on the values of the rest of the variables in the system. We employ the Wald χ^2 statistic as the criterion of significance for this kind of causality.

Lastly, we analyze the dynamic characteristic of the system via the so-called Generalized Impulse Response Functions (GIRF). We employ this procedure to avoid imposing any prior implausible restrictions on the system, given that the underlying mechanism of risk transmission across markets lacks understanding. Moreover, the outcome of the GIRFs is irrelevant to the ordering of the functions in the system. The generalized representation of the GIRF is defined as

$$\widehat{\psi}_j(h) = \sigma_{jj}^{-1/2} \prod_h \sum_\varepsilon e_j, h = 0, 1, 2, \cdots \tag{9}$$

in which $\{\sigma_{jj}\}$ represents the $m \times m$ variance–covariance matrix of the disturbance term ε_t, e_j is the $m \times 1$ vector of a unity matrix. $\prod_i$ is the $K \times K$ coefficients' matrix derived from an inverse expression of the moving average specification. According to Pesaran and Shin (1998), $\prod_i$ can be derived recursively through the functions as

$$\prod_i = \begin{cases} \sum_{j=1}^{i} \prod_{i-j} A_j, i = 1, 2, \cdots, p \\ \sum_{j=1}^{p} \prod_{i-j} A_j, i > p \end{cases} \tag{10}$$

4. Empirical results

4.1. Sample data

For the empirical study, we use high-frequency data for the US dollar, crude oil, gold, and bitcoin for the period spanning January 3, 2016 to June 23, 2022. We select a sampling frequency of fifteen minutes and construct fifteen-minute log-returns. This selection takes into account the trade-off between the issue of lack of liquidity associated with small time windows and the reliability of the realized moment estimator. Data for the US dollar index, Brent crude oil, and gold are collected from Datastream. Price data for bitcoin is drawn from Bitcoincharts. We rely on oil and gold futures contract data because the futures market performs better than the spot market in terms of information processing and price discovery (Lin, Chou and Wang, 2018). In addition, we collect data from the intraday

Table 1
Results of Granger causality tests among the realized distribution moment estimators of the four categories of assets.

Market variables	US dollar	Crude oil	Gold	Bitcoin
Panel A: realized volatility				
US Dollar	–	4.723	2.176	9.576
	–	(0.867)	(1.03)	(0.798)
Crude oil	33.765***	–	8.176	26.765**
	(0.000)	–	(0.779)	(0.001)
Gold	11.76**	11.124	–	30.171**
	(0.001)	(0.858)	–	(0.011)
Bitcoin	28.365**	19.897**	61.675***	–
	(0.001)	(0.001)	(0.000)	–
Panel B: realized skewness				
US Dollar	–	13.711	10.678	3.671
	–	(0.746)	(0.856)	(0.756)
Crude oil	7.676	–	7.561	6.769
	(0.541)	–	(0.471)	(0.657)
Gold	6.576	15.451	–	12.678
	(0.451)	(0.664)	–	(0.341)
Bitcoin	8.674	7.561	40.543***	–
	(0.335)	(0.547)	(0.000)	–
Panel C: realized kurtosis				
US Dollar	–	8.671	16.667	14.276
	–	(0.541)	(0.431)	(0.797)
Crude oil	9.676	–	13.561	31.675**
	(0.412)	–	(0.671)	(0.002)
Gold	7.676	9.671	–	12.676
	(0.335)	(0.335)	–	(0.379)
Bitcoin	11.671	7.897	33.175***	–
	(0.542)	(0.442)	(0.001)	–
Panel D: realized jumps				
US Dollar	–	3.891	5.451	4.575
	–	(0.317)	(0.424)	(0.303)
Crude oil	7.789	–	16.675	41.787***
	(0.355)	–	(0.381)	(0.000)
Gold	9.786	9.785	–	10.671
	(0.402)	(0.436)	–	(0.454)
Bitcoin	10.768	8.838	31.676**	–
	(0.378)	(0.413)	(0.005)	–

Note: The table reports the Wald statistics to test the causality relationship between market variables under consideration. Panel A, Panel B, Panel C, and Panel D refer to realized volatility, realized skewness, realized kurtosis, and jumps, respectively. The notations vertically listed in the panel refer to the response variables, while the horizontal ones refer to the predictor variables. The lag order is determined according to the Akaike information criterion. The *p*-values of the test results are provided in brackets. ***; **; * indicate statistical significance at 1%, 5% and 10% respectively.

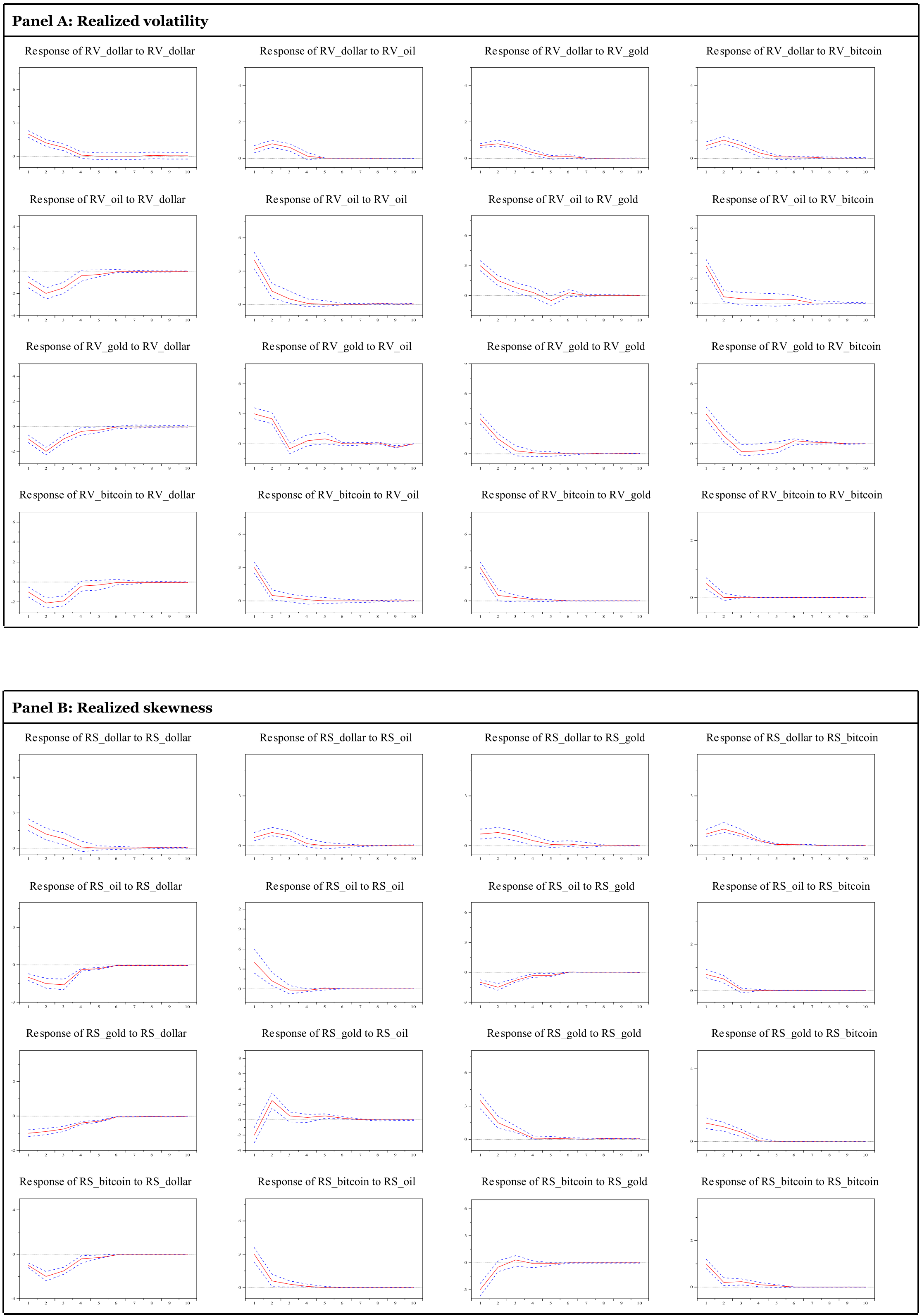

Fig. 1. Impulse-response functions for shocks to the US dollar, crude oil, gold and bitcoin.

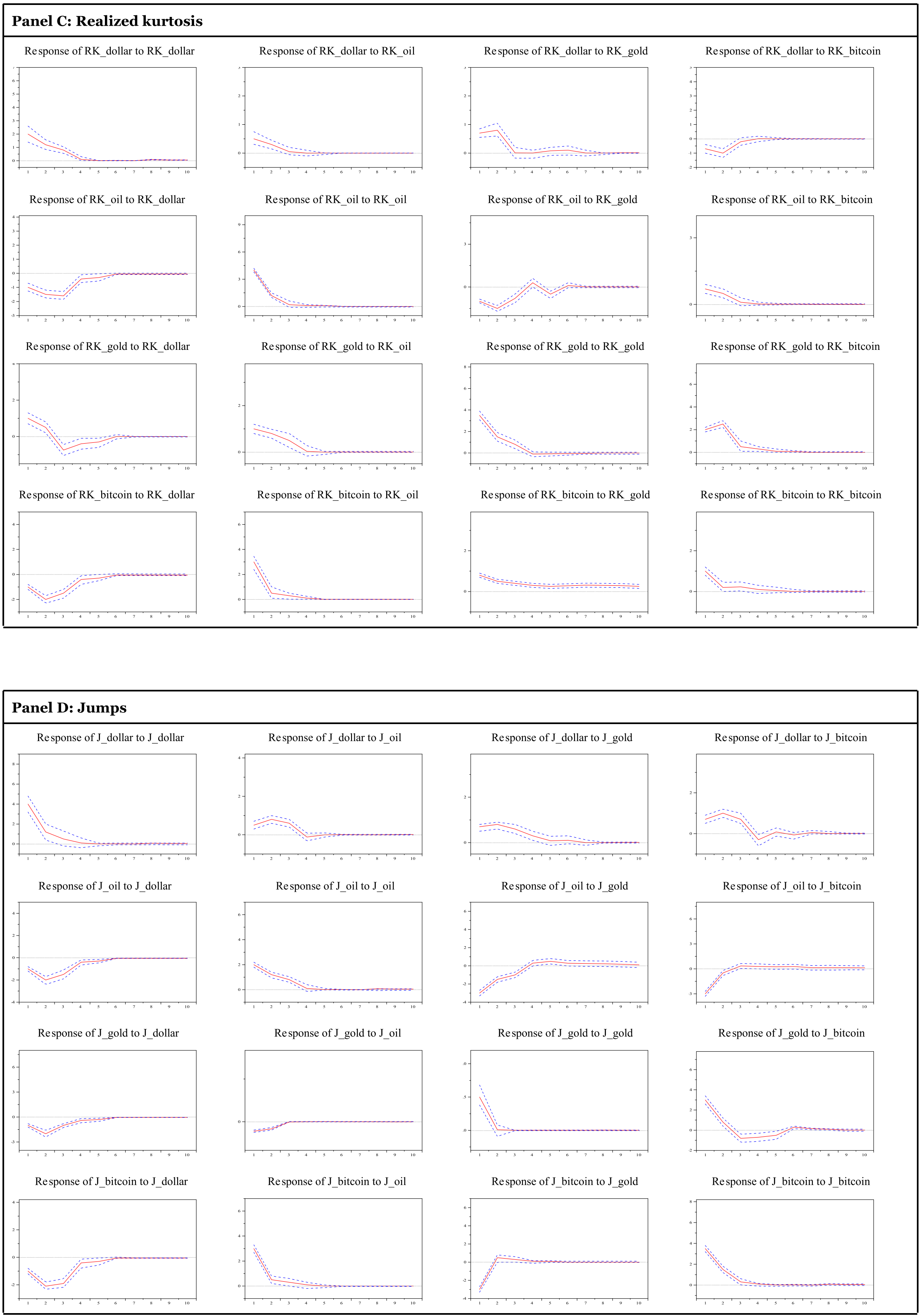

Fig. 1. (*continued*).

overlap trading time period of each market for the sake of synchronization. All the data series have been cleaned, and we omit the non-overlap trading days among the variables, as well as trading days around holidays.

4.2. Empirical findings

Table 1 reports the results of the Granger causality and Wald significance tests among the higher-order moments for the markets investigated. Panels A, B, C, and D in Table 1 respectively cover the realized volatility (second moment), the realized skewness (third moment), the realized kurtosis (fourth moment), and jumps. The lag order in the VAR model is determined by the AIC criterion. The horizontal notation of the variables corresponds to the predictive variables, while the response variables are listed vertically in each panel. Fig. 1 displays the dynamic impulse-response structure among the moment estimators of each variable identified by the quad-variate VAR system. As there are four variables in our VAR specification, a total of sixteen directional relations are generated with respect to a specified moment estimator. Furthermore, we use the error-corrected technique to estimate the 95% bootstrap confidence intervals, as proposed by Efron and Tibshirani (1993).

From panel A of Table 1, we observe that there exists a bidirectional causal relationship between RV^{gold} and $RV^{bitcoin}$, and the results are significant at the level of 1%. A similar bidirectional causality pattern is observed between RV^{oil} and $RV^{bitcoin}$. We also find uni-directional causality delivery from RV^{dollar} to RV^{oil}, from RV^{dollar} to RV^{gold}, and from RV^{dollar} to $RV^{bitcoin}$. Turing to the GIRF results as displayed in Panel A of Fig. 1, it can be seen that the realized volatilities of crude oil, gold, and bitcoin react negatively to RV^{dollar} shock, and the effects decay to around zero three days afterward. RV^{oil} responses positively to RV^{gold} shock at the initial phase; it then fluctuates positively and closely to the zero line for most of the following observing days, with the exception of day five. Shock to $RV^{bitcoin}$ will generate a positive response of RV^{oil}. As for RV^{gold}, it reacts positively to a shock to RV^{oil}, with the exception of day six and day nine, when the effect is negative. The effect from $RV^{bitcoin}$ shock to RV^{gold} is initially positive, but it becomes negative on days three to five, and returns to positive on the remaining days. The responses of $RV^{bitcoin}$ to shocks to crude oil and gold are both positive. However, the effects persist for five and four days respectively and then decay to a negligible level. We also note that both RV^{oil} and RV^{gold} are significantly affected by a shock to their own market. This pattern is also true for $RV^{bitcoin}$, although the effect is small and short-lived. The findings partly accommodate the findings of Corbet et al. (2018), who study the causality between crude oil and bitcoin volatilities, indicating a close connectedness between the two market variables. In a related work, Zeng, Yang and Shen (2020) provide evidence of a bidirectional and asymmetric pattern of volatility linkage between the oil and bitcoin markets.

Panel B of Table 1 presents the results of a causality test between the realized skewness estimators of the four variables. We only observe one case of a Granger causality pattern, which is from RS^{gold} to $RS^{bitcoin}$ at a significance level of 1%. The GIRF results suggest that both RS^{oil} and RS^{gold} are slightly affected, in the short run, by a shock to $RS^{bitcoin}$. This effect disappears after two days for RS^{oil}, and three days for RS^{gold}. The response of RS^{oil} to a shock to RS^{gold} is negative, and the effect lasts for five days and then dies out. RS^{gold} responds negatively to a shock to RS^{oil} on day one, and becomes positive from day two until day six, and then decays. As for $RS^{bitcoin}$, it responds negatively to RS^{gold}, with the exception of day 3, and the effect ends after day 6. We also note that RS^{oil}, RS^{gold}, and $RS^{bitcoin}$ all react negatively in response to a shock to RS^{dollar}. When turning to the response to own shocks, RS^{dollar} and $RS^{bitcoin}$ both respond positively to their own shocks. RS^{oil} initially reacts positively to its own shock, but the effect reverses from day three and fades out after day six. The response of RS^{gold} to its own shock is initially positive, after which the effect fluctuates around the zero level and decays after day seven.

Panel C of Table 1 gives the results of the causality tests between the realized kurtosis estimators of the considered markets. The results provide evidence of a significant causality delivering from RK^{gold} to $RK^{bitcoin}$, and from $RK^{bitcoin}$ to RK^{oil}. For the rest of the cases, no significant causal relations are detected. The GIRF suggests that the initial reactions of RK^{dollar} are positive to RK^{oil} and RK^{gold} shocks, but negative to $RK^{bitcoin}$ shock. Moreover, these effects all fluctuate around the zero line after a few days, specifically two days for RK^{oil} and RK^{gold}, and three days for $RK^{bitcoin}$. RK^{oil} is negatively affected by a shock to RK^{gold}, with the exception of day four, and the response ends after day six. The response of RK^{oil} to a shock to $RK^{bitcoin}$ is positive. In relation to RK^{gold}, it reacts positively to a RK^{dollar} shock in the first two days, then becomes negative for the following three days and decays afterwards. The response of $RK^{bitcoin}$ to RK^{gold} shock is positive, and the response persists to the end of the period at nearly the same size. With respect to shocks originating from own market, RK^{dollar}, RK^{oil}, and $RK^{bitcoin}$ all present a positive response. The initial response of RK^{gold} to its own shock is positive: this effect persists for three days and then turns negative, and perishes after day seven.

Finally, we move to the jump causality analysis, as shown in panel D of Table 1. We observe an unidirectional causal relation from $J^{bitcoin}$ to J^{oil} at a significance level of 1%, and from J^{gold} to $J^{bitcoin}$ at a significance level of 5%. The GIRF analysis suggests that J^{dollar} responds positively to $J^{bitcoin}$ and J^{oil} shocks for most of the observed days. The response of J^{oil} to J^{gold} shock is negative for the first three days, and then turns positive and lasts until the end of the observation period. Similar patterns are found for J^{oil} and $J^{bitcoin}$ causality. The response of J^{oil} to $J^{bitcoin}$ shock is initially negative and then becomes positive from day three. J^{gold} is not significantly affected by a shock to J^{oil}, and it responds negatively to a shock to J^{oil} for the first two days, and then fluctuates around the zero horizon until the end. As for $J^{bitcoin}$, it responds initially negatively to a shock to J^{gold}, and then turns positive from day two to day five, after which it decays. Moreover, jump estimators for all four variables react positively to their own shocks.

5. Discussion

Through the Granger causality and GIRF analysis discussed previously, some insightful implications in relation to the spillovers across the investigated markets emerge:

The bidirectional causal relationship between the realized volatilities of crude oil and bitcoin suggests that the volatility of the crude oil market significantly influences the bitcoin market through feedback. This may be attributed to the close linkage between the mining process of bitcoin and the consumption of energy. The gold market also mutually interacts with the bitcoin market through the second-moment channel due to the similar hedging functions for the two assets. The realized volatility of the US dollar Granger causes that of oil, gold, and bitcoin. This appearance is not difficult to understand, because the US dollar is used as the standard currency in the commodity market and its condition therefore has a direct impact on commodity prices.

There exists a causal relationship between gold and bitcoin market returns in terms of skewness distribution, suggesting that the gold market and the bitcoin market are connected through the asymmetry of the return distribution. Besides, the realized kurtosis of gold significantly affects that of bitcoin, indicating a spillover of extreme risk from the gold market to the bitcoin market. These patterns of higher-moment linkages indicate that investors should not suppose that asymmetric or extreme risk in one market is irrelevant to its related market.

Lastly, bitcoin market jumps Granger cause oil market jumps, and gold market jumps Granger cause bitcoin market jumps. As jump behavior is a discontinuous price movement caused by unanticipated economic and geopolitical events or abnormal trading activity, this finding provides helpful implications for market regulators to avoid potential crash risk of a market induced by the jumps occurring in a related market. In addition, investors in the bitcoin market would require higher risk premia in response to an increased probability of jump risk in the gold market, given that such jumps represent a source of systematic risk in nature.

In conclusion, these findings to a large extent corroborate those of Moussa et al. (2021), Urom et al. (2020), and Elsayed, Gozgor and Lau (2022). Moussa et al. (2021) examine the contagion effect across a variety of assets by showing strong evidence of volatility spillovers from crude oil to bitcoin. In a similar work, Urom et al. (2020) also demonstrate that the oil and bitcoin markets are closely connected in a global asset risk spillover network representation. Moreover, in line with the findings of Matkovskyy and Jalan (2019), our study also supports the volatility spillover assumption between the gold and bitcoin markets in terms of both the continuous and discontinuous volatility components. However, in contrast to Gkillas et al. (2022), we find little evidence of higher-moment linkages between the oil and gold markets, but just a relatively weak connectedness of the continuous component of realized volatility. This inconsistency might be due to our reliance on more recent sample data, which accommodates different market dynamics.

6. Conclusions and implications

This study investigates the relationship of higher distribution moments across the US dollar, oil, gold, and bitcoin markets on the foundation that these higher-order moments may possess useful information in describing asset price movement. We use fifteen-minute high-frequency intraday data covering the period from 2016 to 2021 for our empirical study, and some crucial findings emerge. Most significantly, the gold and bitcoin markets are closely connected through the channels of realized volatility, skewness, kurtosis, and jumps. Besides, some other patterns of market relationships respecting higher-moments are also detected via our procedure. For example, the discontinuous volatility risk of the bitcoin market can be transmitted to the oil market. Moreover, we note that the volatility sourcing from the US dollar market is a common driver for volatility risk in respect to the oil, gold, and bitcoin markets.

These findings reveal the existence of cross-market linkages which pose a significant concern for investors and risk management professionals. As a result, it is essential to consider the linkages among the US dollar, crude oil, gold, and bitcoin through higher moments to avoid disregarding the importance of symmetry and fat-tail risks, which may affect the VaR model and lead to erroneous financial and risk management decisions as well as inaccurate pricing of those assets. For instance, Jang and Kang (2017) present a higher-order CAPM model by incorporating the third and fourth-order systematic risk factors, emphasizing the importance of analyzing different moments when pricing and predicting financial options.

It is crucial to closely monitor the US dollar market and US monetary policy since the behaviors of the US dollar play a pivotal role in the risk formation of the other three assets. Our research underscores the necessity for continuous monitoring of the bitcoin market, as it can propagate volatility risk, jumping in volatility risk, fat-tail risk, and asymmetrical risk to strategic commodities typically viewed as hedges or safe havens. Hence, bitcoin may evolve into a destabilizing factor for these strategic commodities and the global financial system. With the bitcoin market projected to regain its previous levels observed by the end of 2017, this potential source of instability might intensify. Moreover, considering that policymakers need to make decisions during financial (commodity) market turbulence, developing an econometric comprehension of jump behaviors grounded in their authentic generating mechanisms holds substantial financial importance for sustainable market stability.

In future research, we plan to construct and evaluate portfolio performance arising from the inclusion of the assets while considering the higher-moment linkages.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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