| Research Papers

Volatility and Risk Spillovers between CBDC and Digital Currency Markets: Evidence from Copula Switching Models.

Soheil Saliminasab*, Gholamhosein Golarzi, and Abdolsadeh Neisy

Authors
Soheil SalimiNasab*, Department of Economic and Management, Semnan University, Semnan, Iran.
soheilsaliminasab@yahoo.com

Gholamhosein Golarzi, Department of Economic and Management, Semnan University, Semnan, Iran
G_golarzi@semnan.ac.ir

Abdolsadeh Neisy, Department of Mathematics, Faculty of Statistics, Mathematics & Computer, Allameh Tabataba'i University, Tehran, Iran
a_neisy@alumni.iust.ac.ir

* Corresponding author.

Abstract
Central Bank Digital Currency (CBDC), as an innovation in the global monetary system, has attracted significant attention from many countries and researchers. These currencies are digital forms of national money issued and regulated by the central banks of various countries. With the expansion of financial technologies and the increasing popularity of decentralized digital currencies, many countries are exploring and implementing CBDCs as a solution to improve payment systems and increase financial inclusion. In this paper, we aim to examine the impacts and risk spillover from the CBDC market on digital currency markets, particularly the bitcoin market. This research utilizes a combination of copula models and switching models. First, we will analyze marginal models, examining Heston switching and Markov switching models in these markets, and then create a multivariate distribution function using copula models. The data analyzed in this study spans from January 2015 to January 2025 in both the CBDC and Bitcoin markets. This period was chosen to investigate different regimes in these markets and select appropriate marginal models for them. The results indicate that the CBDC market influences the Bitcoin market; therefore, volatility in the CBDC market can also impact the global Bitcoin market. Using the Heston switching model combined with copula models, such as the Gumbel copula, can yield favourable results. Comparing this model with other models, such as Markov switching copulas, confirms this advantage.

Keywords: Heston switching copula model, Gumbel copula, Spillover, Digital currency markets, Fiat currencies.
JEL Classification: G11, G15, C58.

Article Information
Received: 12 February 2026.
Revised: 16 March 2026.
Accepted: 16 March 2026.
Published: 22 May 2026.

Citation:
Saliminasab, S., Golarzi, G., & Neisy, A. (2026). Volatility and risk spillovers between CBDC and digital currency markets: Evidence from copula switching models. *The Journal of Fintech and Digital Assets*, 1(1), 56–73.

1. Introduction

Central Bank Digital Currency (CBDC) is a type of national digital currency issued by a country's central bank, whose status as legal tender depends on the laws or regulations of the issuing country. What has driven central banks to develop national digital currencies is the competition with decentralized encrypted digital currencies. With the advent of blockchain technology, bitcoin, and other cryptocurrencies, governments have realized the importance of these decentralized financial systems.

Moreover, in 2020, with the outbreak of the COVID-19 pandemic, the global financial system showed increased interest in these cryptocurrencies. For this reason, central banks began exploring CBDCs as a suitable alternative to cryptocurrencies. They view CBDCs as a solution to manage the threats posed by cryptocurrencies. In other words, they are trying to offer the benefits of monetary systems like Bitcoin and Ethereum within a framework controlled by themselves.

Unlike decentralized cryptocurrencies, CBDCs are under government supervision and are issued with their backing. Each unit of CBDC acts as a secure digital equivalent of the national currency, so it can be referred to as a fiat currency. As of February 2025, out of a total of 167 CBDC-related projects being carried out by central banks, 160 projects are in various phases of research and implementation.

These currencies offer numerous advantages, such as helping to maintain financial stability, increasing public access to financial services, and addressing issues associated with existing digital currencies. Therefore, policymakers and investors must remain vigilant to ensure market stability and financial growth. Numerous studies have been conducted on CBDCs so far, examining various aspects including their benefits, challenges, and implementation. For instance, the Bank for International Settlements (BIS) concluded in its 2020 research that CBDCs can enhance the efficiency of payment systems, reduce transaction costs, and improve financial inclusion. On the other hand, it is important to note that implementing CBDCs without considering security and privacy challenges could pose risks to the financial system.

One of the areas significantly impacted by the introduction of CBDC is the banking sector, in that CBDCs could lead to the disintermediation of banks (Kim et al., 2022). On the other hand, CBDCs may also affect the lending capacity of banks. Overall, the rise of CBDCs can increase competition and innovation in monetary and banking sectors (Ward and Rochement, 2019).

The implementation of monetary policies can also be influenced by CBDCs. For example, in a financial system with scarce reserves, the central bank must actively manage the flows between reserves, CBDCs, and other liabilities to maintain control over interest rates. On the other hand, in a financial system with abundant reserves, the central bank’s approach may involve increasing the supply of reserves (Kim et al., 2022). Consequently, the risk spillover effects of CBDCs are multifaceted and highly dependent on their design, the structure of the existing financial system, and the central bank's policies. While CBDCs offer potential benefits, significant risks and uncertainties remain that require careful examination. A well-designed CBDC can enhance efficiency and financial inclusion, but if poorly designed, it could lead to instability in financial markets.

Since these currencies are a form of fiat money, it can be predicted that their functionality and spillover effects will resemble those of physical currencies. Research has been conducted on the impact of foreign exchange markets on digital currency markets, including studies by Alsaid et al. (2022), Rahman et al. (2023), and Ubaid et al. (2023).

However, despite the growing body of literature on the operational and macroeconomic implications of CBDCs, the potential risk spillover from CBDC-related uncertainty to cryptocurrency markets remains largely unexplored. Specifically, no study to date has empirically examined whether media-derived sentiment and policy uncertainty surrounding CBDC development transmit volatility to decentralized digital assets such as bitcoin. This gap is significant, given the competitive positioning of CBDCs as sovereign alternatives to cryptocurrencies and the increasing interconnectedness of digital asset markets.

This study aims to address this gap by investigating the risk spillover between CBDC-related uncertainty and the bitcoin market. The primary research objective is to determine whether uncertainty surrounding CBDC development - measured through a text-based index derived from news articles - significantly affects bitcoin's volatility. Unlike previous studies that focus on price-based spillovers between established financial markets, this study introduces a novel theoretical channel: policy-induced uncertainty as a driver of volatility transmission in the absence of a liquid spot market for CBDCs.

Accordingly, we formally test the following hypothesis, the uncertainty regarding CBDC development has a statistically significant positive spillover effect on the volatility of bitcoin. The use of a news-derived uncertainty index alongside a financial price series warrants theoretical justification. In the absence of historical trading data for CBDCs, media coverage and central bank communications constitute the primary channel through which market participants form expectations about the future state of digital fiat competition. Therefore, treating the CBDC Uncertainty Index as a valid proxy for latent policy risk is both conceptually sound and methodologically necessary. To capture the asymmetric and state-dependent nature of volatility transmission, we employ a regime-switching stochastic volatility model, which allows for the identification of spillover effects under different market regimes.

By doing so, this study contributes to the literature in two ways. First, it extends the scope of spillover analysis to include policy-driven uncertainty as a distinct source of risk in cryptocurrency markets. Second, it provides empirical evidence on the interdependence between sovereign digital currencies and decentralized financial assets, offering insights for policymakers and investors regarding the broader risk architecture of the digital economy. The next section provides research background, followed by research methodology. Data and empirical results are presented in section 4, and section 5 concludes the paper.

2. Research Background

The topic of spillover between markets is considered one of the favorite subjects among researchers. As mentioned, with the liberalization of information and the increase in interactions between different markets, the spillover between markets has garnered more attention than ever before. Researchers generally believe that risk spillover can occur due to various factors. For example, factors such as investor behavior and expectations (Mihae and Maria, 2020), market efficiency and the level of information transfer and freedom of information dissemination in the market (Ajaya et al., 2021), regulatory oversight of the market by various institutions, including governments (Fan et al., 2020), and the level of development of financial systems (Alberto et al., 2019) can all influence the level of spillover (Salimi Nasab et al., 2024).

Before the mid-1950s, there were limited studies on the relationship between markets. From the 1960s onward, due to researchers' interest in optimizing investment portfolios, the topic of inter-market relationships began to gain attention. Most of the research conducted during this period utilized statistical models such as simple linear regression, quantile regressions, and vector autoregression. Notable studies include the work of Longin and Solnik (1995) and McQueen et al. (1996).

From the 1990s, nonlinear approaches for examining market spillover and financial market interdependence gained popularity among researchers. Due to the limitations of regression models, copula functions were introduced. Copula models have been explored by various researchers to analyze dependency structures between markets, including studies by Cossin et al. (2000), Patton (2006), and Canela (2006) (Bergkar and Sohrabi, 2020).

The use of copula models marked a significant step in examining the interconnection between markets and assessing the degree of spillover between them. Several studies have investigated spillover between markets using copula models, including Huang et al. (2009), who utilized the Clayton copula; Chang (2017), who employed Gumbel and Clayton copulas to examine the correlation between crude oil markets and futures trading; and Li and Hussain (2018), who analyzed the relationship between the Chinese market and Asian, European, and U.S. markets.

In addition to using copula models, attention must also be paid to marginal models. Many of the aforementioned studies relied on marginal models that were either unable to capture regime changes in the data or used constant-parameter models. The use of switching models, such as the Markov-switching model, as a marginal model can enhance the dynamics of the models. Tan Suchat et al. (2017), Salmi et al. (2019), Tiwari et al. (2020), Mwamba and Mwambi (2021), Suri (2024), Ho et al. (2024), and Ning et al. (2025) have incorporated this dynamism into copula models by using the Markov-switching model as a marginal model.

Although the aforementioned studies have significantly advanced the measurement of spillover effects, they have primarily focused on traditional financial assets and equity markets. The application of these methodologies to sovereign digital currencies -particularly the spillover effects of CBDC-related uncertainty on cryptocurrency markets - remains largely unexplored.

As mentioned, CBDCs can have an impact on various financial and economic sectors. Ward and Rochemont (2019) examined these currencies, discussing their advantages, disadvantages, and the effects they have on the financial sector. Alonso et al. (2021) explored the optimal conditions for creating and launching CBDCs, as well as the countries that are better positioned to implement this monetary system. Wang and colleagues (2022) analyzed the impact of news about these currencies on economic markets and concluded that financial markets react to them. A key point regarding these currencies is their influence on financial and economic sectors, including the cryptocurrency market. Van et al. (2025) investigated the impact of CBDCs on cryptocurrencies and examined risk transmission and spillover using TVP-VAR models.

However, a critical gap remains. While Van et al. (2025) provide preliminary evidence of spillover between CBDCs and cryptocurrencies, their TVP-VAR framework does not explicitly model the volatility transmission channel through which uncertainty regarding CBDC development affects cryptocurrency returns. Furthermore, no study to date has justified theoretically why such a spillover should exist. We argue that in the absence of a liquid spot market for CBDCs, media coverage and central bank communications serve as the primary channel through which market participants form expectations about the future competitive landscape between sovereign and decentralized digital currencies. This information flow shapes investor sentiment and risk appetite, thereby transmitting volatility to cryptocurrency markets. This study provides the first theoretical articulation and empirical test of this uncertainty-driven spillover channel.

To study the spillover between different markets from the CBDC market, a combination of copula models and switching models can be employed. However, considering the limitations of Markov-switching models - such as their performance in short-term intervals with clustered volatility or when data distribution is non-normal - it may be more appropriate to use the Heston-switching model, which addresses some of these limitations. The aim of this research is to examine the relationship between the CBDC market and the bitcoin market. To analyze this relationship, we will utilize a combination of Heston-switching models and different copula functions.

3. Research Methodology

In this study, we will examine the combination of switching models and copula models. First, we will introduce the marginal model, and then we will explore its integration with the copula model. As is well known, regardless of any classification, the task of linking marginal distributions together falls to copula functions. To investigate risk spillover between different markets, we first analyze the marginal distributions and then proceed to examine the multivariate joint model.

In this study, we investigate risk spillover between the CBDC Uncertainty Index - a text-based index derived from news articles - and bitcoin returns. A methodological justification is necessary here. Since CBDCs are still largely in pilot or research phases and no liquid spot market with observable transaction prices exists, media coverage and central bank communications constitute the primary channel through which market participants form expectations about the future of digital fiat currency. Therefore, treating the CBDC Uncertainty Index as a valid proxy for latent policy risk and modeling its volatility dynamics alongside bitcoin returns is both theoretically grounded and methodologically necessary. This approach does not assume equivalence between the two series; rather, it recognizes that uncertainty shocks transmit across heterogeneous asset classes through investor sentiment and expectation formation channels.

Switching models, unlike stochastic volatility models, do not have constant parameters throughout the entire model; instead, their parameters change based on the economic regime. Switching models allow the economy to transition into a regime under any number of constraints and at any point in time. The regime significantly influences the dynamic behavior of time series. Regimes can occur at specific points in time. A Markov-switching model, as shown in Equation (1), allows volatility to shift between regimes, meaning it permits σ to fluctuate and vary between two regimes.

$$\Delta r_t = a_i + b_i r_{t-1} + \sigma_i r_{t-1}^{\gamma} \varepsilon_t \qquad (1)$$

where $i \in \{1,2\}$ is an input for the regime at time t. Here, γ is the diffusion parameter, σ is the volatility parameter, and a and b are constant parameters within each regime. ε_t is a white noise process that is independent of r_t. All ε_t are independent and identically distributed with a mean of zero and variance σ^2. The transition probability from regime i to regime j at time t is defined as $P_{ij} = Pr(S_t = i|S_{t-1} = j)$.

Another model that we will examine as a marginal model is the Heston-switching model[1]. The base Heston model was introduced by Heston in 1993. This model is also defined based on Brownian motion. The base Heston model has a significant weakness because it does not account for different regimes. However, if this model is combined with regime-switching probabilities, it can become a highly effective model.

Consider that we are dealing with a probability space$(\Omega, \mathbb{F} := (\mathcal{F}_t)_{[.,T]}, \mathbb{P})$, where $\mathbb{P}$ represents the risk-neutral measure. We define X_t as a Markov chain on the space $E := \{1, \dots, S\}$ with an initial distribution μ.

[1] Heston

This Markov chain essentially identifies the regime in the data of interest. The generator matrix of X is denoted by Π, where for all $i,j \in E$, we have $\Pi_{ij} \geq 0$ if $i \neq j$, and $\Pi_{ii} = \sum_{i \neq j} \Pi_{ij}$.

We assume that the transition probabilities from state $i \in E$ at time t to state $j \in E$ at time $t+h$ are constant. This assumption leads to the construction of a generator transition function denoted by Π. Let us now denote by $X(h)$ the transition probability matrix, which is defined as follows:

$$X_{ij}(h) = \mathbb{P}(Z_h = j \mid Z_0 = i) \quad (2)$$

Then, for all $i,j \in E$, we will have:

$$\frac{d\,X_{ij}(h)}{d\,h} = \Pi_{ij} \quad for\ all \quad i,j \in E \quad (3)$$

Finally, let us denote the transition matrix as P, similar to the Markov switching model. Therefore, we will have:

$$P_{ij} = \begin{cases} \dfrac{\Pi_{ij}}{\sum_{i \neq j} \Pi_{ij}} & if\ i \neq j \\ 0 & In\ other\ states \end{cases}$$

Now, consider $S = (S_t)$ as a stochastic process in our probability space. This space can exist in any of the markets we are researching. Suppose $V = (V_t)$ is another stochastic process that models the instantaneous variance of S.

It is important to note that all parameters of the stochastic volatility process v, as well as the correlation coefficient between the index of each market and its instantaneous variance v, depend on the state X. In simpler terms, the parameters of each regime are dependent on that specific regime. Consider the baseline Heston model:

$$\mathrm{dS_t} = \mu \mathrm{S_t} + \mathrm{S_t}\sqrt{v_t}\mathrm{d}Z$$
$$\mathrm{d}v_t = \mathrm{k}(\theta - v_t)\mathrm{dt} + \sigma\sqrt{v_t}\mathrm{d}B$$

We know that the processes Z and B are Brownian motions. Here, v_t represents the instantaneous variance, θ is the long-term variance, and k denotes the volatility of variance. The two Brownian motions Z and B are independent of each other. Now, we have:

$$\frac{\mathrm{dS_t}}{\mathrm{S_t}} = \mu + \sqrt{v_t}\mathrm{d}Z \quad (4)$$

And we also have:

$$\mu = rdt$$

where r is the risk-free interest rate. Therefore, we have:

$$\frac{\mathrm{dS_t}}{\mathrm{S_t}} = rdt + \sqrt{v_t}\mathrm{d}Z \quad (5)$$

Now, consider a situation where we are faced with different regimes. Then, we will have:

$$X_t = \begin{cases} (1,0)^t, & Pos\ \text{Regime} \\ (0,1)^t, & Neg\ \text{Regime} \end{cases}$$

And the transition function between the two regimes follows a Poisson distribution. The transition probabilities in this model are also as follows:

$$P = Pr(S_t = 1|S_{t-1} = 1)$$
$$q = Pr(S_t = 2|S_{t-1} = 2)$$

Now, for each regime, we will have:

$$dv_i = k_{\mathrm{i}}(\theta_{\mathrm{i}} - v_{\mathrm{i}})dt + \sigma_{\mathrm{i}}\sqrt{v_{\mathrm{i}}}dB_{\mathrm{i}} \qquad (6)$$
$$dZ_{\mathrm{i}}\, dB_{\mathrm{i}} = \rho_{\mathrm{i}}dt \qquad (7)$$
$$dZ_{\mathrm{i}}\, dZ_{\mathrm{j}} = dB_{\mathrm{i}}\, dB_{\mathrm{j}} = 0 \qquad (8)$$

Where ρ_{i} is the correlation between the two Brownian processes, θ is the long-term variance of volatility, k is the mean reversion speed of volatility, and r is the interest rate. Now, after introducing the marginal models, we proceed to examine and introduce copula models. A copula function is a linking function for multiple marginal functions, defined on the space $[0,1]^n$. For example, the joint distribution function with marginal distributions $F_x(x)$ and $F_y(y)$ is defined as follows:

$$F_{XY}(x,y) = C\left(F_x(x), F_y(y)\right) \quad (9)$$

If the marginal distributions $F_x(x)$ and $F_y(y)$ are continuous and also specified, then we will have:

$$C(u,v) = H\left(F^{-1}(u), F^{-1}(v)\right) \quad (10)$$

Moreover, their joint distribution will also be as follows:

$$F_{XY}(x,y) = c(u,v)F_x(x)F_y(y) \quad (11)$$

In this way, $c(u,v) = \frac{\partial^2 C(u,v)}{\partial u \partial v}$ serves as the copula density function, and $F_x(x)$ and $F_y(y)$ are the marginal distributions. These equations can be extended to consider N marginal distributions connected by a copula function, which then forms the joint distribution. As mentioned earlier, different types of copulas can be used to create multivariate distributions. The various types of copulas provide a flexible space for identifying joint distributions. One type of copula that performs particularly well in creating joint distributions is the Frank copula. This function was introduced by Frank for the parameter $\theta \in R$ as follows:

$$C(u, v; \theta) = \frac{-1}{\theta} \operatorname{Ln}[1 + \frac{\left(e^{-\theta u} - 1\right)\left(e^{-\theta v} - 1\right)}{e^{-\theta} - 1} \qquad (12)$$

The copula density function for this family is as follows:

$$C(u_1, u_2; \theta) = \frac{\theta e^{-\theta(u_1+u_2)}(e^{-\theta} - 1)}{[e^{-\theta(u_1+u_2)} - e^{-\theta u_1} - e^{-\theta u_2} + e^{-\theta}]^4}$$

The Frank copula is used because it is symmetric in both tails and encompasses the full range of correlation limits when analyzing phenomena that exhibit either positive or negative dependence. Due to the symmetry of the Frank copula, the dependence on the upper and lower tails will be equal to zero (Bargkar, 2020).

Another widely used copula is the T- Student copula. In the bivariate case, this copula is expressed as follows:

$$C(u_1,u_2) = T_{\upsilon,\rho}\left(t_\upsilon^{-1}(u_1),t_\upsilon^{-1}(u_2)\right) = \int_{-\infty}^{t_\upsilon^{-1}(u_1)}\int_{-\infty}^{t_\upsilon^{-1}(u_2)} \frac{1}{2\pi\sqrt{1-\rho^2}}\left(1+\frac{s^2-t^2-st\rho}{u_2(1-\rho^2)}\right)\frac{u_2+2}{2}dsdt$$

In this model, $T_{\upsilon,\rho}$ represents the bivariate Student's t-distribution, ρ is the correlation coefficient, υ is the degrees of freedom, and t_ν^{-1} is the inverse of the univariate Student's t-distribution. This function, like the Gaussian copula, is symmetric, but it considers the upper and lower tail dependencies to be equal.
The Clayton copula was first introduced by Clayton for the parameter $\theta \in [-1,0] \cup [0,\infty)$and is defined as follows:

$$C(u_1,u_2;\theta) = \mathrm{Max}\left\{(u_1^{-\theta}+u_2^{-\theta}-1)^{\frac{-1}{\theta}},0\right\} \qquad (13)$$

For $\theta > 0$, this copula will be expressed as follows:

$$C(u_1,u_2;\theta) = \left(u_1^{-\theta}+u_2^{-\theta}-1\right)^{\frac{-1}{\theta}}$$

The density function of this copula is also as follows:

$$C(u_1,u_2;\theta) = (\theta+1)\left(u_1^{-\theta}+u_2^{-\theta}-1\right)^{\left(\frac{-1}{\theta}-2\right)}(u_1u_2)^{(-\theta-1)}$$

This copula function, for $\theta > 0$, exhibits lower tail dependence, where the upper tail dependence is$\lambda_{U_C} = 0$ and the lower tail dependence is $\lambda_{L_C} = 2^{\theta-1}$.

The Gumbel copula was also defined by Gumbel for the parameter $\theta \geq 1$ as follows:

$$C(u_1,u_2;\theta) = (\theta+1)\left(u_1^{-\theta}+u_2^{-\theta}\right)^{\left(\frac{-1}{\theta}-2\right)}(u_1u_2)^{(-\theta-1)}$$
$$C(u_1,u_2;\theta) = \exp\left\{-[-(\ln u_1)^{\theta}+(\ln u_2)^{\theta}]^{\frac{1}{\theta}}\right\} \qquad (14)$$

The copula function for this family is also defined as follows:

$$c(u_1,u_2;\theta) = \frac{[(-\ln u_1)(-\ln u_2)]^{\theta-1}}{u_1u_2}[(-\ln u_1)^{\theta}+(-\ln u_2)^{\theta}]^{\left(\frac{2}{\theta}-2\right)}$$
$$\left\{(\theta-1)\left[(-\ln u_1)^{\theta}+(-\ln u_2)^{\theta}\right]^{\frac{1}{\theta}}+1\right\}$$

This copula exhibits tail dependence. In the Gumbel copula, the upper tail dependence is $\lambda_{U_C} = 2 - 2^{-\theta}$, and the lower tail dependence is $\lambda_{L_C} = 0$

Now, if we wish to transform the marginal functions, which include switching models, into a joint function using copula models, we will have:

$$f(u,v \mid S_t = k) = c(u,v \mid \theta_k)\cdot f_U(u)\cdot f_V(v)$$

Since both marginal models are of the switching type and the time series $x_t = (x_{1t},x_{2t}), t = 1,2,\ldots$ is a two-dimensional vector, the switching copula model can then be defined as follows:

$$RS(\mathrm{X}_t|\mathrm{S_t}) = C_t^{S_t}\left(\mathrm{F_1}(\mathrm{x_{1t}}|\mathrm{S_{1t}}), \mathrm{F_2}(\mathrm{x_{2t}}|\mathrm{S_{2t}})\right) \quad (15)$$

In this equation, $C_t^{S_t}$ represents the Frank copula parameter, and $\mathrm{F}_i(\mathrm{x_{it}})$ denotes the marginal distribution functions. $\mathrm{F}_i(\mathrm{x_{it}})$ in this equation can follow either Markov-switching or Heston-switching distributions. Patton (2006) provided an equation for time-varying copula functions, which is derived from scalar equations. Suppose the copula parameter C can be considered as a simple ARMA function. Then, we will have:

$$C_t = \Lambda(\omega + \varphi C_{t-1} + \psi \Gamma_t) \qquad (16)$$

In this equation, $\Lambda(.)$ is an exponential function, ω, φ, and ψ are constant parameters, and Γ_t represents the pressure variable. This equation allows for mean reversion. The pressure variable Γ_t is also defined as follows:

$$\Gamma_t = \begin{cases} \frac{1}{m}\sum_{j=1}^{m} F_1^{-1}(x_{1,t-j})F_2^{-1}(x_{2,t-j}) & \text{elliptical} \\ \frac{1}{m}\sum_{j=1}^{m} \left| F_1(x_{1,t-j}) - F_2(x_{2,t-j})\right| & \text{Archimedean} \end{cases} \qquad (17)$$

In the above equation, $F_n^{-1}(u_{n,t})$ is the inverse of the marginal distribution function. Additionally, Patton assumed in this equation that $m = 10$. Now, consider that we are dealing with a regime-switching copula function; then, Patton's equation will be as follows:

$$C_t^{S_t} = \Lambda\left(\omega^{S_t} + \varphi C_{t-1}^{S_{t-1}} + \psi \Gamma_t\right) \qquad (18)$$

In this equation, unlike the first case, the copula behaves differently in each regime and may take on different values in each regime based on the pressure variable. In both Markov-switching and Heston-switching models, we are dealing with a transition probability matrix, where the transition probability $\mathrm{p_{ij}}$ is calculated as follows:

$$\mathrm{p_{ij}} = \Pr(\mathrm{s_t} = \mathrm{j}|\mathrm{s_{t-1}} = \mathrm{i})$$

Now, to estimate the parameters of this model, the maximum likelihood method can be employed. Therefore, we will have: (Filho et al., 2012)

$$l(\vartheta|X_t) = \sum_{t=1}^{T} \log(C_\theta(\mathrm{F_1}(\mathrm{X_{1t}}|\vartheta_1), \mathrm{F_2}(\mathrm{X_{2t}}|\vartheta_2) \times \prod_{i=1}^{2} f_{it}(\mathrm{X_{it}}|\vartheta_i)) \qquad (19)$$

In Equation 19, ϑ_i represents the parameters of the marginal model, such as a_i, b_i, σ_{it}. Estimating the parameters using Equation 19 can be complex; however, since this equation is separable, a two-step maximum likelihood estimation method can be applied. Therefore, the IFM (Inference Functions for Margins) method proposed by Joe and Zhu (1996) can be utilized. Equation 19 can be rewritten as follows:

$$l(\vartheta|X_t) = \sum_{t=1}^{T} \log(C_t^{S_t}(\mathrm{F_1}(\mathrm{X_{1t}}|\vartheta_1), \mathrm{F_2}(\mathrm{X_{2t}}|\vartheta_2) \times \prod_{i=1}^{2} f_{it}(\mathrm{X_{it}}|\vartheta_i)) =$$

$$\sum_{t=1}^{T} \log f_{1t}(\mathrm{X_{1t}}|\vartheta_1) + \sum_{t=1}^{T} \log f_{2t}(\mathrm{X_{2t}}|\vartheta_2) + \sum_{i=1}^{2}\sum_{t=1}^{T} \log C_t^{S_t}(U_{it}|\vartheta_i)$$

$$l(\vartheta|X_t) = \ell_{f_1}(\vartheta_1) + \ell_{f_2}(\vartheta_2) + \ell_C(\vartheta_i) \qquad (20)$$

In this equation, $\ell_{f_1}(\vartheta_1)$ and $\ell_{f_2}(\vartheta_2)$ are the maximum likelihood functions for the marginal distributions. To estimate the parameters, we can start with these two functions and, after estimating the parameters of the marginal distributions, proceed to the next step.

Now, to estimate the third part of Equation 20, represented by $\ell_C(\vartheta_i)$, considering that there are likely two regimes, we can expect to encounter two different copulas. For estimating the parameters of each copula, the parameters can be estimated separately within each regime. Finally, it can be stated that in the first step, the parameters of each marginal model should be estimated using the maximum likelihood method, and then, in the second step, the copula parameter should be estimated for each regime.

4. Data and Empirical Results

First, we examine the statistical data of this research. In this study, we analyze the CBDC market and the Bitcoin market. After statistically examining these two markets, we determine the appropriate marginal distribution for each and, ultimately, use copula models to construct their joint distribution function. Finally, we investigate the risk spillover between these two markets. The data related to the CBDCU market are derived from the research conducted by Wang et al. in 2022.

These data were initially obtained by analyzing 663.9 million news articles related to CBDCs, collected weekly from economic and news sources from January 2015 to the end of 2022. They then continued their observations and calculated the uncertainty index up to the beginning of 2025. The data related to the bitcoin market were extracted from global bitcoin markets over the same period, this data was taken from Yahoo Finance.

The statistical description of these markets is as follows:

Table 1: Statistical description of data for the global bitcoin market and CBDC uncertainty

Title	Bitcoin Market	CBDC Market Uncertainty (CBDCU)
Count	2566	522
Mean	11307.5	100.8739
Median	6442.55	100.2443
Maximum	67566.83	115.1469
Minimum	178.1030	99.1167
Standard Deviation	15985.9	1.8119
Skewness	1.9187	2.2812
Kurtosis	5.52	12.3237
Jarque-Bera Test	2253.5	2343.54
Probability	0.00000	0.00000

The trend of these two markets can be observed in the figures below:

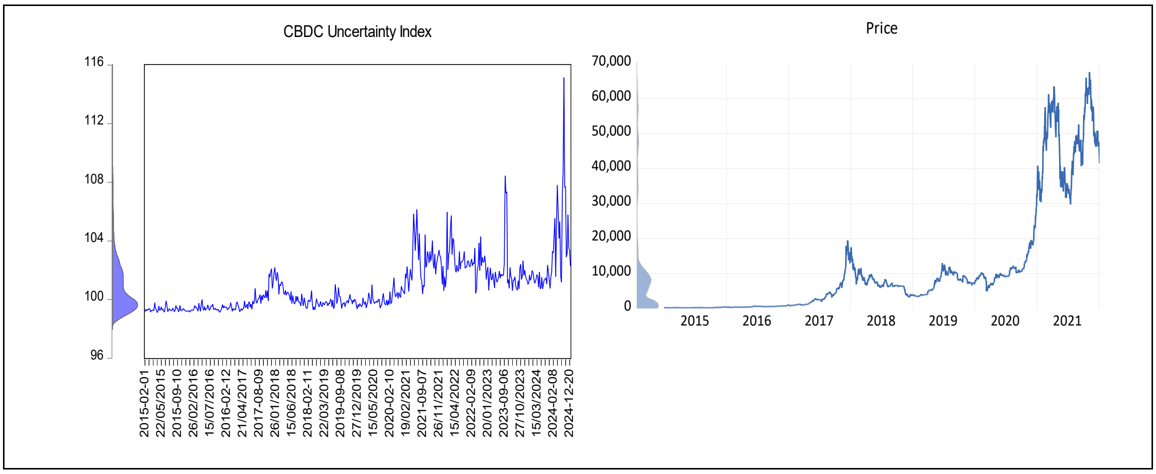

Figure 1: Daily bitcoin price and CBDC uncertainty index

It should be noted that the CBDC Uncertainty Index is a text-based index derived from news articles, while the bitcoin series consists of actual market returns. Since CBDCs are still largely in pilot or research phases and no liquid spot market with observable transaction prices exists, media coverage and central bank communications constitute the primary channel through which market participants form expectations about these currencies. Therefore, treating this index as a proxy for CBDC-related risk and examining its spillover effects on bitcoin is methodologically necessary and theoretically justified.

Time series are one of the most important statistical data used in empirical analysis. It is generally assumed that time series are stationary, and if this assumption does not hold, most statistical tests come into question. Non-stationarity can lead to issues such as spurious regression. Therefore, we use the Dickey-Fuller test to check for stationarity and given the presence of a unit root in the data, we utilize the logarithmic differenced series. Considering that we also observe autocorrelation, it can be concluded that small jumps follow small jumps, and large jumps follow large jumps, which fully supports the assumption of autocorrelation. Now, based on the above evidence, we perform the ARCH test, and we will have:

Table 2: Arch test

Title	F-Statistic	Probability
ARCH Test	61.1611	0.0000

The null hypothesis in this test is that there is no ARCH effect. According to the table, this hypothesis is rejected, and we are faced with the ARCH phenomenon and heteroskedasticity. After determining the coefficients of the GARCH model, we proceed to examine and estimate the parameters of the two switching models in this dataset shown in Table 3 and Figure 2.

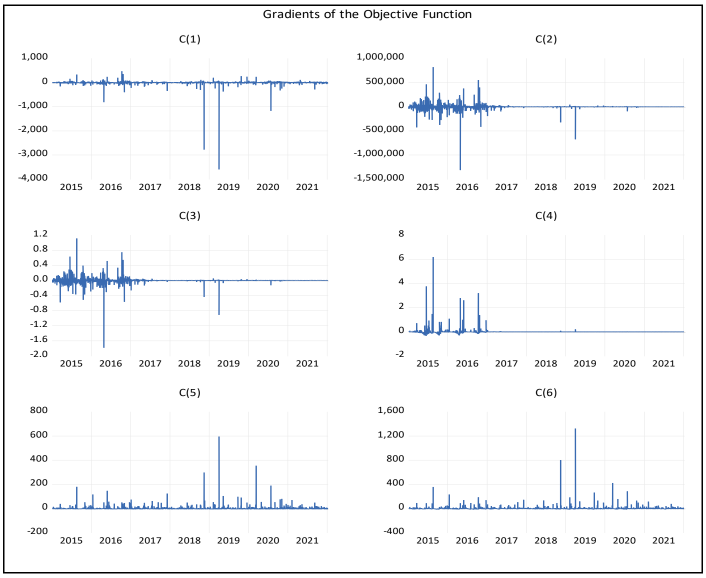

Figure 2: Gradients of the objective functions

Table 3: Estimation of model parameters

Model	Parameters		
Heston Switching Model	Positive Regime	k	0.0643
		θ	5.8654
		v	0.0459
	Negative Regime	k	0.0577
		θ	5.1842
		v	0.0542
	Transition Probability Matrix		$\begin{bmatrix} 0.3151 & 0.6849 \\ 0.6764 & 0.3236 \end{bmatrix}$
Markov Switching Model	Positive Regime	α	-0.0078
		β	-0.0963
		σ	0.9008
	Negative Regime	α	0.0211
		β	-0.0959
		σ	0.8649
	Transition Probability Matrix		$\begin{bmatrix} 0.4976 & 0.5024 \\ 0.5109 & 0.4891 \end{bmatrix}$
Conditional Variance Equation	c		0.55
	$RESID(-1)^2$		0.11
	$GARCH(-1)$		0.91
	$GARCH = C(4) + C(5) \times RESID(-1)^2 + C(6) * GARCH(-1)$		

After estimating the parameters of the two models, the performance of the two marginal models in the bitcoin market, namely Markov switching and Heston switching, is very close to each other. With a slight difference, the Heston switching model performs slightly better. It should also be noted that the variance of these models follows the GARCH model. After examining the marginal models, we can proceed to investigate and select the appropriate copula model.

Table 4: Comparison of copulas in different regimes

Copula	Frank Copula		Clayton Copula		T Student copula		Gumbel Copula	
	Positive Regime	Negative Regime	Positive Regime	Negative Regime	Positive Regime	Negative Regime	Positive Regime	Negative Regime
Copula parameter	17.0996	12.7631	5.0602	4.8106	0.9238	0.8512	2.6395	1.8388
Max likelihood	867.6598	412.0142	793.3967	464.4664	734.0646	294.6065	460.6929	136.1972
AIC	1737.3	826.0284	1588.8	930.9328	1427.1	593.2130	923.3857	274.3943
BIC	1742.1	830.3051	1593.5	935.2094	1481.6	601.7663	928.1310	278.6710

After determining the parameters of the marginal models, the copula parameters have been estimated. Based on the results in Table 4, the best copula is selected according to the Akaike information criterion (AIC) and the lowest information loss. In both the first and second regimes, the Gumbel copula shows the best performance. In the first regime, the value of this index is 2.6395, and in the second regime, it is 1.8388.

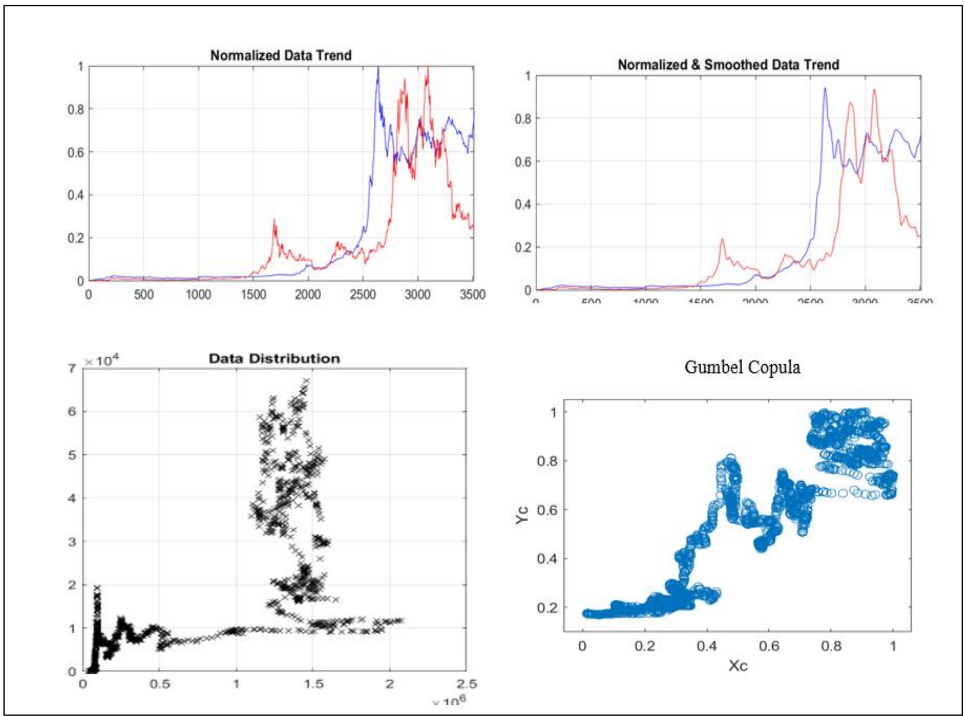

Figure 3: Normalized data trend and copula distribution

The Gumbel copula exhibits upper tail dependence and zero lower tail dependence in Figure 3. This indicates that the two markets are more strongly correlated during periods of high uncertainty and high volatility, while during calm periods they move more independently. This finding is consistent with our theoretical argument that uncertainty shocks - rather than steady-state information - drive spillover effects.

Now, after identifying the appropriate copula index, we need to determine the spillover effect of the bitcoin market from the CBDC market uncertainty index. To examine the spillover effect, we utilize the conditional Value at Risk (VaR). We will now calculate the conditional Value at Risk at the 95% confidence level and the 5% significance level. If we observe volatility at these two levels, it will indicate a spillover effect from the CBDC markets to the bitcoin market.

Table 5: Calculation of Risk Spillover from the CBDC Market to the Bitcoin Market

Title	Positive Domain	Negative Domain
Risk Spillover from the CBDC Market to the Bitcoin Market	9.3	4.21

As shown in Table 5, the positive domain (9.3) is substantially larger than the negative domain (4.21), indicating that spillover effects are asymmetric and stronger during periods of increased CBDC-related uncertainty. This asymmetry is consistent with the Gumbel copula results and supports our research hypothesis.

This finding has several economic implications. First, investors react more strongly to bad news about CBDCs than to good news, consistent with loss aversion in behavioral finance. Second, it validates our theoretical channel that in the absence of a liquid CBDC spot market, media and central bank communications transmit uncertainty shocks to bitcoin through investor sentiment. Third, the Gumbel copula's upper tail dependence confirms that co-movement intensifies precisely during high-uncertainty periods.

For investors, symmetric risk models underestimate tail risk during CBDC news spikes. For policymakers, abrupt policy signals even if benign can generate disproportionate spillover; transparent communication helps mitigate this.

The correlation coefficient (0.78) is consistent with our findings, but correlation alone misses the asymmetric dependence captured by CoVaR and copula analyses, which are the novel contribution of this study. Therefore, CBDC-related news has a significant and asymmetric impact on the bitcoin markets, supporting the hypothesis that CBDC uncertainty constitutes a distinct source of risk spillover to decentralized digital assets.

5. Conclusion

In this paper, we examined the relationship and risk spillover from the emerging CBDC market to digital currency markets, particularly the bitcoin market. Initially, we analyzed marginal models and tested Markov-switching and Heston-switching models in these markets. Ultimately, due to the superior performance of the Heston-switching model, we utilized it as the marginal model. After identifying the regimes in these markets and estimating the regime transition probabilities, we estimated the parameters of this model. Subsequently, to determine the multivariate function, we estimated various copulas such as Frank, Clayton, Gumbel, and Student's t copulas, and selected the best copula based on Akaike information criteria and lost information metrics. The combination of marginal models and the proposed copulas form the final model.

The primary contribution of this study is twofold. First, we provide a theoretical framework explaining why and how CBDC-related uncertainty should transmit volatility to cryptocurrency markets. We argue that in the absence of a liquid spot market for CBDCs, media coverage and central bank communications serve as the primary channel through which market participants form expectations about the future competitive landscape between sovereign and decentralized digital currencies. Second, we empirically validate this channel by demonstrating significant and asymmetric risk spillover from a text-based CBDC Uncertainty Index to bitcoin returns. This addresses a critical gap in the literature, as prior studies have focused primarily on the operational and macroeconomic implications of CBDCs while neglecting their financial market externalities.

In the past, researchers such as Tan Sotchot et al. (2017), Jamal Bouoiyour et al. (2019), Pat Chalok et al. (2019), and Wistras et al. (2021) had explored the combination of copulas with Markov-switching models. However, the limitations of the Markov model - particularly its performance in short-term intervals with clustered volatility and under non-normal data distributions - compelled us to test the Heston-switching model as the marginal model. Our results indicate that the Heston-switching model performs slightly better than the Markov-switching alternative, and its combination with the Gumbel copula yields superior fit and more plausible economic interpretations.

Our empirical findings reveal three key insights. First, the Gumbel copula consistently outperforms other copula specifications in both positive and negative regimes. This dominance indicates the presence of upper tail dependence, meaning that CBDC uncertainty and bitcoin volatility exhibit stronger co-movement during periods of high uncertainty and high volatility, while moving more independently during calm periods. Second, the conditional Value-at-Risk (CoVaR) analysis confirms significant asymmetric spillover effects, meaning that positive uncertainty shocks generate spillover effects more than twice the magnitude of negative shocks. This asymmetry is consistent with behavioral finance theories of loss aversion and confirms that market participants react more intensely to the emergence of new risks than to their resolution. Third, the correlation coefficient of 0.78 between the two data series provides additional validation, though correlation alone fails to capture the asymmetric dependence structure revealed by our copula and CoVaR approaches.

These findings carry important implications. For investors and portfolio managers, conventional risk models that assume symmetric spillover or constant correlations may substantially underestimate tail risk during periods of heightened CBDC-related news activity. Dynamic, regime-aware risk management frameworks are therefore necessary. For policymakers and central banks, the asymmetry documented here implies that abrupt, ambiguous, or contradictory policy signals, even if ultimately benign, can generate disproportionate and potentially destabilizing risk transmission to adjacent markets. Transparent, consistent, and forward-looking communication strategies can help mitigate these unintended spillover effects.

One of the key points to consider regarding the spillover effects of the CBDC market on various markets, including cryptocurrency markets, is the role of government policies concerning CBDCs. Political and social factors play a significant role in these markets. Although CBDCs have not yet been fully implemented, they could play an important role in the future in terms of inter-market relationships. The risk spillover from these markets will be somewhat similar to that of foreign exchange markets, with the difference that the speed of reactions will likely be faster. In such conditions, a robust model is one that can account for sudden jumps, instantaneous changes, and regime shifts. The combination of switching models and copula models provides flexible tools for addressing these fluctuations.

This study is not without limitations. First, the CBDC Uncertainty Index, while methodologically necessary, remains an imperfect proxy for latent policy risk. As CBDC projects mature and spot markets potentially emerge, future research should re-examine these spillover effects using actual transaction data. Second, our analysis focuses exclusively on bitcoin; extending this framework to other cryptocurrencies and digital assets would provide a more comprehensive understanding of spillover dynamics. Third, the specific mechanism through which uncertainty transmits to volatility, whether through retail investor sentiment, institutional portfolio rebalancing, or algorithmic trading, remains unidentified. Future studies employing survey data, trading volume disaggregation, or high-frequency identification strategies could help open this black box. Finally, comparative studies examining CBDC spillovers across different countries with varying policy approaches and institutional frameworks would enrich our understanding of how institutional context moderates these effects.

Despite these limitations, this study provides the first theoretical articulation and empirical evidence of risk spillover from CBDC-related uncertainty to cryptocurrency markets. By demonstrating that policy-driven information flow constitutes a distinct and economically meaningful source of volatility transmission, we hope to open a new avenue of research at the intersection of sovereign digital currency policy and decentralized financial markets.

Acknowledgements

The authors would like to express their sincere gratitude for the valuable support and insightful comments provided by colleagues and anonymous reviewers, which significantly contributed to the refinement of this research. The authors also extend their appreciation to the editorial team of Journal of FinTech and Digital Assets for their professional guidance and assistance throughout the submission and review process.

Conflicts of 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.

References

Ajaya, K. P., Pradiptarathi, P., Swagatika, N., & Parad, A. (2021). Information bias and its spillover effect on return volatility: A study on stock markets in the Asia-Pacific region. *Pacific-Basin Finance Journal*, 69, Article 101653.

Alberto, B., David, L. T., Danilo, L., & Marsiglio, S. (2019). Financial contagion and economic development: An epidemiological approach. *Journal of Economic Behavior & Organization*, 162, 211–228.

Antonakakis, N., Cunado, J., Filis, G., Gabauer, D., & De Gracia, F. P. (2018). Oil volatility, oil and gas firms and portfolio diversification. *Energy Economics*, 70, 499–515.

Arouri, M. E. H., Jouini, J., & Nguyen, D. K. (2012). On the impacts of oil price fluctuations on European equity markets: Volatility spillover and hedging effectiveness. *Energy Economics*, 34(2), 611–617.

Awartani, B., & Maghyereh, A. (2013). Dynamic spillovers between oil and stock markets in the Gulf cooperation council countries. *Energy Economics*, 36, 28–42.

Bouri, E. (2015). Oil volatility shocks and the stock markets of oil-importing MENA economies: A tale from the financial crisis. *Energy Economics*, 51, 590–598.

Bouri, E., Awartani, B., & Maghyereh, A. (2016). Crude oil prices and sectoral stock returns in Jordan around the Arab uprisings of 2010. *Energy Economics*, 56, 205–214.

Bouri, E., Jain, A., Biswal, P. C., & Roubaud, D. (2017). Cointegration and nonlinear causality amongst gold, oil, and the Indian stock market: Evidence from implied volatility indices. *Resources Policy*, 52, 201–206.

Broadstock, D. C., Cao, H., & Zhang, D. (2012). Oil shocks and their impact on energy related stocks in China. *Energy Economics*, 34(6), 1888–1895.

Broadstock, D. C., & Filis, G. (2014). Oil price shocks and stock market returns: New evidence from the United States and China. *Journal of International Financial Markets, Institutions and Money*, 33, 417–433.

Canela, M. A., & Collazo, P. (2006). Modelling dependence in Latin American markets using copula functions (Working Paper). IESE Business School.

Degiannakis, S., Filis, G., & Floros, C. (2013). Oil and stock returns: Evidence from European industrial sector indices in a time-varying environment. *Journal of International Financial Markets, Institutions and Money*, 26, 175–191.

Ding, H., Huang, Y., & Wang, J. (2023). Have the predictability of oil changed during the COVID-19 pandemic: Evidence from international stock markets. *International Review of Financial Analysis*, 87, Article 102620.

Elsayed, A. H., Gozgor, G., & Lau, C. K. M. (2022). Causality and dynamic spillovers among cryptocurrencies and currency markets. *International Journal of Finance & Economics*, 27(2), 2026–2040.

Fan, H. C., Gou, Q., & Peng, Y. C. (2020). Spillover effects of capital controls on capital flows and financial risk contagion. *Journal of International Money and Finance*, 105, Article 102189.

Hamma, W., Jarboui, A., & Ghorbel, A. (2014). Effect of oil price volatility on Tunisian stock market at sector-level and effectiveness of hedging strategy. *Procedia Economics and Finance*, 13, 113–124.

Huang, J. J., Lee, K. J., Liang, H. M., & Lin, W. F. (2009). Estimating value at risk of portfolio by conditional copula-GARCH method. *Insurance: Mathematics and Economics*, 45(3), 315–324.

Hussain, S. I., & Li, S. (2018). The dependence structure between Chinese and other major stock markets using extreme values and copulas. *International Review of Economics & Finance*, 56, 421–437.

Ji, Q., Zhang, D., & Geng, J. B. (2018). Information linkage, dynamic spillovers in prices and volatility between the carbon and energy markets. *Journal of Cleaner Production*, 198, 972–978.

Jin, X. (2015). Volatility transmission and volatility impulse response functions among the Greater China stock markets. *Journal of Asian Economics*, 39, 43–58.

Kang, W., Ratti, R. A., & Yoon, K. H. (2015). The impact of oil price shocks on the stock market return and volatility relationship. *Journal of International Financial Markets, Institutions and Money*, 34, 41–54.

Mensi, W., Hammoudeh, S., Shahzad, S. J. H., & Shahbaz, M. (2017). Modeling systemic risk and dependence structure between oil and stock markets using a variational mode decomposition-based copula method. *Journal of Banking & Finance*, 75, 258–279.

Mihai, N., & Maria, M. P. (2020). Time-varying dependence in European equity markets: A contagion and investor sentiment driven analysis. *Economic Modelling*, 86, 133–147.

Mwamba, J. W. M., & Mwambi, S. M. (2021). Assessing market risk in BRICS and oil markets: An application of Markov switching and vine copula. *International Journal of Financial Studies*, 9(3), 48.

Narayan, P. K., Narayan, S., & Sharma, S. S. (2013). An analysis of commodity markets: What gain for investors? *Journal of Banking & Finance*, 37(10), 3878–3889.

Neisy, A. (2021). An approximation scheme for value at risk under mean reverting stochastic volatility model. *Studies of Applied Economics*, 39(3).

Patton, A. J. (2004). On the out-of-sample importance of skewness and asymmetric dependence for asset allocation. *Journal of Financial Econometrics*, 2(1), 130–168.

Patton, A. J. (2006). Modelling asymmetric exchange rate dependence. *International Economic Review*, 47(2), 527–556.

Peng, C., Zhu, H., Guo, Y., & Chen, X. (2018). Risk spillover of international crude oil to China's firms: Evidence from Granger causality across quantile. *Energy Economics*, 72, 188–199.

Peymani, M., & Neisi, A. (2015). Tehran stock exchange total index modeling by stochastic differential equation. *Journal of Securities Exchange*, 8(30), 147–168.

Salimi Nasab, S., Golarzi, G., & Neisy, A. (2023a). Volatility spillover in crude oil market using Heston switching Clayton model. *Journal of Mathematics and Modeling in Finance*, 3(1), 119–135.

Salimi Nasab, S., Golarzi, G., & Neisy, A. (2023b). Predicting the volatility spillover in the Tehran stock exchange market with Heston switching copula model. *Journal of Mathematics and Modeling in Finance*, 11(42).

Sarwar, S., Tiwari, A. K., & Tingqiu, C. (2020). Analyzing volatility spillovers between oil market and Asian stock markets. *Resources Policy*, 66, Article 101608.

Selmi, R., Mensi, W., Hammoudeh, S., & Bouoiyour, J. (2018). Is Bitcoin a hedge, a safe haven or a diversifier for oil price movements? A comparison with gold. *Energy Economics*, 74, 787–801.

Tansuchat, R., Yamaka, W., Khemawanit, K., & Sriboonchitta, S. (2017). Analyzing the contribution of ASEAN stock markets to systemic risk. In Robustness in Econometrics (pp. 523–536). Springer.

Tiwari, A. K., Jena, S. K., Mitra, A., & Yoon, S. M. (2018). Impact of oil price risk on sectoral equity markets: Implications on portfolio management. *Energy Economics*, 70, 382–395.

Tiwari, A. K., Trabelsi, N., Alqahtani, F., & Raheem, I. D. (2020). Systemic risk spillovers between crude oil and stock index returns of G7 economies: Conditional value-at-risk and marginal expected shortfall approaches. *Energy Economics*, 86, Article 104646.

Zhang, D., & Cao, H. (2013). Sectoral responses of the Chinese stock market to international oil shocks. *Emerging Markets Finance and Trade*, 49(6), 37–51.

Zhang, D., Ji, Q., & Kutan, A. M. (2019). Dynamic transmission mechanisms in global crude oil prices: Estimation and implications. *Energy*, 175, 1181–1193.

Zhang, D., Shi, M., & Shi, X. (2018). Oil indexation, market fundamentals, and natural gas prices: An investigation of the Asian premium in natural gas trade. *Energy Economics*, 69, 33–41.