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Dynamic Market Volatility: Evidence from the Interdependence of Cryptocurrency, Stock Market, and Commodity Market

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Abstract: This study examined the impact of historical volatility and spillover volatility on cryptocurrency (Bitcoin), stock market (Standard & Poor's 500), and commodity market (Bloomberg Commodity Index). The main objective is to shed light on the interrelationships and dynamics of volatility in these three different asset classes, with data collected daily from January 1, 2019 to April 30, 2025. Vector autoregressive (VAR) and structural vector autoregressive (SVAR) models were adopted for analysis, revealing key findings of: (1) a hierarchical volatility structure with Bitcoin often heading other markets; (2) limited short-term spillovers but significant cross-market connections during economic shocks; and (3) the asymmetric role of commodities as partial equity hedges. This study confirmed the principles of modern portfolio theory, as diversification across the three asset classes could still bring benefits during market turbulence. In particular, the combination of Bitcoin and the volatility index (VIX) could improve the portfolio structure and reduce the risk associated with stock volatility. When including these assets in the model, it is, however, necessary to consider long-term imbalances and geopolitical factors.

Keywords: Cryptocurrency; Stock and commodity markets; VAR model; SVAR model

JEL: C32; G15; G17

1. Introduction

Market volatility plays a vital role in making investment decisions, as well as maintaining economic stability. According to Woebbeking (2021), "volatility" refers to the variability of returns over the time. Investors are especially interested in how different markets and asset classes respond to certain economic shocks. When making a good portfolio, investors seek the best combination of assets to mitigate the risk of volatility and losses. Market volatility is usually associated with the stock market and its dynamic nature. Stock prices are changing rapidly, so investors need to be cautious when composing efficient portfolio. The stock market is widely recognized as one of the most attractive investment options. However, the emergence of cryptocurrencies changed the perception of financial markets and their volatility. Since 2021, cryptocurrencies have been considered one of the most volatile assets available to investors. When cryptocurrencies first appeared in 2009, they were considered an alternative to traditional financial instruments and have remained to be major players in the market. Bitcoin (BTC) is essential in the cryptocurrency market due to its volatile tendencies. As cryptocurrencies increasingly enter the global financial market, overcoming volatility is a critical issue among researchers.

Because of the connectivity among all markets in the world, volatility spillovers (i.e., how risk diffuses between markets) have been an essential feature of financial research. General frameworks have been complemented with strong methodologies on assessing this spillover to traditional asset classes (Diebold & Yilmaz, 2012). Above all, the pace at which digital tokens, such as BTC, are making into the international financial system, has already created new complexities that research is just beginning to address.

This study identified the hierarchies in volatility transmission, in order to enhance the comprehension of market dynamics. To examine volatility transmission, daily data was collected from January 1, 2019 till April 30, 2025 for cross-sectional investigation of cryptocurrency, stock, and commodity markets. The strength and direction for the movement of cross-market volatility were measured using vector autoregressive (VAR)/structural vector autoregressive (SVAR) models that were fitted with forecast error variance decomposition and correlation diagnostics. Moreover, the study responded to the following research questions:

Do volatility spillovers exist among the stock market, cryptocurrency, and commodity market, and how are they identified and measured?

What is the effect of one of these markets on the others regarding volatility transmission, and how do the effects differ across markets?

Is volatility transmission hierarchical, with some markets effectively being sources of volatility to others and others mainly sinking?

Although previous work has focused on volatility in single markets, there has been little comparative work across the cryptocurrency, commodity, and equity markets. Considering their dynamic and changing nature, a detailed study should be conducted to determine the markets with less volatility and high returns on economic shocks.

2. Literature Review

The literature review summarized the existing research on the volatility of these three markets and identified areas that require further study. To contextualize this paper, a literature review was undertaken on three sub-topics, which included the nature of individual market volatility, the spillover effect of volatility to other markets, and how external crises and shocks influenced the market. Consideration of these three areas assisted in determining the specific gaps that this research sought to resolve. Markowitz (1952) continued along the line of the classical financial market and offered a theoretical approach to diversification, with a stress that to minimize the risk of a portfolio, assets with imperfect correlations have to be added.

Markowitz (1952) introduced the concept of modern portfolio theory based on the trade-off between expected return and risk, measured by the variance of portfolio returns. Also, he pointed out that diversification allowed investors to reduce portfolio risk by combining assets with imperfect correlations. Studies on specific assets have shown that fundamental economic factors such as inelastic supply and demand are primarily responsible for market volatility (Dwyer et al., 2011). According to Dwyer et al. (2011), volatility in commodity markets was mainly driven by fundamental economic factors. Since commodities had inelastic supply and demand, it was difficult for them to respond adequately to price changes. Different economic events contributed significantly to the volatility of commodities' prices. The emergence of BTC has influenced new research and studies of its unique characteristics. According to Elsayed et al. (2020), gold would eventually lose value. On the other hand, BTC only serves as a means to reduce volatility in different markets. Indeed, the price of something cannot be correlated with another price during stressful times, and the price of something can be correlated with another price, although not precisely (Baur & Lucey, 2010).

Brière et al. (2015) examined the potential benefits of including BTC in investment portfolios for diversification, owing to its relationship with traditional asset classes and its impact on the performance of diversified portfolios. Platanakis & Urquhart (2019) found that adding BTC to a portfolio significantly increased the associated risks, hence suggesting that the unique characteristics of the cryptocurrency helped investors create a more efficient portfolio. Dyhrberg (2016) used the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model to investigate the volatility of BTC compared to gold and dollar. He discovered that the volatility of BTC was like gold's, indicating that past volatility significantly influenced future volatility. This has led to the debate of whether cryptocurrency could act as a hedge, haven, or diversifier relative to traditional assets (Bouri et al., 2017; Cocco et al., 2022).

Second, international financial markets have grown massively over the last few years as economies become increasingly integrated, and information dissemination is accelerating. Global markets today operate as a multi-faceted mechanism in which risk quickly move around to produce volatility that spans all markets. The more they are interconnected, the more isolated individual markets are, thus significantly impacting global diversification and risk management strategies. The concept of global financial interconnectedness cannot be understood without understanding the volatility of stock prices. There is an increasing body of literature on the level of volatility in financial markets, in view of a rising degree of integration, cross-market volatility spillovers, and interdependence (Ahmed & Huo, 2019; Baele, 2005; Nath Mukherjee & Mishra, 2010; Yarovaya et al., 2016). The spread of volatility in financial markets, a crucial part of risk management and forecasting, has been studied extensively. Diebold & Yilmaz (2012) designed a model that could systematically measure the spillover effects. It has been proven that volatility in one market could be transferred to another. Antonakakis & Kizys (2015) revealed spillover effects between commodities and currencies, whereas Chen (1997) and Mittnik et al. (2015) studied stock market volatility using the S&P 500 as a reference.

Diebold & Yilmaz (2012) proposed a broad standard for evaluating the effects of market capitalization on different digital asset pairs. They predicted that loss indices were used to determine the expected losses of individual variables. First, the VAR volatility model was derived from the Dynamic Conditional Correlation Multivariate Generalized Autoregressive Conditional Heteroscedasticity (DCC-MGARCH) model. Variance decomposition was then used to show how much expected loss of one variable caused a shock to other variables. Using a broader decomposition approach ensured that the result was independent of the regression of variables. While the expected loss of one variable affected the 'to' and 'from' terms, the total index represented the predicted variance of the variable. Net spillover is the difference between two aspects; one shows whether the name has a net transmitter with a positive value, while the other is a receiver of shocks with a negative value (Diebold & Yilmaz, 2012).

For example, research has shown that there is a difference between capital markets and commodity markets (Chen, 1997). Given that cryptocurrencies represent a specific form of digital asset, Corbet et al. (2019) analyzed the dynamic relationships between cryptocurrencies and other financial instruments. Their results indicated that cryptocurrencies were partially correlated with other asset classes, which possessed their own unique market risk. The study by Bouri et al. (2018) suggested that market conditions influenced how BTC impacted the volatility of other asset markets. They highlighted that the returns on BTC had a strong correlation with returns of commodities.

Recently, Wang et al. (2022) have studied cryptocurrencies which could cause adverse market shocks in traditional markets. Shahzad et al. (2022) also linked between oil prices and the Bloomberg Commodity Index (BLCOMM), a basic indicator of the broad market. The volatility index (VIX) is a popular measure of market volatility derived from Standard & Poor’s (S&P) 500 index option prices. The VIX could be used in risk management and decision-making for investors and financial analysts focused on understanding market dynamics (Whaley, 2009).

Third, recent world geopolitical and economic crises have raised the uncertainty of financial markets (Chen et al., 2020; Fang & Shao, 2022; Umar et al., 2022). Such factors contributed to greater systemic risk and the need for more effective risk management procedures and practices. Examining volatility dynamics in two periods of the economy, income, and recovery, is essential in understanding the effects of spring storms on the stability of financial and energy markets and formulating effective regulatory policies. The volatility of financial markets has been impacted by several external shocks due to the COVID-19 pandemic, the war between Russia and Ukraine, and the ban on cryptocurrencies in China, particularly in the crypto sector (Chowdhury, 2020; Khan et al., 2024). Similarly, Kang et al. (2024) discovered that commodity prices responded differently during significant crises to stock market shocks, such as COVID-19 and the 2008 financial crisis.

Studies indicated that the volatility of the stock market affected the commodity price more harshly during the Global Financial Crisis between 2008 and 2009, compared to the COVID-19 pandemic. The same authors concluded that, although markets responded to the emergency of the Russia-Ukraine War quicker than to past crises, the magnitude of volatility was relatively low (Izzeldin et al., 2023). The cryptocurrency bans in China in May 2021 greatly destabilized markets. Griffith & Clancey-Shang (2023) and Jana et al. (2024) showed that such restrictive policies created excessive volatility and reduced market size, efficiency, and quality.

Based on the previous literature review, this study set up the following two hypotheses:

It has already been proven that the financial market is mirrored in the cryptocurrency, stock, and commodity markets, and vice versa. Given that cryptocurrency markets are relatively unstable because of volatility and numerous factors that influence the increase or fall of cryptocurrency value, a study of volatility is essential in analyzing the hierarchy of volatility transmission. The study that had already been carried out led to the following three conclusions. To begin with, there are specific volatility patterns of cryptocurrency, commodity, and equity markets. Second, these three markets have volatility spillovers during a crisis; and third, including BTC in a portfolio can bring some advantages.

Nevertheless, the research carried out has some limitations as well. Although many studies confirmed the relationship between markets, a few of them used a network-based approach to examine how volatility spread hierarchically. One critical question that has not been resolved is whether markets such as BTC and the VIX are chronic net transmitters of volatility and commodity, and whether such markets are net receivers or hedging vehicles. To bridge this literature gap, this study applied the techniques of volatility measurements and models and tested a hierarchical structure of volatility transmission in cryptocurrencies, stock markets, and commodity markets. This gave more understanding of risk management and portfolio diversification.

2.1 Development of Hypotheses

This study filled this gap by measuring spillovers and explicitly modelling and assessing the hierarchical structure of volatility transmission. Drawing on financial theory, appropriate hypotheses for further research were developed.

H1: It is easier for the volatility of BTC to affect the global stock and commodity markets rather than having such markets to affect BTC.

In line with the suggestion of the modern portfolio theory (MPT) and segmentation, assets that exhibit dissimilar fundamental risk drivers provide diversification benefits. The value of BTC is based on technological utility, network effects, and the presence of a specific regulatory environment, but not on the earnings of corporations or the forces of demand and supply that influence commodity prices. The segmentation implies that the crypto ecosystem shocks are mostly idiosyncratic to traditional markets. As a result of 24/7 trading and retail sentiment, such shocks are subject to behavioral finance contagion like sentiment contagion and attention effects (Barberis et al., 1998); in other words, a steep decline in BTC could cause a sell-off in other risky assets. Empirically, scholars such as Wang et al. (2022) suggested that crypto trading was vulnerable to adverse stock shocks although the channel of reversal was not well developed. In turn, BTC is highly volatile and ever-growing in importance. In the current SVAR model, it is anticipated that the concurrent effects of BTC shocks on both stocks and commodities (parameters a_{21} and a_{31} to be large), with the impact of shocks in traditional markets on BTC being small, are indicative of its leadership.

H2: Commodity markets have the effect of decreasing stock market volatility during times of turbulence but have little to no impact on cryptocurrency volatility.

The modern portfolio theory (MPT) suggests that hedging is characterized by low or negative correlation with other assets. Anticipated corporate incomes influence stocks, and commodity prices are affected by actual demand and inflationary strain. In times of market turbulence due to growth anxieties, they can decline alongside stocks. In times of stress due to inflation or supply impetuses, they can rise and offer partial and asymmetric hedging (Baur & Lucey, 2010). These effects are further exacerbated by behavioral factors: in a stock market shock, investors tend to sell all risky assets including commodities, due to the so-called flight to liquidity. Unlike stocks, commodities being real assets, could quickly recover once the crisis is not caused by a global fall in demand. BTC volatility, conversely, is highly speculative, regardless of regulatory news and the physical economy determining commodity prices; therefore, no systematic hedging relationship between the two should be anticipated. According to this mechanism, a negative shock in the stock returns should provoke a concurrent, albeit weaker, negative response in commodities (a_{32} coefficient in the SVAR model between 0 and -1). The impact of BTC shocks in driving the volatility of commodities will be insignificant.

By testing these hypotheses, the study went beyond merely identifying spillovers. It explained the directional dominance and economic implications, thereby providing more profound and nuanced insights into strategic risk management and portfolio diversification.

3. Methodology

This paper explored the volatility transmission between three financial markets, as a sample of cryptocurrencies, i.e., BTC; as a sample of commodities, i.e., the BLCOMM (Bloomberg, 2025); and as a sample of equities, i.e., the S&P 500 (S & P Dow Jones Index, 2025), using VAR/SVAR models and forecast error variance decomposition. Being the leading cryptocurrency, BTC sets the trends in crypto markets, whereas the S&P 500 (encompassing 80% of the U.S. market capitalization) mirrors the dynamics of equities. To quantify volatility spillovers between these networks of markets, the VIX index is used by the Chicago Board Options Exchange (CBOE) to gauge expected volatility in the stock market. The daily data for the indexes included in the research was taken from the website of *Yahoo!Finance* in 2025. The empirical analysis recorded the closing prices for all indexes to be integrated in the model, covering the period from January 1, 2019, to April 30, 2025. As a result of different economic shocks during the period of observation, the prices of the observed variables were changing constantly.

3.1 Preliminary Tests

Jorion (2003) defined value at risk (VaR) to be the maximum desirable loss that a given investment would suffer during a specific period, when there was a low probability of the actual loss surpassing that. The portfolio is held at the anticipated risk amount of VaR throughout time. Anyway, it is possible to calculate theoretical income or expenditure. The basic assumption of the VAR model is that the time series are stationary, that is, they have a stable mean and variance over the time. Augmented Dickey-Fuller (ADF) statistical unit root test and Phillips-Perron (PP) test could be used to confirm stationarity after the first differentiation officially. The results showed that all return series were stationary ($p < 0.01$), meaning VAR analysis could be applied without differentiating the data.

Moreover, the best lag length (p) must specify the VAR model correctly. Models with lags up to 10 periods were estimated based on standard information criteria: Akaike (AIC), Schwarz-Bayesian (BIC), and Hannan-Quinn (HQ). The three-lag model achieves the lowest levels of the above criteria; it is chosen to be the optimal model accordingly, due to its ability to describe the process of data generation without excessive adjustments.

3.2 VAR Models

To understand the relationships between returns of stocks, commodities, and cryptocurrencies, the VAR models were employed. VAR model is widely used in the analysis of multivariate time series to describe the dynamic behavior of different economic variables, analyze their relationships, and forecast changes in the future. Sims (1980) introduced VAR models, which were applied in various fields but mainly in economics. A primary focus of structural VAR (SVAR) analysis is to identify shocks that are of economic interest.

For VAR model, the study starts with the base model as follows:

$$y_t = \varphi_0 + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \ldots\ldots \varphi_{\mathrm{p}} y_{t-\mathrm{p}} + Þ_{\mathrm{p}} x_t + \varepsilon_t \tag{1}$$

where, y_t refers to a ($k \times 1$) vector of endogenous variables at time t, where $k = 3$: [r_{BTC}, r_{SP500}, r_{BLCOMM}]; φ_i is a ($k \times k$) matrix of autoregressive and cross-variable coefficients for lag i (for i = 1,...,p); x_t is the exogenous variable, the VIX return; p is a lag of order; $Þ$ is a ($k \times 1$) vector of coefficients for the exogenous variable; ε_t is a ($k \times 1$) vector of serially uncorrelated error terms.

If it is extended to include dependent variables: r_{BTC} (BTC) (2), r_{SP500} (S&P 500) (3), r_{BLCOMM} (Commodities) (4), the base model can be extended as follows:

$$\begin{aligned} r_{BTC,t} = {} & \varphi_{10} + \varphi_{11}^{1} r_{BTC,t-1} + \varphi_{12}^{1} r_{\mathrm{SP500},t-1} + \varphi_{13}^{1} r_{\mathrm{BLCOMM},t-1} + \varphi_{11}^{2} r_{BTC,t-2} + \varphi_{12}^{2} r_{\mathrm{SP500},t-2} \\ & + \varphi_{13}^{2} r_{\mathrm{BLCOMM},t-2} + \varphi_{11}^{3} r_{BTC,t-3} + \varphi_{12}^{3} r_{\mathrm{SP500},t-3} + \varphi_{13}^{3} r_{\mathrm{BLCOMM},t-3} \\ & + Þ_1 r_{\mathrm{VIX},t} + \varepsilon_{1,t} \end{aligned} \tag{2}$$

$$\begin{aligned} r_{SP500,t} = {} & \varphi_{20} + \varphi_{21}^{1} r_{BTC,t-1} + \varphi_{22}^{1} r_{\mathrm{SP500},t-1} + \varphi_{23}^{1} r_{\mathrm{BLCOMM},t-1} + \varphi_{21}^{2} r_{BTC,t-2} \\ & + \varphi_{22}^{2} r_{\mathrm{SP500},t-2} + \varphi_{22}^{2} r_{\mathrm{BLCOMM},t-2} + \varphi_{21}^{3} r_{BTC,t-3} + \varphi_{22}^{3} r_{\mathrm{SP500},t-3} \\ & + \varphi_{23}^{3} r_{\mathrm{BLCOMM},t-3} + Þ_2 r_{\mathrm{VIX},t} + \varepsilon_{2,t} \end{aligned} \tag{3}$$

$$\begin{aligned} r_{BLCOMM,t} = {} & \varphi_{30} + \varphi_{31}^{1} r_{BTC,t-1} + \varphi_{32}^{1} r_{\mathrm{SP500},t-1} + \varphi_{33}^{1} r_{\mathrm{BLCOMM},t-1} + \varphi_{31}^{2} r_{BTC,t-2} \\ & + \varphi_{32}^{2} r_{\mathrm{SP500},t-2} + \varphi_{33}^{2} r_{\mathrm{BLCOMM},t-2} + \varphi_{31}^{3} r_{BTC,t-3} + \varphi_{32}^{3} r_{\mathrm{SP500},t-3} \\ & + \varphi_{33}^{3} r_{\mathrm{BLCOMM},t-3} + Þ_3 r_{\mathrm{VIX},t} + \varepsilon_{3,t} \end{aligned} \tag{4}$$

VAR and SVAR models may be described as models that explain the values of a variable or set of variables, based on the past values of set of variables (Alvarez-De-Toledo et al., 2008; Geurts, 1977). Fernández-Villaverde & Rubio-Ramírez (2008) pointed out that Structural Vector Autoregressions (SVARs) are a multivariate and linear model that represent a vector of observable variables on its own past values along with other factors, such as a trend or constant.

Since time series analysis includes the analysis of log returns of the chosen underlying variables, the following equation has been used to calculate them:

$$y = \ln\left(\frac{S_t}{S_t - 1}\right) \tag{5}$$

where, S_t is the closing value for the current trading day.

Eq. (5) shows how much an asset price has changed from one period to the next, providing log returns.

3.3 Structural VAR Model

The validity of structural impulse responses depends on the chosen order of variables in the Cholesky decomposition. Our order starts with BTC → S&P 500 (SP500) → BLCOMM and this is not arbitrary. On the contrary, it was based on a hierarchy of market segmentation, trading structures, and fundamental drivers of each asset class. This order was formed based on the assumption that markets higher in the order could simultaneously influence those lower, but not vice versa.

In the first place of ranking, BTC is chosen as the most volatile and fastest reacting market. Some empirical studies often treated cryptocurrency as an exogenous or leading variable due to its unique nature (Cheah et al., 2018; Härdle et al., 2020; Khuntia & Pattanayak, 2018; Urquhart, 2017).

The S&P 500 (SP500) is in second place, simultaneously influenced by BTC but not commodities. In their study on volatility spillovers, Dyhrberg (2016) pointed out when BTC could simultaneously affect the stock market and confirmed that the "attention effect" and sentiment from the crypto market could quickly affect stocks. This agrees with the ideas of Wang et al. (2022), who hypothesized that the cryptocurrency market might have negative consequences, adversely affecting the cryptocurrency market. This meant a two-way relationship in which the stock market was not entirely isolated.

The BLCOMM ranks last in the hierarchy and is influenced by BTC and the S&P 500 index. Numerous studies confirmed the strongly simultaneous correlation between stock and commodity markets (Buyuksahin & Robe, 2014; Cayón Fallon & Sarmiento, 2021), and documented an increase in the correlation between these markets during crises. The obtained results from the SVAR analysis reveal that a highly significant coefficient a_{32} (BLCOMM ← SP500), hence providing direct empirical confirmation of this channel within the analyzed data set.

Even though covariance is used in VAR, it fails to remove underlying structural shocks, which can be interpreted economically. The structural elements of the VAR model aim at minimizing the effect of shocks on the underlying structure. The linear relationship between structural errors and underlying structure will be used in the following form. The VAR residuals ϵ_t are transformed in the SVAR model via:

$$A_{\varepsilon t} = B_{ut} \tag{6}$$

where, A is a $(k \times k)$ matrix defining the contemporaneous relationships among the endogenous variables; B is a $(k \times k)$ matrix defining how the structural shocks impact the variables; u_t is a $(k \times 1)$ vector of mutually uncorrelated structural shocks with zero mean and a unit variance-covariance matrix (Khadan, 2017).

3.3.1 A-matrix (structural effects in the same time period)

The following limitations were imposed:

BTC is not influenced by anything else and is seen as exogenous.

1 at a_{22} and 0 at a_{23} mean the S&P 500 responds to BTC at the same time, not to BLCOMM.

$a_{33} = 1$: Commodities can react to BTC and SP500 at about the same time. In fact, BTC responds the fastest, the S&P 500 is in the middle, and BLCOMM adjusts most after the others.

$$A = \begin{matrix} 1 & 0 & 0 \\ a_{21} & 1 & 0 \\ a_{31} & a_{32} & 1 \end{matrix} \tag{7}$$

where, BTC: [1, 0, 0], S&P 500 index: [a_{21}, 1, 0], and BLCOMM: [a_{31}, a_{32}, 1].

BTC's returns will not be proportionally subject to market shocks in the price of gold or the S&P 500. The first impact of this is that, unlike classic market shocks that require at least a day to respond, cryptocurrency markets can respond immediately.

The S&P 500 is currently driven by the price of BTC (via a_{21}) but not by the shock of commodity price (0 in the columns). The increasing role of cryptocurrency in investment choices in conventional equities is one rationale leading to this assumption, which explains the assumption that the effect it exerts on the prices of products is time-balanced.

In accordance with points a_{31} and a_{32}, the commodity can quickly react to fluctuations in BTC and the S&P 500. Its dependence on global economic expectations and financial market liquidity, representing the other two markets, enables the trading sector to become the most flexible.

Thanks to the structure, pure and orthogonal structural shocks u_t from correlated reduced residuals ε_{twe} could be created.

3.3.2 B-matrix (impact of structural shocks)

Here some constraints were imposed:

No shock spillovers occur between two equations at the same time. In other words, when $b_{12} = 0$, shocks to the SP500 do not immediately affect BTC.

This structure enables the separation of shocks from BTC, the SP500 or commodities (i.e., these are called pure shocks).

While the A matrix regulates how pure shocks are spread throughout the system, the B matrix allows the shocks to remain pure and independent. Each structural shock in matrix B is directed to one and only one variable and with unique meanings (1:1) during that time interval in Eq. (8).

$$B = \begin{matrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{matrix} \tag{8}$$

4. Empirical Results

Table 1 reports a statistical summary of daily returns (excluding S&P 500 data due to 384 instead of 386 observations), where there was apparent volatility clustering. The maximum risk (*SD* = 1.75%, low end = -11.59%, high end = 5.5%) was on BTC (r_{BTC}), followed by the VIX (r_{VIX}, *SD* = 3.62%, worst end = -15.96% and best end = 21.02%) due to its reputation as a fear gauge. The S&P 500 (r_{SP500}) was a relatively stable statistic (*SD* = 0.68%, range -3.78% to 3.33%), and the BLCOMM (r_{BLCOMM}) was not very volatile (*SD* = 0.467%, range -2.47% to 1.44%), indicating that commodities had an intermediate risk profile compared to the other studied markets.

Table 1. Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
r_{BTC}	386	0.0015301	0.0175262	0.0175262	0.0550416
r_{SP500}	384	0.0004574	0.0068286	-0.0378497	0.0332844
r_{BLCOMM}	386	-0.0000507	0.004671	-0.0247229	0.0143908
r_{VIX}	386	-0.0053722	0.0362204	-0.1596029	0.2102107

The correlation matrix in Table 2 showed weak linear associations between the variables. BTC returns (r_{BTC}) were very weakly correlated with all the other markets (r_{SP500} = 0.0907; r_{BLCOMM} = 0.0455; r_{VIX} = 0.0613), rendering an independent market asset. The S&P 500 exhibited relatively low interdependency with commodities (r_{BLCOMM} = 0.2250) but little relationship in other places. Most notably, the VIX kept very low correlations in every market, including an unusually close neutral relationship with equities (r_{SP500} = -0.0047) that obscured the normal expectations of negative volatility-equity interactions. All the coefficients of these low values (< 0.23) indicated a low degree of linear dependence between the considered asset classes.

Table 2. Correlation matrix

Variable	r_{BTC}	r_{SP500}	r_{BLCOMM}	r_{VIX}
r_{BTC}	1.0000			
r_{SP500}	0.0907	1.0000		
r_{BLCOMM}	0.0455	0.2250	1.0000	
r_{VIX}	0.0613	-0.0047	0.0105	1.0000

To analyze the patterns of volatility, weekly returns of BTC, S&P 500, and BLCOMM were examined during weeks 3000–3400 as in Figure 1. As witnessed in the plot, different volatility patterns existed in these markets. Figure 1 provides a graphic representation of respective average returns throughout the period, in order to illustrate how varying volatility is more pronounced in cryptocurrencies than equities and commodities.

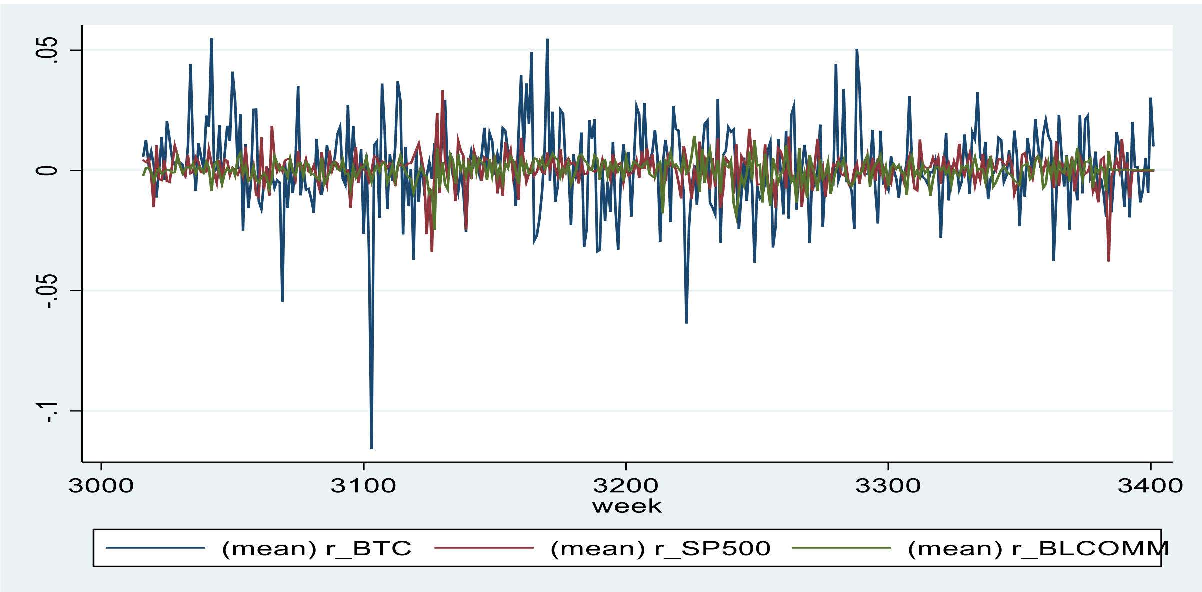

Figure 1. Plot of the mean for selected variables

BTC was the most volatile, and massive fluctuations characterized its high-risk behavior, whereas the S&P 500 had standard equity-like volatility. Commodities exhibited a lot more stable trends with spikes due to supply shock. The inverse turns indicated the potential of diversification and term-by-term simultaneous fall (e.g., week 3300) indicated complex market connections during macroeconomic shocks. The blue line in the series of returns of BTC signaled significant volatility, thus proving its role as the most volatile cryptocurrency in the present cycle and providing an inadequate reason to consider it the leader in volatility (H1). Isolated boom and bust research demonstrated that many price fluctuations could be attributed to non-radioactive macroeconomic factors and alterations in the crypto sphere, including new technologies, regulatory efforts, and speculative positions. Series often moved in different directions or with different intensity; for example, during the sharp decline of BTC in around week 3150, the S&P 500 and commodities might remain flat or have positive returns. This visual indicator of separation and imperfect correlation intuitively confirmed the benefits of diversification as predicted by modern portfolio theory, which was tested by the hypotheses. It was precisely this kind of asynchronous movement that the VAR model formally examined through insignificant spillover delays.

Figure 1 also depicts coherent declines in all three asset classes, especially in and around week 3300. These instances of co-movement were usually caused by significant systemic shocks, e.g., the start of the COVID-19 pandemic or the beginning of the Russia-Ukraine war, that flood asset-specific fundamentals and cause a general flight to safety. This trend explained the value of the SVAR model, which aimed at decomposing complex simultaneous causation under stress events and testing the capability of commodities to serve as a buffer against capital market shocks (H2). These trends also indicated: (1) the fact that SVAR-GARCH modeling was required to model volatility transmission effectively; (2) that BTC had a different risk-reward than conventional assets; and (3) that future studies with event highlights and regime-switching analysis would be helpful in conducting tests of stationarity as in Table 3, both Dickey-Fuller and Phillips-Perron methods. The unit root test significant results (p < 0.05) of these tests proved that there were no unit roots, and so, all-time series of this study were stationary. The result confirmed the reliability of the volatility analysis to be carried out as well as the econometric modeling, thus illuminating dynamics during times of crisis.

Table 3. Stationarity analysis

Returns	Dickey-Fuller		Phillips-Perron	
	Test Statistics	**P-value**	**Test Statistics**	**P-value**
r_{BTC}	-31.709	0.0000	-31.638	0.0000
r_{BLCOMM}	-32.165	0.0000	-32.164	0.0000
r_{SP500}	-39.975	0.0000	-39.798	0.0000
VIX	34.078	0.0000	-34.105	0.0000

All the series of returns were stable at levels (r_{BTC}: DF = -31.709, PP = -31.719, p = 0.000; r_{BLCOMM}: DF = -32.165, PP = -32.172, p = 0.000; r_{SP500}: DF = -39.975, PP = -39.981, p = 0.000; VIX: DF = -34.078, PP = -34.10). The lag selection criteria (AIC, SBIC, FPE, and HQIC) all pointed to the optimal lag length 3 (Table 4), which was an assurance of good model specification. Because the LR test is statistically significant at lag 3 (*) and FPE, and AIC are also clearly in support of lag 3 as the optimal lag length. This option can be explained by the fact that it can be better fitted to FPE and AIC and the statistical significance of LR tests. This eventually makes the model accurately reflect the dynamics of the system that are important.

Table 4. Choosing the optimal lag length in the VAR model

Lags	LL	LR	*DF*	*p*	FPE	AIC	HQIC	SBIC
0	2419.68				1.0e-09	-15.0166	-15.0073*	-14.9932*
1	2423.13	6.9099	4	0.141	1.0e-09	-15.0133	-14.9852	-14.9429
2	2425.98	5.6849	4	0.224	1.0e-09	-15.0061	-14.9593	-14.8888
3	2432.6	13.257*	4	0.010	1.0e-09*	-15.0224*	-14.9569	-14.8583
4	2432.82	0.43553	4	0.979	1.0e-09	-14.9989	-14.9147	-14.7879
5	2433.56	1.4763	4	0.831	1.0e-09	-14.9786	-14.8757	-14.7207
6	2436.03	4.9427	4	0.293	1.0e-09	-14.9691	-14.8475	-14.6644
7	2436.8	1.5346	4	0.810	1.0e-09	-14.9491	-14.8087	-14.5974
8	2438.46	3.3665	4	0.498	1.0e-09	-14.9347	-14.7756	-14.5361

Note: (*) denotes the optimal lag length based on each individual criterion.

Table 5 demonstrates the results of VAR analysis of the market, including lagged effects (intraday spillovers), signifying short-term market separation. BTC had low positive momentum (L1.coef = 0.110; p = 0.032), which implied a lack of information efficiency relative to conventional markets. It could be because of retail investor sentiment, groupthink, or slower dissemination of information. Conversely, since there was no significant correlation between sellers and the S&P 500, this market was shown to be efficient, with prices fluctuating quickly without prior changes.

Moreover, Table 5 displays the results of VAR and indicates three fundamental settings. To begin with, BTC (L1.coef = 0.110, p = 0.032) had low effects, and then as a conventional model, it showed efficient price tracking with no autocorrelation. Second, there were no cross-market effects (p > 0.1), which signaled a strong potential in diversification in the two days; and third, although the VIX did not exhibit a strong relationship with returns (p > 0.2), this could be a sign that the movement was through channel volatility, rather than the mean return. The high-frequency returns were noisy, thus indicating the specification validity of the model (AIC = -20.28) when the values of R2 were very low (1.4–2.4%).

Table 5. Output of VAR model

Equation	Lag	Variable	Coefficient	Std. Error	*Z*-Stat	*P*-Value
	L1	r_{BTC}	0.110*	0.051	2.15	0.032
	L2	r_{BTC}	-0.025	0.051	-0.49	0.621
	L1	r_{SP500}	0.063	0.135	0.47	0.639
r_{BTC}	L2	r_{SP500}	0.132	0.134	0.98	0.325
	L1	r_{BLCOMM}	-0.321	0.196	-1.64	0.101
	L2	r_{BLCOMM}	-0.002	0.196	-0.01	0.99
		r_{VIX}	0.029	0.025	1.17	0.242
	L1	r_{BTC}	0.003	0.02	0.15	0.881
	L2	r_{BTC}	0	0.02	-0.02	0.987
	L1	r_{SP500}	-0.074	0.053	-1.4	0.162
r_{SP500}	L2	r_{SP500}	0.01	0.053	0.19	0.85
	L1	r_{BLCOMM}	-0.1	0.077	-1.3	0.193
	L2	r_{BLCOMM}	0.056	0.077	0.72	0.471
		r_{VIX}	-0.001	0.01	-0.07	0.945
	L1	r_{BTC}	0.002	0.014	0.15	0.88
	L2	r_{BTC}	0.003	0.014	0.21	0.833
	L1	r_{SP500}	0.047	0.036	1.3	0.194
r_{BLCOMM}	L2	r_{SP500}	0.057	0.036	1.58	0.113
	L1	r_{BLCOMM}	-0.027	0.053	-0.52	0.604
	L2	r_{BLCOMM}	0.046	0.053	0.87	0.384
		r_{VIX}	0.001	0.007	0.22	0.83

Note: The z-statistics represent the null hypothesis test statistic, which assumes the coefficient to be zero. The coefficient *p*-value with (*) indicates the 5% level of statistical significance ($p < 0.05$).

The financial implications of small cross-market spillovers were captured by the fact that all cross-market lag coefficients were negligible ($p > 0.1$), indicating that the short-term gains from diversification were high. The returns in one market of the previous day provided no valuable information for predicting today's returns in another, suggesting that price movements occurred independently. For portfolio managers, this confirmed that combining these assets reduced the overall volatility of the portfolio.

The VIX index measured expected volatility rather than predicted returns. Its insignificance in all equations ($p > 0.2$) did not indicate irrelevance but rather the nature of its influence (Table 5). As the VIX index reflected expected future volatility, it confirmed that it affected the variance (second moment) and not the average (first moment) returns.

Based on the stability test of VAR model with every eigenvalue inside the unit circle (< 1), the largest was 0.327, corresponding to the real eigenvalue (-0.327), and the complex pairs exhibited modest cyclical behavior (e.g., 0.183 corresponding to $0.077 \pm 0.166i$). This verified that the system was covariance-stationary and included no exploding roots or artificial trends, which justified impulse response analysis and the reliability of long-range forecasts (Table 6).

Table 6. Stability of the VAR model (eigenvalue stability condition)

Eigenvalue		Modulus
-0.3273113		0.327311
0.2553543		0.255354
0.07735539	+ 0.1655392i	0.182721
0.07735539	- 0.1655392i	0.182721
-0.03678948	+ 0.1780155i	0.181777
-0.03678948	- 0.1780155i	0.181777

Every eigenvalue was inside the unit circle (maximum modulus = 0.33), and VAR was thus stable. The nonexistence of near-unit roots implied a quick shock dispersion keenest to witness quick adjustments in the financial records, when referring to high-frequency financial details. Although the complex eigenvalues [$-0.037 \pm 0.178i$] would indicate damp oscillatory responses, the magnitude of the eigenvalues (0.182) indicated minimal cyclicality, so the model would be applicable in studying short-term market interconnections.

Before addressing impulse response functions (IRFs) and/or variance decompositions or establishing a SVAR, a stable VAR model was required. Figure 2 demonstrates the roots of the companion matrix, a standard diagnostic for checking the stability of VAR models. The model is stable if the absolute values of all roots are less than 1, or all origins roots are within the unit circle. As can be seen in Figure 2, all roots are neatly located within the unit circle, thus confirming that the estimated VAR model satisfies the stability condition.

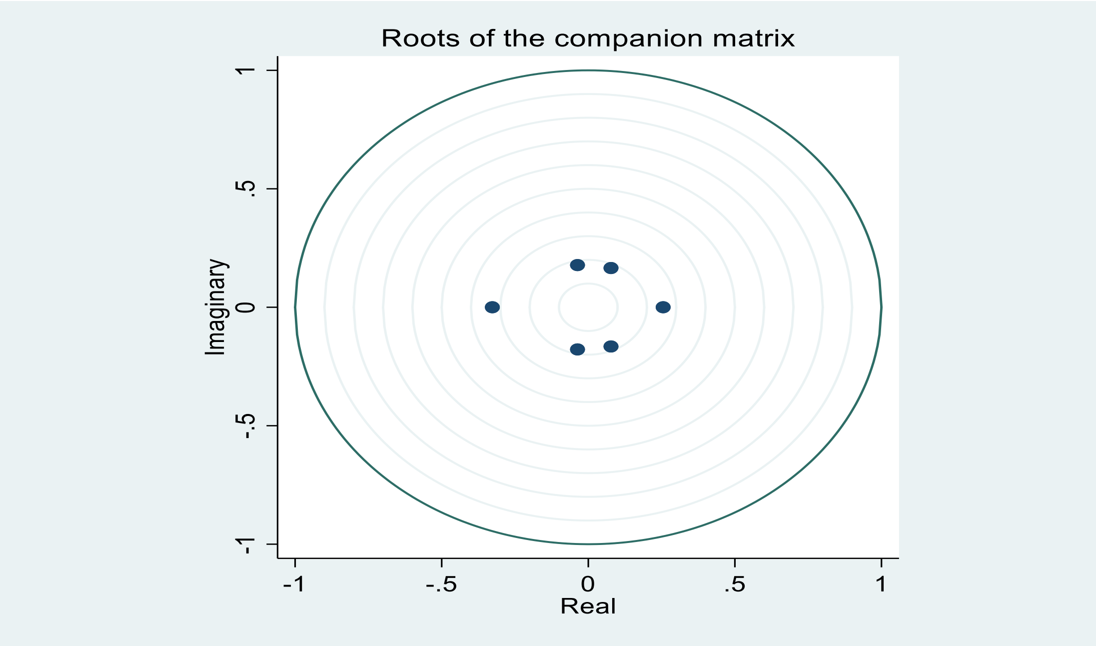

Figure 2. Roots of companion matrix

On the one hand, the SVAR curves in Table 7 illustrated an apparent market dynamic, a model established by Cholesky (BTC SP500 BLCOMM), as BTC showed a significant individual jolt (volatility = 0.017, $p < 0.001$), with commodities being highly sensitive to engaging in the activity in the equity markets (coefficient = -0.156, $p < 0.001$). Further, the SVAR model (Cholesky order: BTC, S&P 500 BLCOMM, $N = 380$) highlighted some significant dynamics of short-run market relations. It appeared that BTC shocks had a negligible influence on S&P 500 returns (coefficient = -0.035, $p = 0.079$) but did not affect commodities ($p = 0.728$), whereas commodities were very responsive to equity market dynamics (coefficient = -0.156, $p < 0.001$). The structural shock volatilities put a strong emphasis on the dominant idiosyncratic risk of BTC (0.017, $p < 0.001$) compared with the S&P 500 (0.007) and commodities (0.005), which proved the outstanding volatility profile of the crypto market. The adequacy of the model was supported by the high log likelihood (3876.454). Still, the poor BTC → SP500 association indicated there might be little contemporaneous spillovers, as investors found it beneficial to diversify across markets over such a horizon. In contrast, the responsiveness of commodities to equities was substantial, emphasizing strong dependence and interconnectedness under stress conditions.

Table 7. Estimation output of short run parameters—SVAR model

Model Identification		
Cholesky Ordering: BTC → SP500 → BLCOMM		
Sample: 3018–3401 ($N = 380$)		
Log Likelihood: 3876.454		
Matrix A (Short-Run Relationships)		
Parameter	**Coefficient**	**P-value**
a_{21} (SP500 ← BTC)	-0.035	0.079
a_{31} (BLCOMM ← BTC)	-0.005	0.728
a_{32} (BLCOMM ← SP500)	-0.156	0
Matrix B (Structural Shock Volatilities)		
Shock	**Volatility**	
BTC	0.017***	
SP500	0.007***	
BLCOMM	0.005**	

Note: (***), (**) respectively signify 1% and 5% significance levels.

Although the model had successfully converged (log likelihood = 3876.45), it could only marginally be determined that the S&P 500 reacted to BTC shocks (-0.035, $p = 0.079$). The fact that the VIX was statistically insignificant suggested that its effect probably went through the spread of volatility rather than direct return effects (Table 7). The findings highlighted the special role of BTC as a market leader, given its idiosyncratic volatility, interdependence between commodity and capital markets, and hierarchical transmission of shocks. While the classic VAR could not detect dynamics between markets and identify simultaneous causal relationships, the SVAR model was proposed. Based on the results of the SVAR model a weak spillover from BTC to stocks (a_{21} = -0.035; p = 0.079) was confirmed. While BTC and stocks had different investor bases, the S&P 500 market was many times larger than BTC (Table 7).

The strong reaction of commodities to capital market shocks (a_{32} = -0.156; $p < 0.001$) was the result of a combination of "investor flight to liquidity" to reduce risk and cover losses which further strengthened the connection and simultaneous reactions of these two markets. The standard deviation of BTC's structural shock, more than twice of that of the S&P 500 (0.007) and commodities (0.005), confirmed the extreme volatility of BTC and its high idiosyncratic risk.

Figure 3 shows the impulse response, indicating varied shock propagation patterns. The commodities served as shock absorbers, which responded effectively to the stock markets but did not respond to BTC shocks. While the cryptocurrency market was only shock resistant to itself, there was a lack of evidence showing that shocks in the BTC and commodity markets impacted the stock markets. Any short-term spillover effects disappeared within 3 to 5 periods. It indicated that BTC's decoupling from traditional assets and commodities' asymmetric role served as partial equity hedges, suggesting a hierarchical shock transmission system where equities drove commodities but not vice versa.

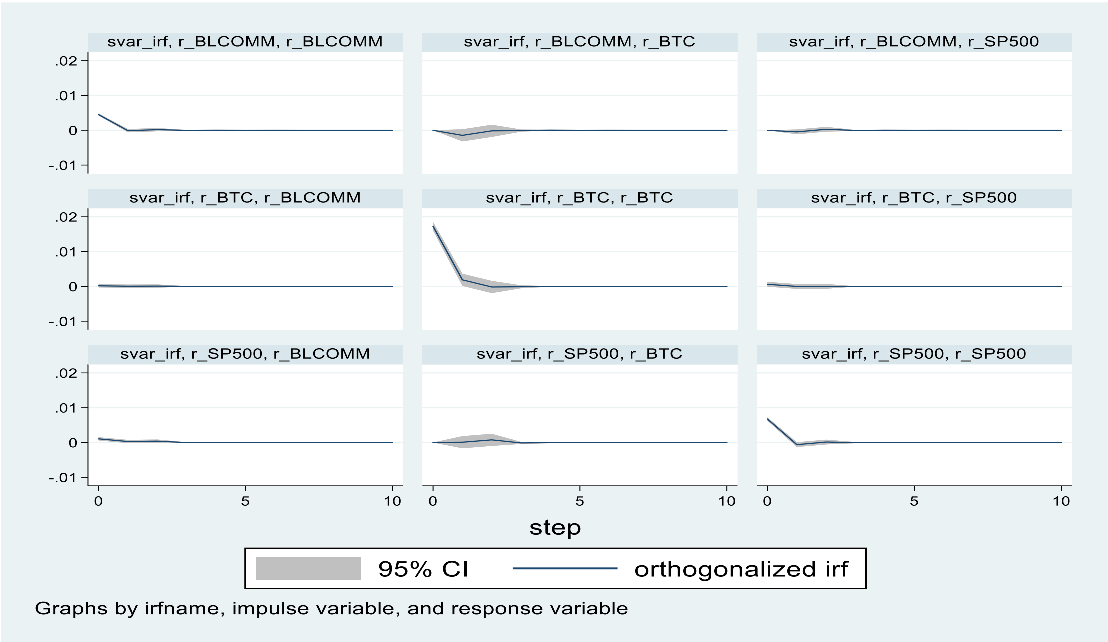

Figure 3. Impulse response functions

BTC's (r_{BTC}) response to its shock (middle left of the chart) was immediate, positive, and long-lived; it dissipated only after a few periods and demonstrated high idiosyncratic volatility. Key to H1 and shocks to BTC caused negligible and statistically insignificant reactions in the S&P 500 (r_{SP500}, lower left of the chart) and commodities (r_{BLCOMM}, upper middle of the chart), thus confirming its "net transmitter" status. While BTC was a highly volatile asset, its volatility mostly stayed in the crypto ecosystem and did not significantly spill over into traditional markets. The response of commodities (r_{BLCOMM}) to the S&P 500 shock (top right of the chart) showed a negative and statistically significant simultaneous response: a positive stock shock was followed by a negative move in commodities and vice versa. This inverse relationship visually confirmed the protective role of commodities predicted in H2. However, the short-lived effect faded quickly. It reflected a "partial" and transitory protection, which was effective in the immediate short term but potentially insufficient during longer-term or demand-driven crises, when both asset classes might fall simultaneously. The S&P 500 (r_{SP500}, bottom row) reported little or no significant response to shocks from BTC or commodities, while its dynamics were largely shaped by its own shocks (bottom right of the chart). This finding reinforced the hierarchical structure of the system: the stock market, as the largest and most central market, acts as a primary source of shocks to other asset classes, especially commodities, rather than as a sink for volatility.

As shown in Figure 4, the forecast error variance of each asset was mainly carried out by asset innovations, with little effect on the other assets.

It revealed an explicit hierarchy of influence and confirmed the short-term independence of the market, with several essential nuances. Each market was predominantly driven by innovations, especially on a very short horizon (horizon 1). High idiosyncratic risk and separation from traditional markets for BTC empirically confirmed H1 hypothesis as a net recipient of its own unique shocks. The S&P 500 (r_{SP500}) and commodities (r_{BLCOMM}) also exhibited strong autocorrelation, with over 90% of the variance explained by own shocks, empirically confirming the diversification benefits as predicted by modern portfolio theory.

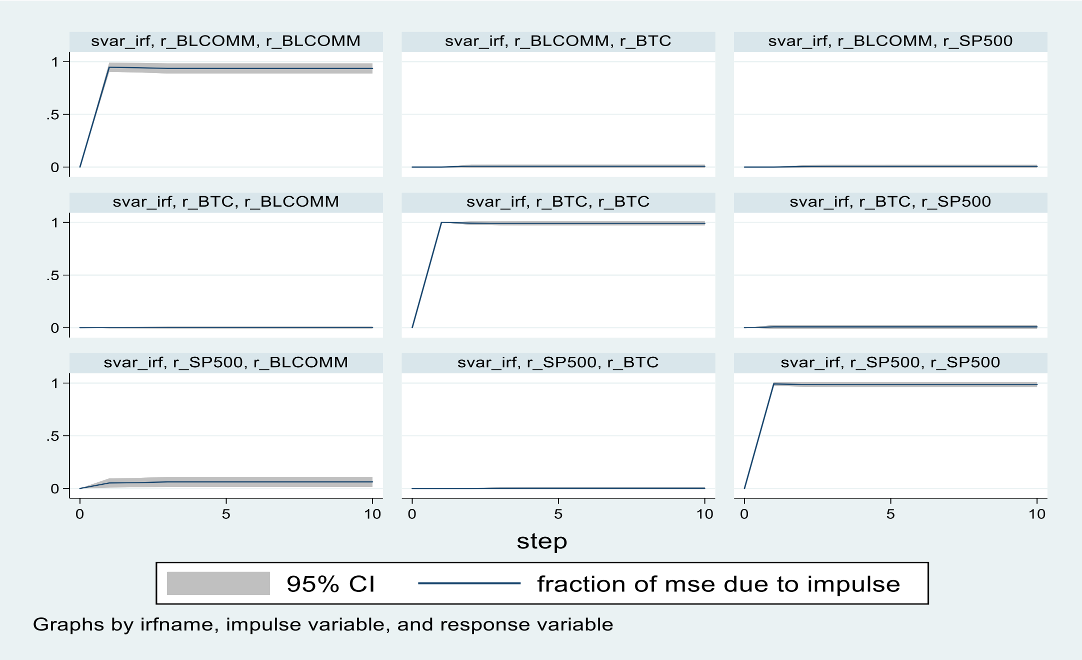

Figure 4. Forecast error variance decomposition (FEVD)

The variance of the S&P 500 (middle row, first graph) recorded a small but non-zero contribution from BTC shocks (around 5–8%), thus indicating that BTC act as a weak but noticeable net transmitter of volatility to stocks, and confirming the directional relationship predicted in H1. Commodity variance (top row) was moderately affected by BTC shocks, but more significantly by S&P 500 shocks. This is consistent with the H2 hypothesis, which confirmed that commodities act as a partial sink of volatility from other markets, especially stocks. It revealed that these contributions stabilized after a few days, hence suggesting the short-lived nature of shock transmission and minimally extended dynamic interdependence.

The FEVD results shed light on the fact that BTC, stock, and commodity markets offered significant diversification potential with a weak but statistically significant hierarchical pattern of spillovers.

5. Conclusions

In this paper, the volatility transmission between cryptocurrency (BTC), stock (S&P 500), and commodity (Bloomberg Index) was analyzed by the VAR/SVAR models. According to the results obtained, it was concluded that a hierarchical volatility structure existed, with BTC as a leader outperforming other market. Similarly, short-term spillovers were low but cross-market connections were severe during economic shocks. The paper also suggested that commodities played an asymmetric role in partial equity hedges. The stationarity tests (Dickey-Fuller/Phillips-Perron) verified the modeling and the impulse responses indicated that the persistence of shocks varied across the asset classes (3–5 periods). The results demonstrated the dual nature of BTC in terms of both market decoupling and volatility leadership, as well as the selective responsiveness of commodities to equity shocks. These insights enabled more informed portfolio strategies, particularly for diversification during economic turbulence, although longer-term analysis might reveal additional spillover patterns.

A hierarchical volatility structure was found in this study to characterize BTC as a leader, commodities as equity hedgers, and the VIX as a volatility driver; all of which conformed to the diversification aspect of modern portfolio theory. Although short-run spillovers were restricted, the results consolidated the economic theory and empirical evidence, thus providing investors with viable information on how to act during turbulent markets. Future studies are advised to improve the size of available data such as newly developed markets and recent shocks from geopolitical war, to examine technological/geopolitical factors to support such findings, and to identify new aspects of cross-market volatility propagation. Apart from a better understanding of volatility spillover among BTC, equities, and commodities provided by this research, it has various shortcomings such as the utilization of merely three asset classes, the use of linear modeling assumptions, and the failure to incorporate macroeconomic factors. Further, more penetrating insights into the dynamics of cross-market volatility in changing financial ecologies might be obtained by investigating the terms network analysis and associations with sustainable finance.

The findings had important practical implications for investors and portfolio managers. In fact, limited short-term spillovers confirmed the benefits of strategic diversification. In other words, including BTC and commodities alongside equities could reduce overall portfolio risk. However, BTC should not be viewed as a replacement for traditional assets. At the same time, commodities could serve as a partial hedge during market downturn although this role was not symmetrical in all conditions. Finally, risk tracking implied that BTC, as a volatility frontrunner, could signal upcoming market turbulence, and its movements could provide useful insights for timely risk management.

The regulators and policy makers should carefully track financial contagion. The increasing use of cryptocurrencies in financial systems necessitates the introduction of control systems to curb the process of transferring risk in volatile crypto markets to institutional institutions. Simultaneously, the loss of BTC in terms of conventional assets proves that the cryptocurrency market is regulated with specific rules set by technology and government organizations. Regulators need to be flexible, considering the specificity of digital assets.

Some limitations open opportunities and directions for further research. The scope of the asset class was limited to three main classes, so including bonds, currencies, and a broader range of cryptocurrencies would provide a comprehensive view of the global financial network. The model could be extended to include some macroeconomic factors (e.g., interest rates and inflation) to shed light on the underlying drivers of spillovers and hierarchies.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

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