PERINATAL JOURNAL

Original Article

Perinatal Journal 2025; 33(1):381-392

https://doi.org/10.57239/prn.25.03310045

Market value, interest rate, and cryptocurrency volatility

Khalid Faris Alomari*

Faculty of Business, Department of Financial and Banking Technology, Ajloun National University, Ajloun. Jordan

Abstract

This research study examines the correlation between several cryptocurrencies and major global economic indexes, both in the short term and over an extended period. The research investigates the relationship between interest rates (DRATE) and the total market capitalization of cryptocurrencies, namely Bitcoin, Dogecoin, Cardano, and Binance Coin. The data covers the period from January 2021 to December 2024, using monthly statistics. A vector error correction model (VECM) was used to analyze short-term variations and long-term trends. The findings demonstrate an unstable link between the studied variables, which is statistically significant regarding interest rate changes and their impact on the amount of investment in digital currencies, specifically concerning price variations of digital currencies. Final Analysis Interest rate variations have a statistically significant impact on the volatility of digital currency prices, however fluctuations in the market value of digital currencies do not have a statistically significant influence on their price volatility.

Keywords: Cryptocurrencies, Interest rates, Investment, Market cap, Economy

Introduction

Contemporary technological advancements have resulted in the development of numerous tools and resources that enhance human society across multiple dimensions, including economic, social, and political spheres, by conserving effort and time for users,(Vidal, Ma, & Sastry, 2016) Consequently, this progress has inspired a plethora of concepts that have facilitated the evolution of the banking sector, particularly through diverse electronic payment methods (Al-Smadi et al., 2024).This ignited the researchers' interest in understanding the nature of this currency, its attributes, and its impact on economic and social dimensions due to its value instability,(Meng, Lee, & Payne, 2017) as well as identifying the entity responsible for its issuance, given that it lacks affiliation with any official issuing authority in any nation. ,(Mao, Wei, & Wang, 2013) The marginalization of ruling regimes coincides with the perception of certain currencies as foreign within a nation's economy, (Kyriazis et al., 2023) resulting in the coexistence of two currencies: one possessing legal status and the other devoid of it, despite calls from some for its acceptance.(Alomari,2024)

As a result of the absence of a central authority that oversees the process of creating, sustaining, and preserving virtual currency, the values of virtual currency are susceptible to experiencing significant volatility, (Salisu & Ogbonna, 2022) Considering this, we have arrived at the issue of the study as a result of the widespread use of digital currencies in recent times. This has resulted in the desire of the economic systems across the globe to adhere to advances in these currencies as a consequence of the dangers that are presented by these currencies. The purpose of this study was to provide answers to the following questions as a result of the significant fluctuations in their value, particularly after a number of individuals and institutions turned to deal with them, and as a result of the question of what constitutes the fluctuation of interest rates on investments in general and investments in digital currencies in particular.

What is the impact of interest rate fluctuations on cryptocurrency price?

What is the impact of cryptocurrency market value fluctuations on cryptocurrency price?

Digital currencies have garnered interest in our period and require additional investigation. The importance of studying this subject lies in the continuous development of digital currencies, the increase in their dealers, and the negative impact these currencies have on real asset investments and financial markets. The paper examines digital

Correspondence: Khalid Faris Alomari, *Faculty of Business, Department of Financial and Banking Technology, Ajloun National University, Ajloun . Jordan, **e-mail:** kf.omari@anu.edu.jo, **Received:** June 30, 2025 **Accepted:** August 17, 2025

currencies' development, ideas, kinds, properties, and dealers' main pros and cons.

This paper is structured as follows. This section presents a review of existing literature regarding digital currencies and their attributes. The subsequent section addresses the study's contributions. Section III outlines the methodology and data utilized in this study. Section IV outlines the results, analysis, and discussion of the findings, while the final section provides a conclusion.

Literature Review

Nakamoto revealed the principles of blockchain and bitcoin in a 2008 paper. The Nakamoto distributed database, launched with bitcoin and the concept of cryptocurrency, proposed a solution to the issue of double spending in virtual money. In 2011, Herpel characterized digital money as transparent and readily accessible data used via the internet without the need for intermediate organization. The virtual currency market has consistently been a focal point within the international financial markets. (Antonakakis, Chatziantoniou, & Gabauer, 2019) Nevertheless, researchers analyzing the phenomena of price surges and declines through the lens of supply and demand in digital currency. Investors' hedging demand and investment demand for digital currency are the primary drivers at the demand level. (Neves, 2020) Additionally, certain scholars have employed behavioral finance theories to elucidate this price fluctuation, (Haferkorn & Diaz, 2015) argued that uninformed investors engaged in digital currencies primarily to identify appropriate investment tools, showing little concern for the potential of digital currency to evolve into a 'new trading system.' This behavior may result in a 'herding effect' that exacerbates investors' expectations regarding the increase in digital currency prices. These studies predominantly employ an economic analytical framework to investigate the factors contributing to digital currency price instability. This string of code, which underlies the digital currency, possesses no intrinsic value. The main findings of this examination have been subject to considerable scrutiny. Consequently, researchers have been investigating the interaction among the values of other assets, including U.S. dollars, metals (e.g. gold and silver), and equities, in an effort to elucidate the mechanisms behind digital currency price volatility, (Dyhrberg, 2015) examined the financial potential of bitcoin. He discovered that Bitcoin has some characteristics with gold and the U.S. dollar, both of which occupy a role in the financial market and portfolio management. (Zhu, Dickinson, & Li, 2017) conducted an analysis of the economic factors influencing Bitcoin prices through the application of VEC model. The analysis revealed that the Consumer Price Index, Dow Jones Index averages, and the US Dollar Index exerted a negative and long-term influence on Bitcoin prices, whereas gold prices showed no long-term impact on Bitcoin prices.

Furthermore, (Antoniadis, Sariannidis, & Kontsas, 2018) used the GJR-GARCH model to examine the influence of Bitcoin on the U.S. dollar index. The findings indicated that Bitcoin has a substantial negative influence on the return of the U.S. dollar index, and the correlation between Bitcoin and the U.S. dollar index was asymmetric. Nonetheless, several experts, like. (Baur, Dimpfl, & Kuck, 2017) possess divergent perspectives on the matter. They asserted that Bitcoin has distinct risk-return attributes and adheres to divergent return mechanisms, thereby indicating that Bitcoin is unrelated to gold, money, or equities. At this juncture, the surplus returns and price volatility of Bitcoin suggested that it resembled a much-speculated asset.

In recent studies, scholars have focused on digital currency price fluctuations. (17) observed that digital currency price correlation rose dramatically amid large price volatility. They also noted that Bitcoin is the most disruptive digital currency and Ripple is crucial, (Elsayed, Gozgor, & Lau, 2020) indicated that Bitcoin and Ethereum had a substantial return spillover impact in the 3rd quarter of 2017, but it reduced in the final quarter of the year. Their findings indicated that the current value of certain digital currencies is contingent upon the prior values of others, suggesting a significant causal relationship among digital currencies, (Jiang, Zhou, & Qiu, 2022) investigated digital currency price fluctuations using the DCC-GARCH model and WTC. They found a strong correlation between digital currency price variations. The digital currency industry is unstable due to Bitcoin, Ethereum, and Ripple, they said, (Hardiyanti, 2024) elucidated the influence of macroeconomic variables, cryptocurrency-specific elements, regulatory frameworks, and market sentiment on price volatility. The findings indicate that Ethereum exhibits more volatility than Bitcoin, influenced significantly by inflation, interest rates, and market sentiment. Factors particular to cryptocurrency, such mining expenses and technical advancements, significantly influence the market. (Mohammed, De Pablos Heredero, & Botella, 2024) examines the intricate relationship between cryptocurrency prices and major global events, such as the Russian-Ukraine war, Covid-19, inflation rates, and economic policy uncertainty in the U.S., U.K., and E.U., that have occurred in recent years. The study also analyzes the impact of disclosing cryptocurrency adoption plans on the prices of Bitcoin, Ethereum, and Binance Coin. The findings yielded several significant insights. During the study period, the adoption of cryptocurrencies by major corporations had a positive impact on their price. Additionally, there is a negative and strong correlation between cryptocurrency prices and times when economic policy is unclear as well as inflation rates in the nations that are being studied (the U.S., U.K., and E.U.).

The studies described above assist in the development of hypotheses. Thus, using econometric regressions and the preceding assumptions, the following hypotheses may be formed and tested.

H1a: There is a statistically significant effect of the fluctuation of interest rates on cryptocurrency price volatility.

H1b: There is a statistically significant effect of market value volatility on cryptocurrency price volatility.

Data and Methodology

This research study analyzes the relationship between several cryptocurrencies and significant global economic indices, both in the near term and longitudinally. The study examines the correlation between interest rates (DRATE) and the aggregate market capitalization of cryptocurrencies, namely Bitcoin, Dogecoin, Cardano, and Binance Coin. The data covers the timeframe from January 2021 to December 2024, using monthly statistics. Interest rate information was sourced from the Federal Reserve System, while cryptocurrency data was acquired from platforms like CoinMarketCap and Investing.com. The Augmented Dickey-Fuller (ADF) test was conducted to assess the presence of unit roots in the time series data. The test indicated that all variables were first order integrated, I(1), necessitating cointegration investigation.

The Johansen cointegration test was used to ascertain the existence of a long-term link among the variables. Following the discovery of cointegration, a vector error correction model (VECM) was developed to examine both short-term fluctuations and long-term patterns. The model's lag duration was determined using the Akaike Information Criterion (AIC) and the Schwartz Bayesian Criterion (SBC) to ensure precision. The research used impulse response functions (IRFs) and forecast error variance decomposition (FEVD) to investigate the interrelationships among these variables. These instruments elucidated the impact of changes in one variable on others over time, offering a more distinct understanding of the interplay between cryptocurrency and economic factors.

Statistical analysis of the study

Before conceptualizing the model, it is necessary to check the stationarity of each variable, in the present study, the ADF test will be employed, predicated on the following assumptions:

$$\begin{cases} H_0: \text{The series has a unit root (non}-\text{stationary).} \\ H_1: \text{The series is stationary} \quad . \end{cases}$$

If the p-value of the ADF test is below 0.05, we reject H_0 and conclude that the series is stationary. Table 1 show the results of ADF test for all study variables

Table 1. ADF test

Variable	ADF	Retard	Valeur critique à 5%	T-stat	Prob	Conclusion
RATE	None	1	-1.95	-0.07941	0.6509	Non-stationary
	Constant		-2.93	-1.45813	0.5456	
	constant and trend		-3.50	-1.15725	0.9074	
CAP	None	1	-1.95	0.558743	0.8334	Non-stationary

	Constant		-2.93	-0.84154	0.7979	
	constant and trend		-3.50	-1.09313	0.9196	
BCT	None	1	-1.95	-0.26952	0.5838	Non-stationary
	Constant		-2.93	-2.00242	0.2849	
	constant and trend		-3.50	-2.48439	0.3341	
DOGE	None	1	-1.95	-0.7411	0.3896	Non-stationary
	Constant		-2.93	-2.71395	0.0791	
	constant and trend		-3.50	-2.66516	0.2551	
ADA	None	1	-1.95	-1.61016	0.1005	Non-stationary
	Constant		-2.93	-2.95602	0.0465	
	constant and trend		-3.50	-3.41683	0.0610	
BNB	None	1	-1.95	0.424337	0.8011	Non-stationary
	Constant		-2.93	-4.57671	0.0005	
	constant and trend		-3.50	-4.63676	0.0027	

The results of the examination of the series' stationarity show that the hypothesis that there is a unit root for every variable is not supported by the data. Therefore, there is a possibility that the research variables have two-unit roots. The test will only be used once on differentiated variables to check for the presence of two-unit roots in the variables under study. Stated differently, the test concentrates on series variations. The results are shown as follows in table 2:

Table 2. Test after differentiation

Variable	ADF	Retard	Valeur critique à 5%	T-stat	Prob	Conclusion
DRATE	None	1	-1.95	-2.19086	0.0288	stationary
	Constant		-2.93	-2.38024	0.1528	
	constant and trend		-3.50	-2.59471	0.2845	
DCAP	None	1	-1.95	-6.01357	0.0000	stationary
	Constant		-2.93	-6.04043	0.0000	
	constant and trend		-3.50	-6.07723	0.0000	
DBCT	None	1	-1.95	-8.70188	0.0000	stationary
	Constant		-2.93	-8.69597	0.0000	
	constant and trend		-3.50	-8.72551	0.0000	
DDOGE	None	1	-1.95	-7.73443	0.0000	stationary
	Constant		-2.93	-7.73443	0.0000	
	constant and trend		-3.50	-7.68401	0.0000	
ADA	None	1	-1.95	-1.61016	0.1005	stationary
	Constant		-2.93	-2.95602	0.0465	
	constant and trend		-3.50	-3.41683	0.0610	
BNB	None	1	-1.95	0.424337	0.8011	stationary
	Constant		-2.93	-4.57671	0.0005	
	constant and trend		-3.50	-4.63676	0.0027	

The results of the stationarity test for the various series introduced into the model, as shown in the table 2 above, that the DCAP, DRATE, DBTC, ADA, and DBNB series are stochastic in nature and are stationary in first difference: I (1), which makes the ARDL model ineffective, and the choice remains between the ARDL and VAR models.

Cointegration test

To observe the prevalence of a co-integration relation amongst the variables. The Johansen cointegration test was used to ascertain the existence of a long-term link among the variables. The following table 3 shows the results of Johansen's cointegration test:

Table 3. Cointegration test

Nombre de relation	La statistique du test	Les valeurs critiques	p-value
r=0	96.08917	95.75366	0.0474
r=1	54.45789	69.81889	0.4419
r=2	33.70561	47.85613	0.5180
r=3	17.77245	29.79707	0.5829
r=4	6.297124	15.49471	0.6604

The cointegration test indicates that there is a single cointegrating relationship between the variables, since the statistic for r= 0 is significant (p-value = 0.0474), but for r≥1, the p-value is greater than 0.05, meaning there are no additional relationships.

Determination of the optimal lag

The optimum delay is determined using information criteria. This is the for the Akiake (AIC), Schwars (SC) and Hanan-Quin (HQ) criteria.

Table 1. Choosing the optimal number of delays

Retard	LogL	LR	EPE	AIC	CS	HQ
0	-2055.173	NA	1.97e+33	93.68969	93.93298	93.77991
1	-1873.680	305.2387*	2.69e+30	87.07636	88.77945*	87.70794*
2	-1845.159	40.18797	4.14e+30	87.41633	90.57921	88.58928
3	-1807.573	42.71149	4.97e+30	87.34424	91.96691	89.05855
4	-1750.424	49.35620	3.31e+30	86.38291	92.46537	88.63858
5	-1682.250	40.28432	2.40e+30*	84.92048*	92.46273	87.71751

The model with 1 lag is the best, according to the AIC, CS and likelihood test (LR) criteria. It offers a good fit with optimal values for these criteria.

Table 2. VECM(1) model estimation

Cointegrating Eq:	CointEq1	
CAP(-1)	1	
RATE(-1)	3.24E+11	
	-7.50E+10	
	[4.34851]	
DOGE(-1)	-1.24E+13	
	-3.00E+12	
	[-4.12267]	
ADA(-1)	1.91E+12	
	-4.00E+11	
	[4.72388]	
BNB(-1)	3.83E+09	
	-1.60E+09	
	[2.46814]	

BTC(-1)	-14581406					
	-1.00E+07					
	[-1.42965]					
C	-3.41E+12					
Error Correction:	D(CAP)	D(RATE)	D(DOGE)	D(ADA)	D(BNB)	D(BTC)
CointEq1	-0.123608	-5.32E-14	-5.09E-15	-2.89E-13	-4.73E-11	-2.54E-09
	-0.05579	-4.10E-14	(1.3E-14)	(7.6E-14)	(2.4E-11)	(2.5E-09)
	[-2.21567]	[-1.29602]	[-0.38890]	[-3.78835]	[-1.97370]	[-0.99941]
D(CAP(-1))	0.117411	-1.75E-13	7.80E-14	5.98E-13	2.67E-10	1.56E-08
	-0.14719	-1.10E-13	(3.5E-14)	(2.0E-13)	(6.3E-11)	(6.7E-09)
	[0.79766]	[-1.61840]	[2.25843]	[2.96889]	[4.21881]	[2.32522]
D(RATE(-1))	-3.61E+11	0.304025	-0.057448	-0.429037	-150.966	-9857.952
	-2.00E+11	-0.14726	(0.04696)	(0.27379)	(86.0441)	(9121.56)
	[-1.80538]	[2.06460]	[-1.22329]	[-1.56700]	[-1.75452]	[-1.08073]
D(DOGE(-1))	-2.53E+12	-0.098605	-0.30116	-1.465313	-991.7535	-51324.9
	-9.10E+11	-0.67284	(0.21458)	(1.25103)	(393.154)	(41678.4)
	[-2.76844]	[-0.14655]	[-1.40350]	[-1.17129]	[-2.52256]	[-1.23145]
D(ADA(-1))	4.69E+10	0.046092	-0.018545	-0.080751	141.4733	-606.0164
	-1.40E+11	-0.10491	(0.03346)	(0.19505)	(61.2979)	(6498.21)
	[0.32910]	[0.43936]	[-0.55431]	[-0.41400]	[2.30796]	[-0.09326]
D(BNB(-1))	4.32E+08	0.000101	2.66E-05	0.000553	-0.432476	5.114264
	-3.70E+08	-0.00027	(8.6E-05)	(0.00050)	(0.15832)	(16.7836)
	[1.17232]	[0.37454]	[0.30760]	[1.09803]	[-2.73165]	[0.30472]
D(BTC(-1))	6876400	-7.85E-07	1.03E-06	5.97E-06	0.002019	-0.182683
	-4623848	-3.40E-06	(1.1E-06)	(6.3E-06)	(0.00199)	(0.21075)
	[1.48716]	[-0.23070]	[0.95033]	[0.94415]	[1.01577]	[-0.86683]
C	7.57E+10	0.071313	0.009863	0.020821	23.56942	2060.615
	-5.20E+10	-0.03814	(0.01216)	(0.07091)	(22.2830)	(2362.23)
	[1.46080]	[1.87001]	[0.81097]	[0.29365]	[1.05773]	[0.87232]
R-squared	0.246681	0.267062	0.213165	0.378413	0.564168	0.233610
Adj. R-squared	0.11147	0.135509	0.071938	0.266847	0.485941	0.096053
Sum sq. resids	4.13E+24	2.2378	0.227596	7.736178	764043.3	8.59E+09
S.E. equation	3.26E+11	0.23954	0.076392	0.445380	139.9673	14837.97
F-statistic	1.824418	2.030072	1.509378	3.391809	7.211989	1.698276
Log likelihood	-1308.218	4.859266	58.57269	-24.29047	-294.5516	-513.7378
Akaike AIC	56.00926	0.133648	-2.15203	1.374063	12.87453	22.20161
Schwarz SC	56.32418	0.448567	-1.837111	1.688982	13.18945	22.51653
Mean dependent	4.55E+10	0.090426	0.007712	0.015136	14.23440	1360.755
S.D. dependent	3.45E+11	0.257631	0.079298	0.520156	195.2182	15606.41
Determinant resid covariance (dof adj.)		3.19E+30				
Determinant resid covariance		1.04E+30				
Log likelihood		-2024.401				
Akaike information criterion		88.44261				
Schwarz criterion		90.56832				
Number of coefficients		54				

H1a: There is a statistically significant effect of the fluctuation of interest rates on cryptocurrency price volatility.

The cointegration equation reflects the long-term equilibrium relationships between the variables. In this model, the variable CAP is taken as the reference, with all other variables expressed in relation to it. More specifically, the coefficient of CAP (-1) is 1, meaning that it serves as the anchor point in the cointegration equation. The coefficients of the other variables show the extent and direction of their relationship with CAP in the long term:

$$CointEq1 = CAP(-1) + 3.24 \times 10^{11} \cdot RATE(-1) - 1.24 \times 10^{13} \cdot DOGE(-1) + 1.91 \times 10^{12} \cdot ADA(-1) + +3.83 \times 10^{9} \cdot BNB(-1)$$

$$-1.45 \times 10^{7} \cdot BTC(-1)$$

The coefficient for RATE (-1) is 3.24E+11, suggesting a positive relationship with CAP. This means that when CAP increases by 1 unit, RATE increases by 3.24E+11 units in the long term. The relationship between CAP and DOGE (-1) is negative, with a coefficient of -1.24E+13, indicating that an increase in CAP leads to a decrease in DOGE in the long term. Similarly, ADA (-1) shows a positive coefficient of 1.91E+12, suggesting that as CAP increases, so does ADA. BNB (-1) also shows a positive relationship with CAP, with a coefficient of 3.83E+09. In contrast, BTC (-1) has a negative coefficient of -14581406, indicating that CAP and BTC are inversely related in the long term.

The error correction term (ECT) in short-term equations shows how each variable adjusts its deviations from the long-term equilibrium. A negative and significant ECT indicates that the variable is correcting any deviation from the long-term relationship. The ECT coefficients in the short-term equations are all negative, suggesting that the variables are indeed adjusting their values towards the long-term equilibrium.

For DOGE, the ECT coefficient is -2.89E-13, which is statistically significant. This means that DOGE is adjusting its deviations from long-term equilibrium, although the amplitude is small, indicating a relatively slow correction process. In the ADA equation, the ECT coefficient is -3.78E-13, also negative and significant, indicating a slight correction towards equilibrium, although the speed of the process remains low. The BNB equation shows an ECT coefficient of -4.73E-11, which is also negative and indicates a correction process, although at a relatively slow speed. BTC has an ECT coefficient of -2.54E-09, reflecting a similar slow adjustment towards long-term equilibrium.

H1b: There is a statistically significant effect of market value volatility on cryptocurrency price volatility.

In the short-term equations for DOGE, ADA, BNB and BTC, the impact of CAP and RATE is analyzed. CAP has a significant but very small impact (almost 0) on all the crypto currencies. RATE has a large but insignificant coefficient (-0.057448, -0.429037, -150.9660 and -9857.952), so rate has no impact on crypto currencies. Neither CAP nor RATE have much influence on its short-term movements, indicating that these variables are more important in the long term than in the short term.

Overall, this analysis shows that CAP and RATE are key drivers of long-term relationships in the system, as shown by the cointegration equation. These variables, in particular CAP, have a significant impact on the behavior of DOGE, ADA, BNB and BTC over time. The error-correction terms show that all variables adjust slowly towards their equilibrium in the long term, although the speed of adjustment is modest. In the short term neither CAP nor RATE have much influence, indicating that these variables are more important in the long term than in the short term.

Model validation

After estimating our VECM model, we need to test the validation of the statistical to ensure the model's significance and reliability. In the residuals of our model, including autocorrelation, heteroscedasticity and normality of the residuals, and normality of residuals, and tests for the structural stability of our model and coefficients.

Table 1. Validation test results

The tests	Null hypothesis	p-value	Result
Normality.test	The normality	0.000	Non-normality of residuals
Arch.test	Homoscedasticity	0.1025	Homoscedasticity of residuals
Serial.test	The non-utocorrelation	0.1769	Non-autocorrelation of residuals

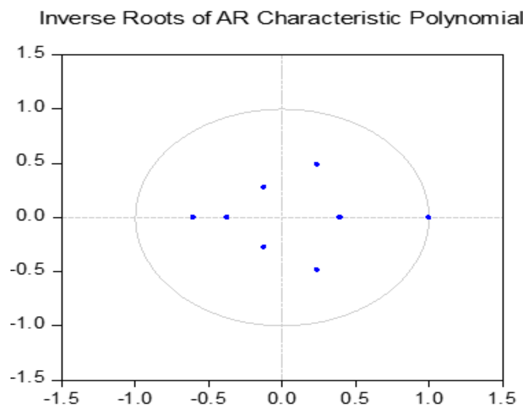

Figure 3: model stability

As far as model stability is concerned, the test graph shows that there is no point outside the red interval, which indicates the stability of our model.

Shock analysis

This test provides us with information on the evolution of different variables following a shock.

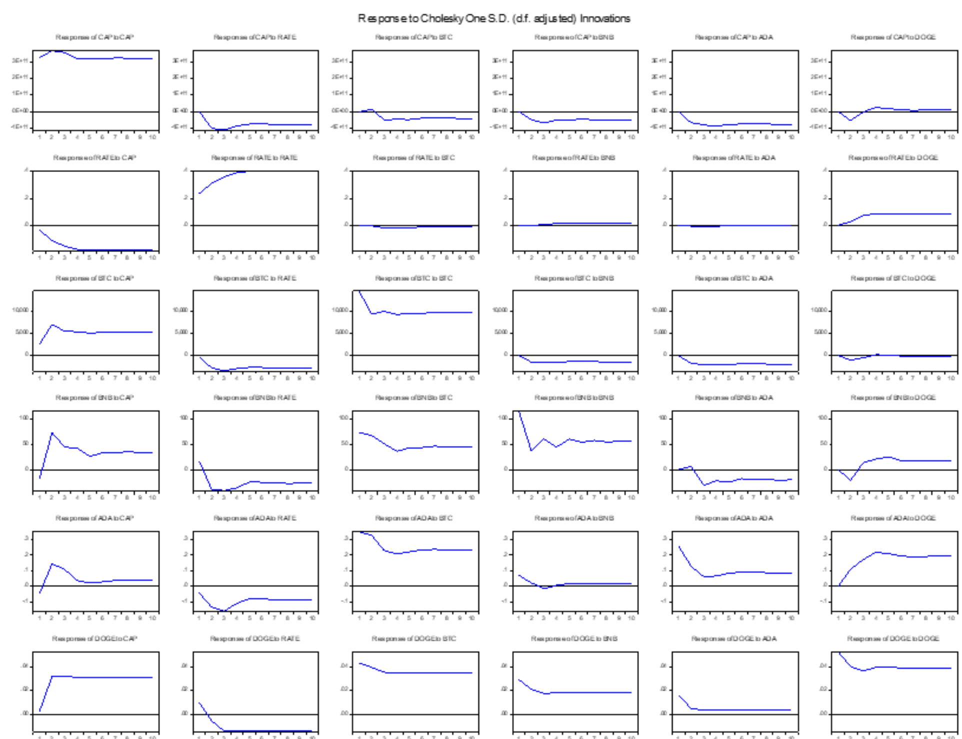

Figure 4: Impulse response of variables

4.4.1 Responses of CAP (Market Capitalization)

CAP to its own shock

From the graphs, it is evident that a shock to CAP causes an immediate and significant response in its own value, which gradually declines over time. This suggests a strong self-sustaining effect in market capitalization, indicating that shocks to market value can have a prolonged influence before equilibrium is restored.

CAP to RATE shocks

The graph (first row, second column) illustrates that volatility in RATE significantly impacts CAP, particularly in the initial periods. This implies that changes in interest rate volatility directly influences market sentiment and lead to shifts in total market capitalization. A change in interest rate volatility might prompt investors to reassess their investments in the crypto market, causing fluctuations in overall market capitalization.

CAP to Cryptocurrency shocks (BTC, DOGE, ADA, BNB)

Shocks from CAP appear to have relatively minimal impacts on cryptocurrencies compared to the relationship between CAP and RATE. This suggests that individual cryptocurrencies might be less sensitive to macro-market changes (CAP) and are influenced by other factors, such as specific use cases, adoption rates, or market conditions.

4.4.2 Responses to RATE (Interest Rate Volatility):

RATE to its own shock

The graph (second row, second column) shows that RATE responds strongly to its own shocks initially but decreases over time. This indicates a temporary instability caused by its own shocks, but it diminishes as markets adapt to the new conditions. The attenuation over time reflects the market's ability to absorb shocks to interest rate volatility and establish new stability.

RATE to CAP shocks

The influence of CAP on RATE (second row, first column) suggests that an increase in market capitalization triggers a moderate effect on interest rate volatility, which tends to diminish over time. A booming market (higher CAP) initially increases uncertainty or expectations regarding interest rate fluctuations, but this relationship stabilizes as the market digests the growth.

RATE to cryptocurrencies (BTC, DOGE, ADA, BNB)

Cryptocurrencies like BTC and DOGE seem to be more responsive to RATE shocks than others (e.g., ADA or

BNB). Cryptocurrencies with higher adoption or speculative activity might show higher sensitivity to changes in interest rate volatility.

The study's findings regarding digital currencies indicate that investing in them entails numerous risks that can result in investment failure, primarily due to the level of risk and the absence of regulatory controls governing their operation. The lack of regulatory laws governing digital currency trading in central banks globally has rendered investments in digital currencies very perilous, resulting in bankruptcy and a range of economic and social issues. Investments in digital currencies are influenced by several factors that cause price volatility, particularly swings in interest rates, as the study's findings indicate a strong correlation between these fluctuations and digital currency values.

Discussion

From the results of the study, it becomes clear to us that there is a long-term parallel relationship between the variables, as there is an impact of the market value on the following currencies directly, ABA and BNB, and an inverse relationship with the currencies DOQE, BTC, as well as the short-term interest rate, as its effect is evident in the long-term effect of the interest rate on digital currencies. This is consistent with the study, (Bouri et al., 2017) in terms of the impact of variables such as the interest rate on currencies such as Bitcoin in the long term, more than the short term. It is also consistent with the study,(Corbet, Lucey, Urquhart, & Yarovaya, 2018) as the study indicated that digital currencies have special factors that affect them in the short term, and that CAP and RATE have an impact exclusively in the long term. The study also agreed with,(Kristoufek,

2015) that the relationship between digital currencies and macroeconomic indicators is very weak in the short term and has a stronger relationship in the long term. On the other hand, the results of the study differed from the study,(Selmi, Mensi, Hammoudeh, & Bouoiyour, 2018) the most prominent results of which were a strong correlation between digital currencies and short-term interest rates, which means that the effect is not only in the long term, but also that there is an immediate and rapid impact on digital currencies. The results of the study differed from the study of , (Ciaian, Rajcaniova, & Kancs, 2016) whose results showed that macroeconomic and financial indicators have a correlation with digital currencies in the short term, and this contradicts the weak effect of CAP and RATE in the short term.

Conclusions

This study examines the correlation between market capitalization of cryptocurrencies, interest rates (DRATE) and price fluctuations of cryptocurrencies, specifically Bitcoin, Dogecoin, Cardano, and Binance Coin. The data spans from January 2021 to December 2024, utilizing monthly statistics. A vector error correction model (VECM) was employed to examine short-term fluctuations and long-term trends. The findings indicate an unstable relationship between the examined variables, which is statistically significant in relation to interest rate fluctuations and their effect on investment levels in digital currencies, particularly with respect to price changes of these currencies. Conclusive Examination Variations in interest rates significantly affect the volatility of digital currency prices; however, changes in the market value of digital currencies do not significantly influence their price volatility. This study recommends that financial authorities examine the relationship between interest rates and digital asset prices, as their influence on monetary policy directly affects digital currencies and their volatility. Improving transparency, regulating frameworks, and offering centralized data for digital markets can mitigate uncertainty and promote market stability,(Baur & Hoang, 2021) The study elucidates the relationship between market value, interest rates, and digital currency fluctuations; however, further research is necessary to explore the various factors influencing investor behavior and the broader social and economic implications of these investments. This involves utilizing artificial intelligence models for the analysis of historical data. This is interconnected with traditional markets, as they demonstrate their function in incorporating macroeconomic requirements into the digital sector.

References

Alomari, K. F. (2024). Catalyst impact of consumer experience over the relationship between FinTech and consumer satisfaction: A study on Jordanian Islamic banks. International Journal of Advances in Soft Computing & Its Applications, 16(2), 298–312. https://doi.org/10.15849/ijasca.240730.18

Al-Smadi, R. W., Alnsour, I. R., Alomari, K. F., Al-Hamad, A. A. A., Almasarweh, M. S., Bani Ahmad, A. Y. A., & Al-Smadi, A. W. (2024). The impact of leadership styles on marketing effectiveness and financial performance in Jordanian banks sectors: Corporate social responsibility as a mediator. Uncertain Supply Chain Management, 12(4), 2673–2682. https://doi.org/10.5267/j.uscm.2024.5.004

Antonakakis, N., Chatziantoniou, I., & Gabauer, D. (2019). Cryptocurrency market contagion: Market uncertainty, market complexity, and dynamic portfolios. Journal of International Financial Markets Institutions and Money, 61, 37–51. https://doi.org/10.1016/j.intfin.2019.02.003

Antoniadis, I., Sariannidis, N., & Kontsas, S. (2018). The effect of Bitcoin prices on US Dollar index price. In Springer proceedings in business and economics (pp. 511–521). https://doi.org/10.1007/978-3-030-02194-8_34

Baur, D. G., Dimpfl, T., & Kuck, K. (2017). Bitcoin, gold and the US dollar – A replication and extension. Finance Research Letters, 25, 103–110. https://doi.org/10.1016/j.frl.2017.10.012

Baur, D. G., & Hoang, L. T. (2021). A crypto safe haven against Bitcoin. Economics Letters, 199, 109696. https://doi.org/10.1016/j.econlet.2021.109696

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., & Hagfors, L. I. (2017). On the hedge and safe haven properties of bitcoin: Is it really more than a diversifier? Finance Research Letters, 20, 192–198. https://doi.org/10.1016/j.frl.2016.09.025

Chen, Y., & Shah, A. (2020). The impact of cryptocurrency on financial markets: A review. Journal of Financial Markets, 45, 100-115. https://doi.org/10.1016/j.finmar.2020.100115

Ciaian, P., Rajcaniova, M., & Kancs, d'Artis. (2016). The economics of Bitcoin price formation. Applied Economics, 48(19), 1799–1815. https://doi.org/10.1080/00036846.2015.1109038

Corbet, S., Lucey, B., Urquhart, A., & Yarovaya, L. (2018). Cryptocurrencies as a financial asset: A systematic analysis. International Review of Financial Analysis, 62, 182–199. https://doi.org/10.1016/j.irfa.2018.09.003

Dyhrberg, A. H. (2015). Bitcoin, gold and the dollar – A GARCH volatility analysis. Finance Research Letters, 16, 85–92. https://doi.org/10.1016/j.frl.2015.10.008

Elsayed, A. H., Gozgor, G., & Lau, C. K. M. (2020). Causality and dynamic spillovers among cryptocurrencies and currency markets. International Journal of Finance & Economics, 27(2), 2026–2040. https://doi.org/10.1002/ijfe.2257

Haferkorn, M., & Diaz, J. M. Q. (2015). Seasonality and interconnectivity within cryptocurrencies - An analysis on the basis of Bitcoin, Litecoin and Namecoin. In Lecture notes in business information processing (pp. 106–120). https://doi.org/10.1007/978-3-319-28151-3_8

Hardiyanti, S. E. (2024). Analysis of Volatility and Factors Affecting Cryptocurrency Prices: A Case Study of Bitcoin and Ethereum. Management Science Research Journal, 3(2), 7–15. https://doi.org/10.56548/msr.v3i2.107

Jiang, S., Zhou, J., & Qiu, S. (2022). Is there any correlation between digital currency price fluctuation? Based on the DCC-GARCH and wavelet coherence analysis. Economic Research-Ekonomska Istraživanja, 36(2). https://doi.org/10.1080/1331677x.2022.2134901

Kristoufek, L. (2015). What are the main drivers of the Bitcoin price? Evidence from wavelet coherence analysis. PLoS ONE, 10(4), e0123923. https://doi.org/10.1371/journal.pone.0123923

Kyriazis, N., Papadamou, S., Tzeremes, P., & Corbet, S. (2023). The differential influence of social media sentiment on cryptocurrency returns and volatility during COVID-19. The Quarterly Review of Economics and Finance, 89, 307-317. https://doi.org/10.1016/j.qref.2022.09.004

Mao, Y., Wei, W., & Wang, B. (2013). Twitter volume spikes: analysis and application in stock trading. In Proceedings of the 7th Workshop on Social Network Mining and Analysis (pp. 1-9). https://doi.org/10.1145/2501025.2501039

Meng, M., Lee, J., & Payne, J. (2017). RALS-LM unit root test with trend breaks and non-normal errors: application to the Prebisch-Singer hypothesis. Studies in Nonlinear Dynamics & Econometrics, 21(1), 31-45. https://doi.org/10.1515/snde-2016-0050

Mohammed, M. A., De Pablos Heredero, C., & Botella, J. L. M. (2024). The driving forces behind the prices of major cryptocurrencies: Evidence from the past five years. Intangible Capital, 20(2), 299. https://doi.org/10.3926/ic.2575

Neves, R. H. D. (2020). Bitcoin pricing: impact of attractiveness variables. Financial Innovation, 6(1). https://doi.org/10.1186/s40854-020-00176-3

Poyser, O. (2019). Exploring the dynamics of Bitcoin's price: a Bayesian structural time series approach. Eurasian Economic Review, 9(1), 29–60. https://doi.org/10.1007/s40822-018-0108-2

Salisu, A. A., & Ogbonna, A. E. (2022). The return volatility of cryptocurrencies during the covid-19 pandemic: assessing the news effect. Global Finance Journal, 54, 100641. https://doi.org/10.1016/j.gfj.2021.100641

Selmi, R., Mensi, W., Hammoudeh, S., & Bouoiyour, J. (2018). Is Bitcoin a hedge, a safe haven or a diversifier? An empirical investigation. Finance Research Letters, 26, 192–198. https://doi.org/10.1016/j.frl.2017.10.012

Vidal, R., Ma, Y., & Sastry, S. S. (2016). Principal Component Analysis. In Generalized Principal

Component Analysis. Interdisciplinary Applied Mathematics, 40. https://doi.org/10.1007/978-0-387-87811-9_2

Zhu, Y., Dickinson, D., & Li, J. (2017). Analysis on the influence factors of Bitcoin's price based on VEC model. Financial Innovation, 3(1). https://doi.org/10.1186/s40854-017-0054-0

Ahmed, F., Naqshbandi, M. M., Waheed, M., & Ain, N. U. (2024). Digital leadership and innovative work behavior: impact of LMX, learning orientation and innovation capabilities. Management Decision, 62(11), 3607-3632.

Derakhshani, Aliakbar, Arezoo Ghadi, and Seyed Ebrahim Vahdat. "Effect of Chemical Additives on Carbon Dioxide in the Sustainable Production of Portland Pozzolanic Cement." Environment and Water Engineering 11, no. 1 (2025): 11-18.

Moghavvemi, S., Jam, F. A., & Iqbal Khan, T. (2025). The Impact of Motivation, Opportunity, Financial Ability, and Willingness on Resident Support for Tourism Development. Tourism Planning & Development, 22(1), 63-84.