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Optimizing AltCoin (ETH) Price Synchronization During the Bitcoin Dominance Era: A Comprehensive Phase Analysis with Vector Error Correction Model

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ABSTRACT

The main objective of this research is to optimize the understanding of AltCoin price synchronization, with a focus on Ethereum, during different periods of Bitcoin dominance. This research uses secondary data through 162 observations for each cryptocurrency collected (BTC and ETH). The Vector Autoregressive (VAR)/Vector Error Correction Model (VECM) method is used as the analytical technique. The findings of this study have the potential to provide a strong foundation for the development of investment strategies in the cryptocurrency market. This study has identified different impact patterns on AltCoin prices during the High, Middle and Low Dominance Phases. The research findings reflect different impact patterns depending on the phase of Bitcoin dominance, indicating the complexity of market dynamics related to certain factors.

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1. Introduction

The global transformation in payment methods driven by technological advances has given rise to cryptocurrencies as an increasingly widely accepted alternative (Hsu et al., 2021). The financial industry is experiencing a significant shift with the presence of blockchain technology, enabling instant transactions across countries and continents with unprecedented speed, security and efficiency (Suryawijaya, 2023). Digital infrastructure is a factor that supports innovation in financial services (Benedetta et al., 2024). Financial services effectiveness need digital skill of the population (Sun et al., 2020). Cryptocurrency, as a key product of this revolution, offers potential as a personal electronic transaction tool and an attractive investment instrument (Gillaizeau et al., 2019; Luo et al., 2021; White et al., 2020). The popularity of cryptocurrencies, especially Bitcoin, has created thousands of altcoins that continue to grow, bringing new dynamics to the global financial ecosystem (Demir et al., 2021; T. V. H. Nguyen et al., 2019). Table 1. shows some of the top-ranking cryptocurrencies according to coin market cap data.

Table 1. Cryptocurrency Market Capitalization

Types of cryptocurrencies		Market Capitalization	Prize
Bitcoin Bitcoin (BTC)		$336.321.258.371	$17.464
Alt-Coin	Ethereum (ETH)	$163.742.031.346	$1.338
	BNB	$44.336.303.835	$277
	XRP	$17.696.996.723	$0,35
	THERE IS	$11.101.300.191	$0,32
	DOGE	$10.274.488.742	$0,08

Source:(Anon, 2023)

BTC dominance is a measure often monitored by experienced crypto traders (Routledge & Zetlin-Jones, 2022). Dominant BTC is the ratio between bitcoin's market capitalization and the market capitalization of all crypto assets. As the first crypto asset, bitcoin has maintained its supremacy over the crypto asset market capitalization for many years (Almeida & Gonçalves, 2023; Wang & Ngene, 2020; Yousaf & Ali, 2020). However, Bitcoin's supremacy has faded as new coins have been discovered, especially as Ethereum and the ERC20 token standard have become more prominent.

Even bitcoin is not big enough to have a serious impact on the stock market (Bazán-Palomino, 2023; Bouri et al., 2018). A decade ago, Bitcoin didn't face many competitors. During this period, BTC Dominance reached 94%. In 2017, when the first cryptocurrency season started, BTC Domination began to experience many changes. In February of that year, the value of BTC Domination fell by 85.4% (with ETH accounting for 5.7% of the overall crypto asset market capitalization). In just four months, BTC Dominance dropped to 40% as liquidity shifted to ERC-20 tokens (Fang et al., 2022; Wątorek et al., 2021). At that time, many Ethereum fans began discussing “Flippening,” or the belief that Ethereum's market capitalization value might one day surpass that of Bitcoin (De Vries, 2023; Jin et al., 2023). Something that hasn't happened yet. Bitcoin is still the crypto asset with the highest market capitalization as of August 16 2021, followed by Ethereum (19.22%) and Binance Coin (3.46%) (Song et al., 2019; Wijaya & Ulpah, 2022; Wu et al., 2023).

While these developments offer great opportunities, fundamental questions arise regarding the dynamics of Bitcoin (BTC) dominance in the cryptocurrency ecosystem (Marzo et al., 2022). How do changes in Bitcoin's dominance phase affect AltCoin price movements, especially Ethereum (ETH)? Are there identifiable patterns and impacts during the high, medium, and low dominance phases? These questions form the basis of research to understand the complex relationship between Bitcoin and AltCoins.

The main goal of this research is to optimize the understanding of AltCoin price synchronization, with a focus on Ethereum, during different periods of Bitcoin dominance. Through a comprehensive phase analysis approach using the Vector Error Correction Model (VECM), this research aims to identify patterns and impacts of AltCoin price movements in various conditions of Bitcoin dominance. Thus, this research will provide deeper insight into the dynamics of the developing cryptocurrency market.

Decentralization & Influence of Blockchain Technology

Decentralization is a key concept in the development of cryptocurrencies, and this is realized through the use of blockchain technology. Blockchain is a form of distribution technology that allows transaction records to be recorded in a decentralized and encrypted manner (Chu et al., 2024; Marzo et al., 2022; Routledge & Zetlin-Jones, 2022). This uniqueness has a positive impact on the security and sustainability of cryptocurrencies (Ghosh et al., 2020). Decentralization also minimizes third-party involvement, gives users greater control, and reduces the risk of data manipulation or falsification. The influence of blockchain technology also involves the concept of transparency (Centobelli et al., 2022; Iranmanesh et al., 2023; T. Nguyen et al., 2023). Every

transaction recorded on the blockchain can be accessed by the entire network, allowing users to verify every transaction activity. This removes the need for trust in a central authority and creates a more open and fair system.

Cryptocurrency as an Investment Instrument

Cryptocurrency has become an investment instrument that has attracted the attention of many parties, both individuals and financial institutions. The uniqueness of cryptocurrencies, especially Bitcoin, as an investment asset lies in its high profit potential and volatility (Dyhrberg, 2016a). Investors are interested in the opportunity to diversify their portfolios by including cryptocurrencies. In recent years, there has been a significant increase in the acceptance of cryptocurrencies as a legitimate and accepted investment instrument by various economic sectors (Dyhrberg, 2016b). Increasingly clear regulations and adoption by large financial institutions have helped legitimize cryptocurrencies as a valid asset class (Sonawane & Motwani, 2023).

Cryptocurrency Revolution

The cryptocurrency revolution has changed the traditional paradigm of the financial system (Astuti et al., 2022). Bitcoin, as the first cryptocurrency, offers a decentralized and secure alternative to conventional currencies (Shahzad et al., 2022). The growth of the cryptocurrency ecosystem has also included the emergence of various altcoins, including Ethereum (ETH), which introduced the concept of smart contracts and tokens. Altcoins provide an experimental platform for innovation and new functionality beyond Bitcoin (Fang et al., 2022; Mikhaylov, 2020). The importance of Bitcoin's (BTC) dominance phase in the cryptocurrency ecosystem provides a special context for further analysis and understanding of AltCoin price synchronization, especially Ethereum (ETH) (Yi et al., 2018). Therefore, this research aims to optimize AltCoin (ETH) price synchronization during the Bitcoin dominance era, using a comprehensive phase analysis approach with a Vector Error Correction Model.

There has been a lot of literature that reviews cryptocurrencies and the dominance of Bitcoin in general. However, there is still a knowledge gap in the specific analysis of Bitcoin's dominance phase and its impact on AltCoin prices, especially Ethereum. This study will attempt to fill this gap by presenting an in-depth and comprehensive analysis to explore the dynamics that have not yet been fully uncovered in the cryptocurrency ecosystem. Thus, this research is expected to make a significant contribution to the literature and practical understanding related to cryptocurrency.

2. Methods

Secondary data is used as material in research methodology and data collection strategies. The data set includes daily closing values of BTC and Altcoins with a market cap of over $500 million in January 2023 (Anon, 2023). Since there are other types of AltCoins, the author chose Ethereum (ETH) because, besides Bitcoin (BTC), ETH is also a leading digital currency, but they are very different (Mensi et al., 2019). Even if Bitcoin continues to lead with twice the market capitalization of Ethereum, the second largest cryptocurrency, with more than 15,550 members, is growing faster than Bitcoin and could potentially surpass it in 2021.

During the period July 29, 2019 to January 9, 2022, 162 observations for each cryptocurrency were collected (BTC and ETH). After collecting data, researchers divided them into three different groups based on their relative levels of dominance. Dominance phases are identified with the help of the Bitcoin Dominance index, and are classified as: a) High Dominance Phase (Dominance ranges between 67.59% to 73.59%) from July 29, 2019 to January 6, 2020, b) Medium Dominance Phase (Dominance ranges between 50.12%-67.59%) on 13 January 2020 to 14 December 2020, and c) Low Dominance Phase (Domination less than 50.12%) on 26 April 2021 to 9 January 2022.

Utilizing Vector Autoregressive (VAR)/Vector Error Correction Model (VECM) as an analytical technique. The purpose of the unit root test is to evaluate whether the data is stable or not. After the data is declared stationary, the next stage is cointegration testing. The cointegration test tries

to determine the research analysis; if the data are cointegrated, VECM is a suitable analysis (see Figure 1). This research uses "Eviews 7.2" software to analyze the collected data.

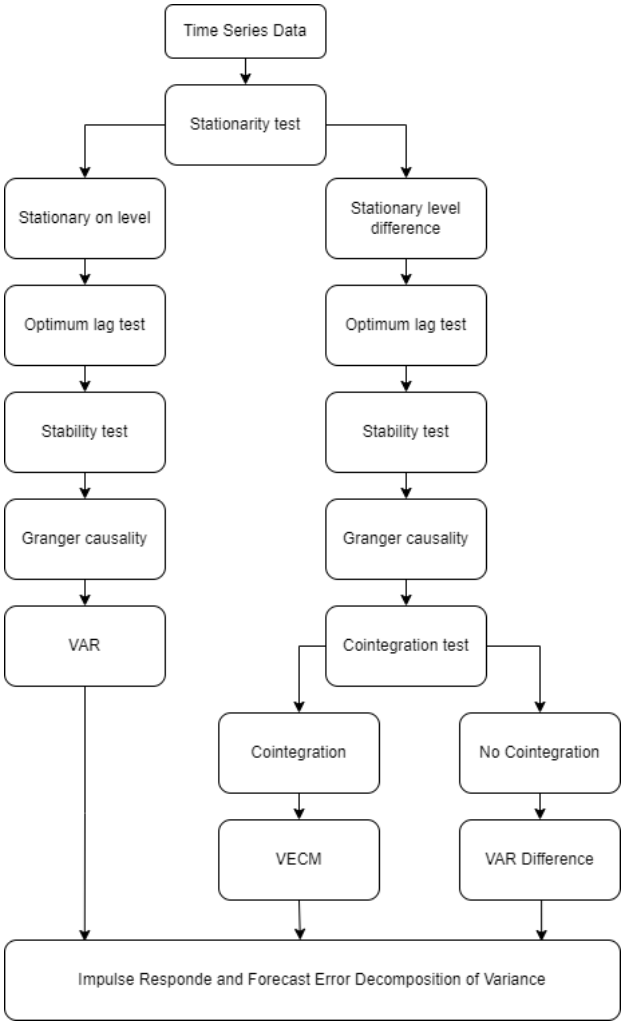


Figure 1. Research Process Using VECM Analysis
Source:(Juselius, 2006; Mills, 2019)

The VECM model of order p and cointegration rank r can be written as follows:

$$\Delta and_t = A_0 + \Pi and_{t-1} + \sum_{i=1}^{p-1} \pi\, \phi_i \Delta and_{t-i} + \varepsilon_t \quad \ldots\ldots (1)$$

Description:

$and_{(1,2)}$: Vector containing the variables being analyzed, and_1 for BTC, $and_2$for ETH
A_0 : intercept vector
π : αβ' where β is a cointegration matrix of size n × r, α is a matrix an n × r size adjustment
ϕ_i : regression coefficient matrix ($\phi_i = \sum_{j=i+1}^{p} \beta\, A_j$)
ε_t : error

3. Results

The early stages of the cryptocurrency era, altcoins were ignored due to bitcoin's market dominance (Wang & Ngene, 2020). However, in recent years, altcoins have gained traction, particularly Ethereum, XRP, ADA, and Doge. While analyzing bitcoin dominance and Altcoin price creation, it was found that the Big Altcoin Super Pump occurs when bitcoin dominance falls below 40% and the Altcoin season begins. Similarly, if Bitcoin's market share exceeds 50%, Altcoins will disappear from the market, and this suggests that risk and reward flow from Bitcoin to Altcoins, i.e. before the split. However, the direction would reverse after the split, and it was noted that the split severely damaged the impact of bitcoin's price and market position in the cryptocurrency market (Katsiampa et al., 2019). Meanwhile, the author divides the dominance phase into 3 phases. High Dominance Phase (Domination ranges from 67.59% to 73.59%) from 29 July 2019 to 6 January 2020, Medium Dominance Phase (Domination ranges from 50.12%-67.59%) from 13 January 2020 to 14 December 2020, and the Low Dominance Phase (Domination less than 50.12%) from April 26 2021 to January 9 2022 shown in Figure 2:

Figure 2. Bitcoin Domination
Source: TradingView (2023)

In recent days, Bitcoin has dominated the cryptocurrency committee, indicating that the acceptance and profitability of alternative cryptocurrencies (altscoins) primarily depends on Bitcoin's performance (Jia et al., 2024). Researchers in the fields of price formation, portfolio implications, blockchain technology, market efficiency, asymmetric relationships with altcoins, legal issues, and risk-return analysis have all been noted (Enilov & Mishra, 2023). When compared based on factors such as price and transaction volume, altcoins and bitcoin are closely related. When looking at the bitcoin and altcoin markets, over a period of time, the two markets are interconnected.

At the same time, Bitcoin's behavior relative to fiat currencies (such as USD and EUR) is relative, but its asymmetric relationship with altcoins has not been well investigated. Market movements show how more volatile and prevalent cryptocurrencies are compared to fiat money (Aquilina et al., 2024). On the other hand, a small number of studies use Johansen and Engle-Granger cointegration tests to identify cointegration between cryptocurrencies and the Vector Auto-Regression (VAR) method to find strong correlations between cryptocurrencies and information transmission. Therefore, the author uses VECM to test bitcoin's dominance in price synchronization with alternative cryptocurrencies. Table 2 exhibits descriptive statistics for this study.

After obtaining secondary data, the stationarity of the data was then checked. The data is not stationary at the degree level, on the contrary if the statistical ADF value is smaller than the Mackinnon critical value. Consequently, the ADF test must be performed as a first difference test. To get data that is stationary to the same degree, proceed to the second differentiation if the data is not stationary (Prüser, 2023). The results of the VECM estimation test can be influenced by data

stationarity. A variable regression equation that is not stationary will produce an incorrect regression. The equation for the stationarity test with ADF analysis is as follows:

Table 2. Descriptive Statistics

	High Phase		Medium Phase		Low Phase	
	BTC	ETH	BTC	ETH	BTC	ETH
Mean	8860.976	174.4953	8483.944	197.2032	42261.66	2818.722
Median	8582.225	179.6432	8902.202	201.3348	41930.87	2778.751
Maximum	11966.41	234.215	10326.05	284.2175	58803.78	4168.701
Minimum	6640.515	122.6039	4970.788	110.6059	29807.35	1787.511
Std. Dev.	1358.437	26.14696	1347.958	41.28844	7423.970	595.4236
Skewness	0.350871	-0.1291	-0.857805	-0.154596	0.350006	0.143526
Kurtosis	1.970632	2.432444	2.651603	2.218796	2.177083	2.061567
Jarque-Bera	10.47628	2.624317	20.68672	4.764682	7.878660	6.500631
Observations	162	162	162	162	162	162

Source: Author's Elaboration (Processed, 2023)

$$\Delta F_T = \beta_1 + \beta_2 t + dAND_{t-1} + \alpha_1 \Delta AND_{t-2} + \ldots + \varepsilon_T \quad \ldots\ldots (2)$$

Description:
ΔF_T : Form the first difference/second difference
α_0 : Intercept
AND : Variables are tested for stationarity
ε_T : Error

Table 3. ADF Test Results Using Intercepts at Levels

		Level		1st Diff	
		t-Statistic	Prob.*	t-Statistic	Prob.*
High Phase	BTC	-1.1662	0.6884	-10.9171	0.0000
	ETH	-1.59235	0.4842	-12.0343	0.0000
Medium Phase	BTC	-1.63425	0.4628	-14.3377	0.0000
	ETH	-1.80832	0.3755	-14.1806	0.0000
Low Phase	BTC	-1.86687	0.3473	-14.4253	0.0000
	ETH	-1.85066	0.3550	-14.6584	0.0000

Source: Author's Elaboration (Processed, 2023)

Table 3 shows all variables have fulfilled the stationarity requirements of the ADF test data where the ADF t-statistic value is smaller than the Mckinnon Critical Value of 10% at the first difference level. Given the fact that all data variables are stationary at the first difference level, the following VECM estimation step—determining the ideal lag length—can be completed (Todea & Todea, 2023). Equation 3 and equation 4 shows utilizing the Akaike Information Criterion (AIC) or Schwarz Criterion (SC), for example, can help determine the ideal lag length.

$$ln(AIC) = ln\left(\frac{\Sigma \widehat{\iota n_\iota^2}}{n}\right) + \frac{2k}{n} \quad \ldots\ldots (3)$$

$$ln(SC) = ln\left(\frac{\Sigma \widehat{\imath n_i^2}}{n}\right) + \frac{k}{n} ln(n) \ldots\ldots (4)$$

Description:

$\widetilde{\imath n}_i^2$: The sum of the squared residuals

k : Number of Observations variables

n : Number of observations

Table 4. shows the latency used is the criterion with the minimum AIC or SC value,

Table 4. The Outcomes Lag Test

	High Phase		Medium Phase		Low Phase	
Lag	0	1	0	1	2	3
AIC	19.35645	19.30090*	26.07975	20.76211*	29.87356	29.83649*
SC	19.39607*	19.41974	26.11920	20.88043*	30.07077	30.11258
Desc	Lag 1		Lag 1		Lag 3	

Source: Author's Elaboration (Processed, 2023)

After the ideal time interval has been completedidentified, then a cointegration test can be carried out. If, when determining the ideal lag, all variables have a Roots of Characteristic Modulus valuePolynomial lower than one, then the VECM model is considered stable. VECM can be calculated after carrying out a VECM stability test. Table 5. Shows that the VAR model used in this research is stable.

Table 5. Stability Analysis

	Root	Modulus
High Phase	0.242111	0.242111
	0.097362	0.097362
Medium Phase	-0.109404	0.109404
	0.054614	0.054614
Low Phase	0.921294 - 0.032203i	0.921857
	0.921294 + 0.032203i	0.921857
	-0.412688 - 0.249019i	0.481998
	-0.412688 + 0.249019i	0.481998
	0.345988 - 0.167573i	0.384433
	0.345988 + 0.167573i	0.384433

Source: Author's Elaboration (Processed, 2023)

The optimal lag length and stability tests have been found, so that further testing can be carried out, namely the cointegration test with Johansen's Cointegration Test. The Johansen cointegration test uses tracing statistical analysis and/or statistical tests of maximum eigenvalues and critical values at a 5% confidence level. The existence of a cointegration relationship is a prerequisite for VECM estimation. Table 6. Shows that the VAR (Vector Autoregression) model should be used instead of VECM estimation if there is no cointegration relationship.

Table 6. Cointegration Analysis

	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
High Phase	0.321966	106.4389	15.49471	0.0001
	0.244873	44.65822	3.841466	0.0000
Medium Phase	0.357263	131.6092	15.49471	0.0001
	0.320033	61.32809	3.841466	0.0000
Low Phase	0.098219	17.18849	12.32090	0.0071
	0.005390	0.853909	4.129906	0.4104

Source: Author's Elaboration (Processed, 2023)

There are two rank variables related to cointegration at the 5% test level. For example, the Trace Statistics values are 106.4389 and 44.65822 which are higher than the Critical Value of 0.05, namely 15.49471 and 3.841466. This shows that the variables used have a long-term relationship (cointegration) with each other. Therefore, VECM estimates can be used in this investigation (Xu et al., 2022). Table 7. Exhibits the use of VECM estimates is in line with the formulation of the research problem, namely to determine the short-term and long-term relationship between the influence of independent factors on the dependent variable.

Table 7. Long-Term VECM Analysis

Phase	Variable	CointEq1	T-Table	Remark
High Phase	of the coeffs	15.69923	1.974902	(+) Significant
	t-partial stat	[2.27555]		
Medium Phase	of the coeffs	-42.42284		(-) Significant
	t-partial stat	[-18.4622]		
Low Phase	of the coeffs	-14.69846		(-) Significant
	t-partial stat	[-42.4615]		

Source: Author's Elaboration (Processed, 2023)

The degree of long-term dependence of alternative currencies on bitcoin is seen in Table 7. The partial T statistic for AltCoin in the high phase at lag 1 is 2.27555 or higher and more than + 1.97 (=TINV(0.05,160). In the long term at lag 1, AltCoin in the High Phase influences the increase in BTC movements positively and significantly. This shows that during the period of high bitcoin dominance, a 1% increase in BTC prices during the High Phase causes an increase in AltCoin prices of 15.69923 % during the Next Period, a 1% increase in BTC prices during the Mid Phase causes a 42.42284 % decrease in AltCoin prices during the Next Period, and a 1% increase in BTC prices during the Low Phase causes a 14.6984 % decrease in AltCoin prices during the Next Period. Table 8, shows the VECM analysis of the period short.

Based on the analysis results Tabel 8, for example, in a short period of time, during the high phase, a change of 1% in BTC over the previous period (daily) significantly influences a change of 0.006646% in ETH the following day. In the Intermediate Phase, BTC's 1% daily move had a sizable impact on ETH's -0.024848% daily move the next day. In the Low Phase, ETH's 1% daily move had a major impact on BTC's -7.491871% daily move the following day.

Table 8. Short-Term VECM Analysis

Phase	Variable	Value	D(BTC)	D(ETH)	Remark
High Phase	CointEq1	of the coeffs	-0.690259	-0.015045	(-) Significant
		t-partial stat	[-8.29381]	[-7.83547]	
	D(BTC(-1),2)	of the coeffs	- 0.00915	0.006646	(+) Significant
		t-partial stat	[-0.07204]	[2.26748]	
	D(ETH(-1),2)	of the coeffs	2.668007	-0.377989	(-) Significant
		t-partial stat	[0.55682]	[-3.41925]	
Medium Phase	CointEq1	of the coeffs	0.387347	0.033176	(+) Significant
		t-partial stat	[1.77021]	[5.29741]	
	D(BTC(-1),2)	of the coeffs	-0.885171	-0.024848	(-) Significant
		t-partial stat	[-4.70167]	[-4.61138]	
	D(ETH(-1),2)	of the coeffs	11.79843	0.381539	(+) Significant
		t-partial stat	[1.72121]	[1.94476]	
Low Phase	CointEq1	of the coeffs	-1.064545	-0.02447	(-) Significant
		t-partial stat	[-4.12652]	[-0.93680]	
	D(ETH(-1),2)	of the coeffs	-7.491871	-1.129989	(-) Significant
		t-partial stat	[-4.75939]	[-7.08959]	
	D(ETH(-2),2)	of the coeffs	-3.482399	-0.533805	(-) Significant
		t-partial stat	[-2.06722]	[-3.12952]	
	D(ETH(-3),2)	of the coeffs	-2.306608	-0.404978	(-) Significant
		t-partial stat	[-1.74556]	[-3.02676]	

4. Discussion

Equations can be made after understanding the type and level of interaction between Bitcoin and altcoins via VECM. This formula helps readers and investors in estimating altcoin prices based on Bitcoin price changes through various stages of dominance. Based on the phase it is divided into the following:

a) High Phase:

D(BTC,2) = - 0,690259078494*(D (BTC (-1)) + 15,6992323047*D (ETH (-1)) + 21,1428226738 - 0,794430175153

D(ETH,2) = - 0,0150452437605*(D (BTC (-1)) + 15,6992323047*D (ETH (-1)) + 21,1428226738) + 0,00664606578018*D (BTC (-1),2) - 0,377989024778* D (ETH (-1),2) + 0,00764970280766

b) Medium Phase:

D(BTC,2) = - 0,0235722066324*D (BTC (-1)) - 0,325894813531 -42,42284*D (ETH (-1) + 0,885171260488*D (BTC (-1),2) - 0,030993495499

D(ETH,2) = 0,381538876249*D (ETH (-1),2) - 42,42284*D (ETH (-1) - 0,024847828229*D (BTC (-1),2) + 0,0249577741082

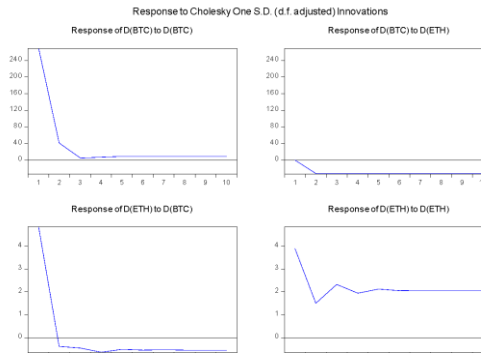
c) Low Phase:

D(BTC,2) = -14,69846*D (ETH (-1) - 1,06454521838*(D (BTC (-1)) - 7,49187093195*D (ETH (-1),2) - 3,48239899172*D (ETH (- 2),2) - 19.3924329366

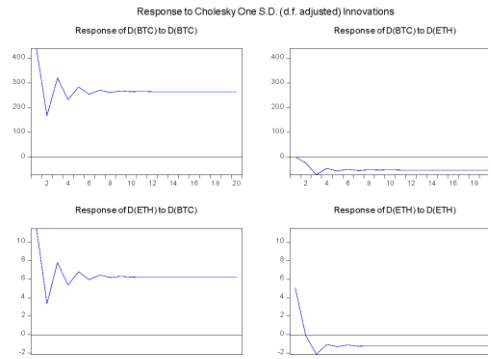
D(ETH,2) = -14,69846*D (ETH (-1) - 1,12998878476*D (ETH (-1),2) - 0,533805411538*D (ETH (-2),2) - 0,404978099243*D (ETH (-3),2) - 0,315810366369

For example, in the high phase in the equation D(BTC,2) = - 0.690259078494*(D (BTC (-1)) + 15.6992323047*D (ETH (-1)) + 21.1428226738 - 0.794430175153 means a movement of 1 % BTC in a difference of 1, resulting in price synchronization in the short and long term. In the long term, AltCoin in the High Phase positively and significantly influences the rise of BTC. A 1% increase in the price of BTC during the High Phase causes an increase in the Price of AltCoin (ETH) by 15.69923% during the Next Period. In a short time, during the high phase, a 1% change in BTC compared to the previous period (every day) significantly influences a 2.66800740691% change in ETH the next day (but not significantly so the formula is reconstructed).

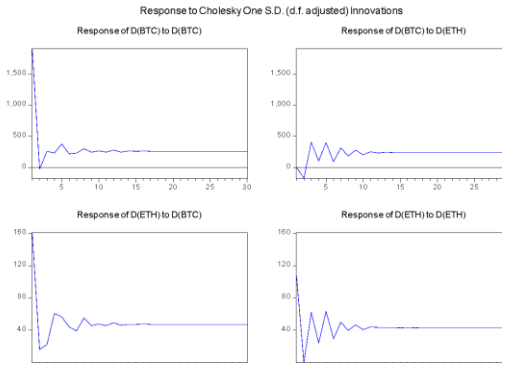
The IRF (Impulse Response Function) and VDC (Variance Decomposition) features in VECM estimation allow us to see the response and time required for variables to return to their equilibrium point as well as the size of their composition. This allows us to see how the independent variable affects the dependent variable. the influence of each independent variable on how the dependent variable is created. The results of the IRF are as follows:



a) High Phase



b) Medium Phase

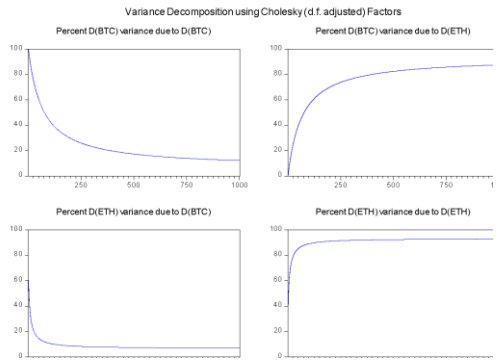


c) Low Phase

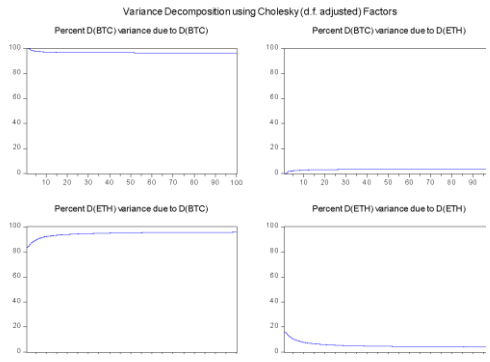
Figure 3. Impulse Response Function
Source: Processed Data (2023)

Figure 3 explained that in the high phase, the response of ALT (ETH) price movements to BTC variable shocks was in a negative trend and began to slope in period 3. The response of BTC price movements to ALT (ETH) variable shocks was in the high phase. negative trend and began to slope

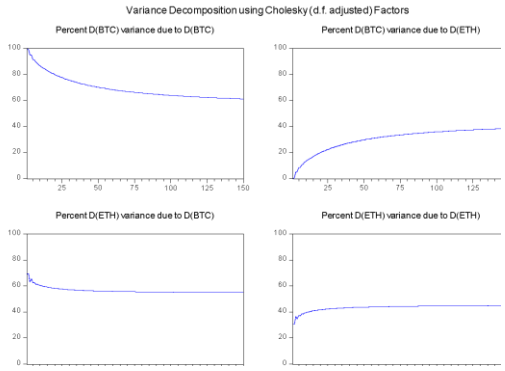
in period 2. In the medium phase, the response of ALT (ETH) price movements to BTC variable shocks was in a positive trend and began to decline in period 8. BTC price movement response to variable ALT (ETH) shocks was in a negative trend and began to decline in period 6. In the low phase, the response of ALT (ETH) price movements to BTC variable shocks was in a positive trend and began to decline in period 15. The response of BTC price movements to ALT (ETH) variable shocks was in a positive trend and began decreased in period 12 which was continued in the VDC analysis which is shown as follows:



a) High Phase



b) Medium Phase



c) Low Phase

Figure 4. Variance Decomposition
Source: Processed Data (2023)

Figure 4. shows variance decomposition. The high phase shows that the ALT (ETH) shock response to the BTC variable shock has decreased sufficiently and begins to slope in the 250 period. BTC's shock response to the ALT (ETH) variable shock increased and began to slope in period 250. In the medium phase, the ALT (ETH) shock response increased to the BTC variable and began to decline in period 10. BTC's shock response to the ALT (ETH) variable shock) increased. and starts to decrease in period 5. In the low phase, the ALT (ETH) shock response to the BTC variable shock decreases and begins to slope in period 25. The BTC shock response to the ALT (ETH) variable shock increases and starts to slope in the 2nd period. 25.

5. Conclusion

The technology in the financial industry that can replace cash is called Cryptocurrency using Blockchain Technology. BTC dominance is a measure often monitored by experienced crypto traders. Dominance Phases are identified with the help of Bitcoin Dominance index and are classified as: High Dominance Phase (Domination ranges between 67.59% to 73.59%) from July 29, 2019 to January 6, 2020, Medium Dominance Phase (Domination ranges between 50.12%- 67.59%) on 13 January 2020 to 14 December 2020, and Low Dominance Phase (Domination less than 50.12%) on 26 April 2021 to 9 January 2022.

At lag 1, AltCoins in the High Phase have a long-term, beneficial and significant impact on BTC growth. It has been shown that during periods of high bitcoin dominance, a 1% increase in BTC prices during the previous period leads to a 15.69923% increase in AltCoin prices during the following period, a 1% increase in BTC prices during that period. the previous period causes a decrease in AltCoin prices of (42.42284%) during the following period, and a 1% increase in BTC prices during the previous period causes a decrease of (-14.69846%) in Alt In the High phase, a BTC movement of 1% in the previous period (daily) has a significant short-term impact on ETH's movement of 0.006646% the following day. In the Intermediate Phase, BTC's 1% daily move had a sizable impact on ETH's -0.024848% daily move the next day. In the Low Phase, ETH's 1% daily move had a major impact on BTC's -7.491871% daily move the following day.

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