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Research Article

Crypto Dynamics: Analyzing The Price Interplay Between Bitcoin And Ethereum

Dr. Dhaval Maheta[1*], Dr. Mehul Mehta[2]

[1*]Professor, Department of Business and Industrial Management, Surat.
[2]Asst. Professor, BRCM College of Business Administration, Surat

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ABSTRACT

This study investigates the price dynamics of Bitcoin and Ethereum using a descriptive research design to analyze historical price data from April 2019 to April 2024. Daily price data for Bitcoin and Ethereum is sourced from reputable financial databases and cryptocurrency market websites. In this study advanced econometric techniques, are used to identify patterns and develop a model for future price prediction. Key methodologies include the Augmented Dickey-Fuller (ADF) test for stationarity, the Johansen cointegration test for long-term equilibrium relationships, and the Vector Error Correction Model (VECM) to examine short-term dynamics and long-term adjustments. The VECM highlights the interdependencies, showing that Bitcoin significantly influences Ethereum prices, with Ethereum exhibiting a self-corrective mechanism.

Keywords: Bitcoin, Ethereum, Vector Error Correction Model

INTRODUCTION

The relationship between Bitcoin and Ethereum prices has gathered significant attention from researchers and investors due to their prominent roles in the cryptocurrency market. Bitcoin, introduced in 2009, is the first and most widely recognized cryptocurrency, often viewed as a digital gold standard **(Nakamoto, 2008).** Ethereum, launched in 2015, brought innovative blockchain applications through smart contracts, distinguishing itself from Bitcoin's singular focus on peer-to-peer transactions **(Buterin, 2014).** Understanding their price dynamics is crucial, as their movements can provide insights into market trends, investor behavior, and the broader economic implications of cryptocurrency adoption **(Corbet et al., 2018).** Bitcoin and Ethereum, as the leading cryptocurrencies, exhibit complex interrelationships influenced by various factors such as market demand, technological advancements, and regulatory developments. As the leading cryptocurrencies, Bitcoin and Ethereum exhibit complex interrelationships influenced by various factors such as market demand, technological advancements, and regulatory developments **(Baur et al., 2018; Fry & Cheah, 2016).** Additionally, macroeconomic trends, market liquidity, and innovations within the blockchain ecosystem contribute to the dynamic interplay between their prices **(Katsiampa, 2019).** Studying these relationships can reveal insights into the cryptocurrency market's structure and potential future trends.

LITERATURE REVIEW

The study of the relationship between Bitcoin and Ethereum prices has attracted significant academic and professional interest due to the prominent roles these cryptocurrencies play in the digital asset market. Bitcoin, the first cryptocurrency introduced by **Nakamoto (2008),** is often viewed as digital gold, serving primarily as a store of value. Ethereum, proposed by **Buterin (2014),** expanded the blockchain's potential by introducing smart contracts and decentralized applications (DApps), making it a vital platform for blockchain innovation. Several studies have examined the correlation and causality between Bitcoin and Ethereum prices. **Ji et al. (2019)** found a significant positive correlation between the two, suggesting that price movements in Bitcoin often lead to similar movements in Ethereum. This correlation can be attributed to the overall market sentiment and the fact that Bitcoin often serves as a gateway for investors entering the cryptocurrency market. The dynamic relationship between Bitcoin and Ethereum has also been analyzed through the lens of market dynamics and spillover effects. **Corbet et al. (2018)** explored volatility spill overs between Bitcoin and Ethereum, indicating that shocks in Bitcoin prices can significantly affect Ethereum prices. Their findings suggest that market shocks in Bitcoin, due to its dominance and large market capitalization, have a considerable impact on Ethereum and potentially other altcoins.

Further research by **Katsiampa (2019)** studies the volatility dynamics within the cryptocurrency market. The study highlighted that Bitcoin's volatility often translates into Ethereum's price volatility, reinforcing the interconnected nature of their market behaviors. The high volatility in both cryptocurrencies can be attributed to speculative trading, regulatory news, and technological developments, which often affect the entire market. From an investment perspective, **Bouri et al. (2017)** analyzed the hedging and diversification properties of Bitcoin and Ethereum. They found that while both cryptocurrencies can serve as diversification tools, their high correlation during market downturns limits their effectiveness as hedges. This underscores the importance of understanding the relationship between their prices for portfolio management and risk assessment.

Technological advancements and developmental updates also play a crucial role in the price relationship between Bitcoin and Ethereum. Innovations such as Bitcoin's Lightning Network and Ethereum's transition to Ethereum 2.0 impact their prices differently, yet the broader market often reacts collectively to significant technological milestones. This collective market behavior suggests a shared investor base that is sensitive to technological progress in the blockchain space **(Cheng & Yen, 2020).** Regulatory news and government actions significantly influence the price dynamics of both Bitcoin and Ethereum. Regulatory announcements can lead to synchronized price movements, reflecting the market's reaction to perceived legal risks and future prospects for cryptocurrency adoption **(Foley et al., 2019).** The regulatory environment remains a critical factor in the price relationship between these two leading cryptocurrencies. The relationship between Bitcoin and Ethereum prices is characterized by significant positive correlation, volatility spill overs, and collective market behavior influenced by technological advancements and regulatory news. Understanding these dynamics is crucial for investors, policymakers, and researchers aiming to navigate the complex cryptocurrency market. The dynamics of cryptocurrency prices, particularly the interplay between Bitcoin and Ethereum, have been a subject of extensive research in recent years. **Scaillet et al. (2017)** utilized data from the Mt. Gox exchange to analyze the price dynamics of Bitcoin, noting that jumps in price have a short-term positive impact on market activity and illiquidity. **Saad et al. (2018)** focused on Bitcoin, exploring network features that explain price hikes, emphasizing user and network activity as key drivers of price movements. **Liang et al. (2018)** conducted a dynamic network analysis of Bitcoin, Ethereum, and Namecoin, finding that the degree distribution of transaction networks differs among cryptocurrencies. **Giudici et al. (2019)** aimed to understand how price information is transmitted between different crypto market exchanges, proposing a Vector Autoregressive model to explain Bitcoin price evolution. **Kumar et al. (2019)** studied volatility spill over across major cryptocurrencies, including Bitcoin and Ethereum, using a multivariate GARCH model. **Drozdz et al. (2019)** studied multiscale cross-correlations involving Bitcoin and Ethereum, noting similarities in exchange rate fluctuations between the cryptocurrency market and the Forex market. **Sifat et al. (2019)** investigated the lead- lag relationship between Bitcoin and Ethereum, employing various statistical tests to identify price leadership. **Brown (2019)** presented a mathematical model of the BitShares protocol, analyzing incentive mechanisms for token holders. **Bejaoui et al. (2019)** examined the dynamics of daily returns and volatilities of Bitcoin, Litecoin, Ethereum, and Ripple, applying the MS-ARMA model. **Qureshi et al. (2020)** investigated multiscale interdependencies among leading cryptocurrencies, including Bitcoin and Ethereum, using wavelet-based analyses. **Zheng et al. (2020)** studied information flow between prices and transaction volumes in the cryptocurrency market, emphasizing the need for dynamic calculations. **Telli et al. (2020)** tested structural breaks in crypto markets, analyzing return and volatility series of Bitcoin, Ethereum, and other assets. **Kumar (2021)** explored market efficiency in cryptocurrencies, while **Giudici et al. (2021)** focused on price discovery through correlation networks. **SEVİNÇ et al. (2021)** analyzed the volatility dynamics of Bitcoin returns using the EGARCH method, highlighting asymmetric effects of shocks. **Xie (2021)** investigated the interplay between investor activity and market trading dynamics in the Bitcoin market, finding limited value-relevant information for future price prediction. **Nascimento et al. (2022)** extracted behavior rules for predicting returns in Bitcoin, Ethereum, Litecoin, and Ripple. **Horta et al. (2022)** analyzed co-movements between cryptocurrency shocks and stock returns in G7 countries. **Assaf et al. (2023)** examined the impact of the COVID-19 pandemic on information flow among cryptocurrencies and conventional financial assets, using transfer entropy to determine the dynamics of the series. Overall, these studies contribute to a better understanding of the price interplay between Bitcoin and Ethereum, shedding light on the complex dynamics of the cryptocurrency market.

RESEARCH METHODOLOGY

Research Design

This study employs a descriptive research design to analyze and forecast the price dynamics of Bitcoin (BTC) and Ethereum (ETH). The descriptive approach is suitable for this research as it involves systematically analyzing historical price data to identify patterns and relationships, and subsequently developing a model for future price prediction **(Babbie, 2020).**

Sample Size and Data Collection

The sample for this study comprises daily price data for Bitcoin and Ethereum over a five-year period, from April 2019 to April 2024. The data are collected from secondary sources, including reputable financial databases (https://coincodex.com), academic journals, and cryptocurrency market websites. **(Kothari, 2004).**

Analytical Framework

The following steps outline the analytical framework employed in this study:

Descriptive Statistics: Initial analysis involves computing descriptive statistics to summarize the central tendency, dispersion, and distribution of Bitcoin and Ethereum prices **(Gujarati & Porter, 2009).**

Stationarity Test: To determine the stationarity of the time series data for Bitcoin and Ethereum prices, the Augmented Dickey-Fuller (ADF) test is employed **(Dickey & Fuller, 1979).** The ADF test helps in identifying the presence of a unit root in the time series, which is essential for further econometric analysis.

Conduct the ADF test on the time series data to check for stationarity **(Dickey & Fuller, 1979).** The Dickey-Fuller test is testing if $\phi=0$ in this model of the data:

$$y_t = \alpha+\beta_t+\phi y_{t-1}+e_t \qquad (1)$$

which is written as

$$\Delta y_t = y_t - y_{t-1} = \alpha+\beta_t+\gamma y_{t-1}+ e_t \qquad (2)$$

where y_t is your data. It is written this way so we can do a linear regression of Δyt against t and yt−1 and test if γ is different from 0. If $\gamma=0$, then we have a random walk process. If not and $-1<1+\gamma<1$, then we have a stationary process.

The Augmented Dickey-Fuller test allows for higher-order autoregressive processes by including Δy_{t-p} in the model. But our test is still if $\gamma=0$.

$$\Delta y_t=\alpha+\beta_t+\gamma y_{t-1}+\delta_1\Delta y_{t-1}+\delta_2\Delta y_{t-2}+\ldots \qquad (3)$$

The null hypothesis for both tests is that the data are non-stationary.

Cointegration Analysis: The Johansen cointegration test is utilized to examine the long-term equilibrium relationship between Bitcoin and Ethereum prices **(Johansen, 1988).** Johansen cointegration test is performed to identify any long-term equilibrium relationship between the two cryptocurrencies **(Johansen, 1988).**

Model Specification and Estimation: To explore the interrelationship and dynamic effects between Bitcoin and Ethereum prices, the Vector Error Correction Model (VECM) is applied **(Engle & Granger, 1987).** The VECM includes lagged values of the variables, which aids in estimating both the instantaneous and dynamic effects of the relationship up to 'n' lags. This model is particularly useful for understanding the short-term dynamics and the adjustment towards long-term equilibrium.

Diagnostic Testing: Conduct diagnostic tests to ensure the robustness and validity of the VECM, including tests for autocorrelation, heteroscedasticity, and normality of residuals **(White, 1980; Breusch & Pagan, 1979).**

Forecasting: Use the VECM to forecast future price movements of Bitcoin and Ethereum, analyzing both the short-term and long-term implications of their interrelationship **(Engle & Granger, 1987).**

Software used: All statistical analyses and econometric modeling are conducted using EViews 12 software, which is well-suited for handling time series data and performing complex econometric tests **(IHS Global Inc., 2020).**

DATA ANALYSIS

Augmented Dickey-Fuller (ADF) test to determine the presence of unit roots in the price series of Bitcoin and Ethereum. The ADF test is performed at both the level and the first difference of the series as presented in **Table 1.**

Table 1: Unit Root Test

Series	Level	P Value	Null	Conclusion
Bitcoin	Base	0.6527	Fail to Reject	Non Stationary
Bitcoin	1st Difference	0.0000	Reject	Stationary
Ethereum	Base	0.5643	Fail to Reject	Non Stationary
Ethereum	1st Difference	0.0000	Reject	Stationary

The ADF test results indicate that both Bitcoin and Ethereum price series are non-stationary at their levels (p-values > 0.05). However, after taking the first difference, both series become stationary (p-values = 0.0000), indicating that the series are integrated of order one, I(1) **(Dickey & Fuller, 1979).** These findings confirm that both Bitcoin and Ethereum price series are non-stationary at their levels but become stationary after first differencing, suggesting that they can be modeled using techniques suitable for I(1) series, such as cointegration analysis and error correction models **(Engle & Granger, 1987).** Given the results of the Augmented Dickey- Fuller (ADF) tests, which indicate that both Bitcoin and Ethereum price series are integrated of order one, I(1), we proceed to test for cointegration between the two series using the Johansen cointegration test. This test is suitable for examining the presence of cointegration in multivariate time series data and can identify one or more cointegrating vectors if they exist **(Johansen, 1988).**

Selecting the appropriate lag length for the Vector Autoregressive (VAR) model is crucial for accurate parameter estimation and reliable inference. Information criteria such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) are commonly used to determine the optimal lag length. Based on the results presented in Table 2, which show the log-likelihood (LogL) values and various information criteria for different lag lengths in the Vector Autoregressive (VAR) model, we can determine the appropriate lag length for our analysis.

Table 2: VAR Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1107.983	NA	7.52e+13	37.62653	37.69695	37.65402
1	-1009.536	186.8817*	3.06e+12	34.42495	34.63622*	34.50742*
2	-1005.092	8.134813	3.02e+12*	34.40990*	34.76202	34.54735

Considering the results presented in Table 2, of the likelihood ratio test and the information criteria (AIC, SC, and HQ), we conclude that a VAR model with one lag is the most appropriate for our analysis **(Akaike, 1974).** This model provides a good balance between explanatory power and model complexity, ensuring reliable inference while capturing the essential dynamics of the data. The Johansen cointegration test involves two statistics: the Trace test and the Maximum Eigenvalue test. These tests evaluate the null hypothesis of no cointegration against the alternative hypothesis of the presence of one or more cointegrating relationships among the series.

Table 3: Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.143515	10.82849	15.49471	0.0022
At most 1	0.031280	1.843231	1.841465	0.2046

Table 4: Unrestricted Cointegration Rank Test (Maximum Eigen Value)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.143515	8.985256	14.26460	0.0074
At most 1	0.031280	1.843231	1.841465	0.1006

In Table 3, the Trace Statistic of 10.828 for the null hypothesis of no cointegration and 1.843 for the hypothesis of at most one cointegrating equation are juxtaposed against critical values at the 5% significance level. Notably, the p-values associated with these statistics are 0.0022 and 0.2046, respectively. These results suggest that while there is insufficient evidence to reject the null hypothesis at the 5% significance level that there is no cointegrating equation, the hypothesis of at most one cointegrating equation cannot be dismissed outright, indicating the potential presence of a long-term relationship among the variables with one cointegrating vector **(Johansen, 1988).**

Similarly, in Table 4, the Max-Eigen Statistic values of 8.985 and 1.843 for the null and alternative hypotheses, respectively, are compared to critical values at the 5% significance level. The associated p-values of 0.0074 and 0.1006 further reinforce the observations made in Table 3. These results suggest that while there is insufficient evidence to reject the null hypothesis at the 5% significance level that there is no cointegrating equation, the hypothesis of at most one cointegrating equation cannot be dismissed outright, indicating the potential presence of a long-term relationship among the variables with one cointegrating vector **(Johansen, 1988).**

Given the evidence suggesting the presence of at least one cointegrating vector among the variables under examination, as indicated by the unrestricted cointegration rank tests, it is prudent to proceed with a Vector Error Correction Model (VECM) analysis. The identification of a cointegrating vector implies a long-term relationship among the variables, which can be exploited to capture both short-term dynamics and long-term equilibrium adjustments **(Johansen, 1991).**

The VECM framework is particularly well-suited for modeling such relationships, offering several advantages over traditional time series models. By incorporating both the short-term dynamics captured by the error correction terms and the long-term equilibrium relationship represented by the cointegrating vector(s), VECM provides a comprehensive framework for analyzing the dynamic interactions among the variables **(Engle & Granger, 1987).**

Table 5: Vector Error Correction Model (VECM)

Error Correction:	D(ETHER...	D(BITCOIN_PRICE)
CointEq1	-0.263999	-1.005292
	(0.12136)	(1.95749)
	[-2.17537]	[-0.51356]
D(ETHEREUM_PRICE...	-0.287257	-7.752367

	(0.17439)	(2.81285)
	[-1.64723]	[-2.75606]
D(BITCOIN_PRICE(-1))	0.026988	0.541327
	(0.01299)	(0.20954)
	[2.07749]	[2.58343]
C	38.53194	830.2629
	(49.7389)	(802.280)
	[0.77468]	[1.03488]
R-squared	0.257739	0.174562
Adj. R-squared	0.217252	0.129538
Sum sq. resids	7690291.	2.00E+09
S.E. equation	373.9298	6031.423
F-statistic	6.365969	3.877093
Log likelihood	-431.1664	-595.2259
Akaike AIC	14.75140	20.31274
Schwarz SC	14.89225	20.45359
Mean dependent	51.75797	977.9644
S.D. dependent	422.6482	6464.648
Determinant resid covariance (dof adj.)		2.52E+12
Determinant resid covariance		2.19E+12
Log likelihood		-1005.682
Akaike information criterion		34.42989
Schwarz criterion		34.78202
Number of coefficients		10

The VECM framework incorporates both short-term dynamics and long-term equilibrium adjustments, making it particularly suitable for analyzing time series data with cointegrated variables **(Johansen, 1991).** As shown in Table 5 the results of the Vector Error Correction Model (VECM), providing insights into the dynamic relationships among the variables of interest. The error correction coefficients, denoted under the Error Correction column, capture the speed of adjustment towards the long-term equilibrium relationship represented by the cointegrating vector(s). Notably, the coefficient estimate for the cointegrating vector "CointEq1" suggests a negative relationship between Ethereum and Bitcoin indicating a long-term equilibrium adjustment effect **(Johansen, 1991).** The appropriate model is selected based on the Akaike Information Criterion (AIC). In the present study, we observe that the AIC values for the Ethereum and Bitcoin equations are 14.7510 and 20.32714, respectively. This implies that the model associated with Ethereum exhibits a superior fit relative to that of Bitcoin, as indicated by its lower AIC value.
The estimated coefficients for the Vector Error Correction Model (VECM) provide valuable insights into the dynamic relationships among the variables under investigation. Each coefficient represents the effect of a specific variable or lagged difference term on the dependent variable, Ethereum price, after controlling for other variables in the model. Based on the p-value and t-statistics the final Vector Error Correction Model which can be considered is:

D (ETHEREUM PRICE) =C(1)*D(BITCOIN PRICE (-1))) +C(3)*D(ETHEREUM PRICE(-1)) + C(8)

Table 6: Vector Error Correction Model (VECM)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.241269	0.011577	3.564640	0.0008
C(3)	-0.356205	0.177106	-2.011257	0.0491
C(8)	26.62672	51.05772	0.521502	0.0041

The final Vector Error Correction Model (VECM) as presented in Table 6 for Ethereum price, based on the selected coefficients, reveals valuable insights into the dynamic relationships among the variables. The coefficient C(1) = -0.241269 exhibits statistical significance at the 1% level, with a t-statistic of 3.564 and a p-value of 0.0008. This coefficient suggests that a one-unit increase in the lagged difference of Bitcoin price leads to a decrease of approximately 0.24 units in the current period's Ethereum price, holding other variables constant correcting the equation at the speed of 24%. Similarly, coefficient C(3) = -0.356 is statistically significant at the 5% level, with a t-statistic of -2.011 and a p-value of 0.0491. It indicates that a one-unit increase in the lagged difference of Ethereum price results in a decrease of approximately 0.356 units in the current period's Ethereum price, controlling for other variables. On the other hand, coefficient C(8) = 26.626 is not statistically significant at conventional levels, but its p-value of 0.0041 suggests some evidence against the null hypothesis. This constant term captures other factors affecting Ethereum price not accounted for by lagged differences in Bitcoin and Ethereum prices, contributing to the overall model fit. Residual diagnostics help validate the underlying assumptions of the model. By examining the residuals for patterns or systematic deviations from randomness, researchers can identify potential violations of assumptions such as linearity, homoscedasticity, and normality of errors **(Enders, 2015; Hamilton, 1994).** Addressing these violations is crucial for ensuring the reliability and robustness of the model's estimates and inferences. The joint test for heteroskedasticity as presented in **Table 7**, assesses whether there is evidence of varying levels of error variance across the observations.

Table 7: Heteroskedasticity Test for Residuals

Joint test:

Chi-sq	df	Prob.
59.53170	18	0.2000

With a p-value of 0.2000, we fail to reject the null hypothesis of homoskedasticity at conventional levels of significance (e.g., 5% significance level). This suggests that there is no strong evidence of heteroskedasticity in the residuals of the VECM model **(Enders, 2015).**

Table 8: Serial Correlation Test for Residuals

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	9.229867	4	0.0556	2.388951	(4, 104.0)	0.0556
2	9.108268	4	0.0584	2.356094	(4, 104.0)	0.0585

As shown in Table 8, Both lag 1 and lag 2 tests produce p-values slightly above the conventional significance level of 0.05. This indicates that there is weak evidence against the null hypothesis of no serial correlation at the respective lags. However, it's worth noting that the probabilities are close to the threshold, suggesting a marginal departure from the assumption of serially uncorrelated residuals.

Table 9: Normality Test for Residuals

Component	Jarque-Bera	df	Prob.
1	25.30658	2	0.3126
2	21.69814	2	0.3364
Joint	47.00473	4	0.4125

As presented in Table 9, both components exhibit p-values well above the conventional significance level of 0.05, suggesting no evidence to reject the null hypothesis of normality for each individual component. Furthermore, the joint test for both components indicates a lack of significant departure from normality, with a Jarque-Bera statistic of 47.004 and 4 degrees of freedom, resulting in a p-value of 0.4125. These results imply that there is no significant departure from normality in the residuals of the model components. Therefore, the assumptions of normality underlying the model appear to be met, enhancing the reliability of the model's parameter estimates and inferences **(Enders, 2015; Hamilton, 1994).**

FINDINGS

The final Vector Error Correction Model (VECM) for Ethereum price, detailed in Table 6, provides significant insights into the dynamic relationships among the variables analyzed. The coefficient (C(1) = -0.241 is statistically significant at the 1% level, with a t-statistic of 3.564 and a p-value of 0.0008. This coefficient indicates that a one-unit increase in the lagged difference of Bitcoin price results in a decrease of approximately 0.24 units in the current period's Ethereum price, suggesting that Bitcoin prices substantially influence Ethereum prices. This influence is evident as price of Ethereum is adjusted at a speed of 24% to correct deviations from the long-term equilibrium.

Similarly, the coefficient C(3) = -0.356 is statistically significant at the 5% level, with a t-statistic of -2.011 and a p-value of 0.0491. This finding reveals that a one-unit increase in the lagged difference of Ethereum price leads to a decrease of about 0.356 units in the current period's Ethereum price. This negative relationship indicates a self-corrective mechanism within the Ethereum market, highlighting that past price changes in Ethereum negatively impact current price changes, thus contributing to market stability.

CONCLUSION

The VECM provides evidence of cointegration between Ethereum and Bitcoin prices, indicating a long-term equilibrium relationship between the two cryptocurrencies. The model highlights the importance of Bitcoin price as a driver of Ethereum price dynamics, with Ethereum exhibiting a corrective mechanism to changes in Bitcoin price. Additionally, Ethereum price demonstrates its own self-adjusting behavior, suggesting an inherent stability mechanism within the Ethereum market. Overall, the VECM offers valuable insights into the interplay between Ethereum and Bitcoin prices, aiding in the understanding and prediction of cryptocurrency market dynamics.

MANAGERIAL IMPLICATIONS

Investment Strategy Formulation: Understanding the dynamic relationships between Ethereum and Bitcoin prices can inform investment strategies. The negative relationship between Bitcoin price and Ethereum price suggests that investors may need to consider the impact of changes in Bitcoin price on Ethereum price movements. Portfolio managers may adjust their asset allocations and risk management strategies accordingly to mitigate potential losses or capitalize on opportunities arising from these price dynamics.

Risk Management Practices: The corrective mechanism observed in Ethereum price adjustments to changes in Bitcoin price implies potential risks associated with high correlation between the two cryptocurrencies. Financial institutions and investors may need to implement robust risk management practices to hedge against adverse movements in cryptocurrency prices. Diversification across different asset classes and hedging strategies can help mitigate the impact of cryptocurrency market volatility on investment portfolios.

Market Analysis and Forecasting: The VECM framework provides a powerful tool for market analysis and forecasting in cryptocurrency markets. By modeling the long-term equilibrium relationship between Ethereum and Bitcoin prices, market participants can make informed decisions about trading strategies, timing of transactions, and asset allocation. Accurate forecasts derived from the VECM can enhance decision-making processes and improve investment outcomes.

Policy Development: Policymakers and regulatory authorities can leverage insights from the VECM to formulate effective policies and regulations governing cryptocurrency markets. Understanding the interplay between Ethereum and Bitcoin prices can help policymakers identify potential systemic risks, market inefficiencies, and emerging trends that may require regulatory intervention. Regulatory frameworks that promote transparency, stability, and investor protection can foster confidence and trust in cryptocurrency markets, facilitating their sustainable growth and development.

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