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Tracking Crypto Tremors: A Data-Centric Look at Volatility

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ABSTRACT: Cryptocurrency markets are known for their high volatility, influenced by factors such as market demand, regulatory developments, investor sentiment, and technological advancements. This study focuses on analyzing the price fluctuations and volatility of five major cryptocurrencies—Binance Coin (BNB), Bitcoin (BTC), Corden Coin, Dogecoin (DOGE), and Ethereum (ETH). Using historical price data and statistical models, we examine how these digital assets respond to external influences and market shocks. The research findings indicate that Bitcoin and Binance Coin exhibit relatively lower volatility due to strong investor confidence and widespread adoption, whereas Dogecoin and Corden Coin show higher fluctuations driven by speculative trading. Ethereum, with its extensive smart contract applications, displays moderate volatility influenced by both market trends and technological updates. The study also highlights the importance of price discovery mechanisms and their role in predicting future trends. Understanding these price movements is essential for investors and traders to develop informed strategies and manage risks effectively in the highly dynamic cryptocurrency market.

KEYWORDS: Cryptocurrency, Market Volatility, Price Discovery, Investment Strategies, Risk Management, Bitcoin, Ethereum, Binance Coin, Dogecoin, Corden Coin.

I. INTRODUCTION OF THE STUDY

Cryptocurrency markets are marked by extreme price swings and operate across a decentralized, 24/7 infrastructure. These conditions make volatility a critical subject of study. Market dynamics—shaped by macroeconomic shifts, regulation, investor sentiment, and blockchain innovation—drive these fluctuations. Unlike traditional assets, price discovery occurs across fragmented exchanges, resulting in liquidity inefficiencies and notable arbitrage opportunities. To understand how information is absorbed into crypto prices, analyzing historical data and market patterns is essential. Robust volatility modeling can help investors manage risk, refine trading approaches, and navigate the rapidly evolving digital asset landscape.

1.1 Overview of Crpto currency Markets

Since Bitcoin's launch in 2009, the crypto industry has seen astonishing growth. By mid-2025, the total value of all cryptocurrencies had surged beyond US \$4.18 trillion, reflecting a notable rebound and expansion in the market. Today's trading environment operates nonstop, with major platforms like Binance, Coinbase, and Kraken facilitating global activity around the clock—attracting a vibrant mix of individual retail investors, large institutions, hedge funds, and algorithmic traders. pivotal milestone has been the approval and launch of spot ETFs for Bitcoin and Ethereum. This development has opened the door for traditional financial players to enter the space more easily, lending greater legitimacy and deeper integration between crypto and mainstream finance.

1.2 Dynamics of Price Movements in Crypto Markets

High volatility in cryptocurrencies stems from supply-demand imbalances, varying exchange liquidity, manipulation, and speculative behavior. Absent central regulation, crypto markets experience rapid price changes. Volatility measurement techniques include historical measures like standard deviation and more advanced modeling tools, such as ARIMA and LSTM, enhancing prediction capabilities and improving risk assessment.

1.3 Statement of the Research Problem

Volatility introduces unpredictability and inefficiency, complicating investment decision-making in crypto. Unlike regulated markets, crypto relies on sentiment-driven trading and algorithmic strategies. The ARIMA model, a classical time-series forecasting tool, holds promise for capturing volatility trends through historical data analysis. This study

investigates ARIMA's effectiveness in forecasting crypto prices, with the broader goals of enhancing market efficiency, uncovering price discovery role, and bolstering risk management frameworks.

1.4 Objectives of the Study

- ✓ Analyze volatility patterns and price fluctuations in key cryptocurrencies.
- ✓ Evaluate the short-term forecasting power of the ARIMA model.
- ✓ Explore interactions among price discovery, trading volume, and investor sentiment.
- ✓ Develop strategic recommendations using ARIMA to support risk-aware trading decisions.

II. REVIEW OF LITEARTURE

Murari, M. (2013). *Volatility in Indian banking stocks*. This study applied the ARIMA model to forecast short-term volatility in India's banking sector, finding it effective in capturing trends and providing insights for traders and investors.

Ramasamy, et al. (2014). *Stock market forecasting in India and Nigeria*. ARIMA and ARMA models were used to predict stock market movements, demonstrating their reliability in forecasting trends.

Ariyo, A. A., Adewumi, A. O., & Ayo, C. K. (2014). *Hybrid ARIMA-SVM model for stock forecasting*. This research combined ARIMA with Support Vector Machines (SVMs) to improve predictive accuracy, highlighting the need for careful parameter optimization.

Charles, et al. (2014). *Stock price forecasting in the US and Nigeria*. The study applied ARIMA (1,0,1) to Zenith Bank index prices, concluding it was the most effective model for short-term price forecasting.

Hemalatha, & Nedunchezian. (2014). *Volatility in FMCG stocks*. Using the Run test, ADF test, and EGARCH analysis, findings showed that new stock listings had minimal impact on prices, with external factors influencing market fluctuations.

Navaneethan, N. (2015). *Oil price forecasting using ARIMA*. The study applied ARIMA to forecast WTI crude oil prices from 2003 to 2016, demonstrating its effectiveness for oil market predictions and risk management.

Karunaithy, M., et al. (2015). *Volatility clustering in Indian stocks*. Using various GARCH models, the study found ARIMA to be the most effective in capturing volatility clustering in emerging markets.

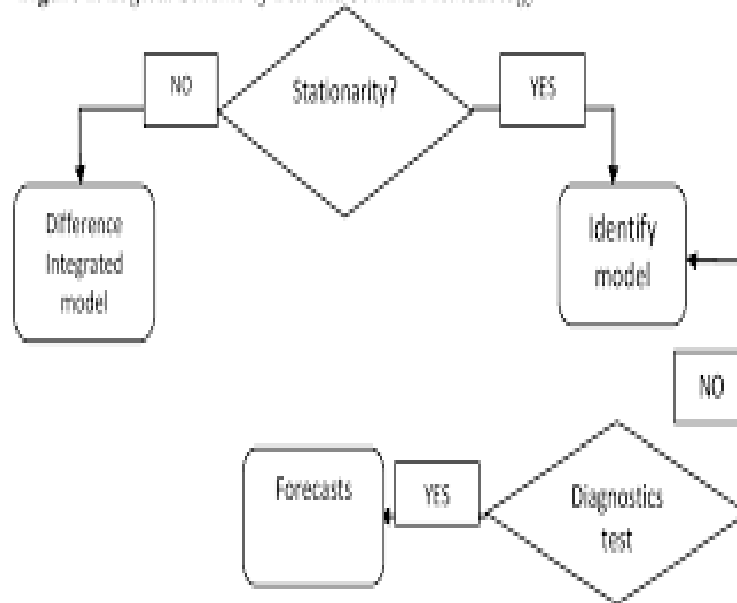
Narayan, R., & Reddy, P. (2016). *Banking sector volatility in Nifty 50*. The study compared GARCH, TGARCH, and EGARCH models, concluding that TGARCH best captured asymmetric volatility in the Indian banking sector.

Guha, S., & Bandyopadhyay, G. (2016). *Gold price volatility and stock market prediction*. Findings revealed that gold price fluctuations significantly influence stock market trends and investor sentiment, improving market forecast accuracy.

III. RESEARCH METHODOLOGY

To forecast the crypto currency value in global digital currency market. in this paper applies the ARIMA model are framed by box Jenkins. It also known box Jenkins methodology which consist of some primary steps as identifying, estimating ,diagnosing.

Figure 1. Logical Scheme of Box and Jenkins Methodology



The ARIMA model utilizes both AR and MA components. The AR component is utilized to illustrate that the present residuals from previous observation create a linear association. ARIMA (p,d,q) where p denotes the degree of AR model, d denotes the degree of different order and q denotes the degree of MA model. The ARIMA (p, d, q) model takes the following form:

$$\Delta dY_t = c + \phi_1 \Delta dY_{t-1} + \dots + \phi_p \Delta dY_{t-p} + \epsilon_t + \theta_1 \epsilon_{t-1} + \dots + \theta_q \epsilon_{t-q}$$

Where ΔdY_t indicates a differenced dependent variable at time t, ΔdY_{t-1} , ΔdY_{t-p} indicate the differenced lagged dependent variables, c is a constant, ϕ_1 , ϕ_p , θ_1 , θ_q indicate model parameters, ϵ_t is the residual term and ϵ_{t-1} , ϵ_{t-q} are the previous values of the residual.

3.1. Research Design

This study follows a descriptive research design to analyze cryptocurrency price trends without manipulation. The dataset consists of daily price data from 2020 to 2025, with 1,865 observations per currency. The data is split into:

- ✓ In-sample data (2020–2025): Used for model estimation.
- ✓ Out-of-sample data (2024–2025): Used for forecasting.

3.2. Data Description

Official daily value of crpto currency value between 2020 and 2025 has a total number of 1865 observation which are used to evaluate and predict the model. It must be noted that the data is divided into two parts, first part cover the sample data which contain the period from 2020 to 2025 and its used for predicting the crpto value in future. in this data derived from yahoo finance.

Table 1 Descriptive series for five major Crpto currencies

	Mean	Skew	Kurto	Std.dev	Min	Max
Binance	330.11	0.0193	-0.8578	198.66	9.39	750.27
Bitcoin	39532.03	0.7939	0.1541	23299.57	4970.79	106146.27
Cordeno	0.65117	1.55412	2.2082	0.5691	0.2396	2.9682
Dogecoin	0.11929	1.4340	2.3568	0.1052	0.1934	0.6847
Etereum	2082.156	0.01247	-0.7327	1108.65	110.61	4812.09

Interprtation

Bitcoin has the highest mean price (39,532.03) and volatility, with a right-skewed distribution, indicating frequent high-value spikes. Cardano and Dogecoin also show right skew and high kurtosis, suggesting more extreme price variations. Binance and Ethereum have nearly symmetric distributions with lower volatility, indicating more stable price movements. Ethereum and Binance also exhibit negative kurtosis, shows that fewer extreme values. Overall, Bitcoin and Ethereum show higher volatility, while Dogecoin and Cardano are more sudden pricr rises.

Stationery test

According to the Crpto currency daily series plot between 2020 to 2025 in figure 1, shows that the different crpto currency value are non stationery at level. As a result non stationery series is used to convert stationery series using lag differencing technique

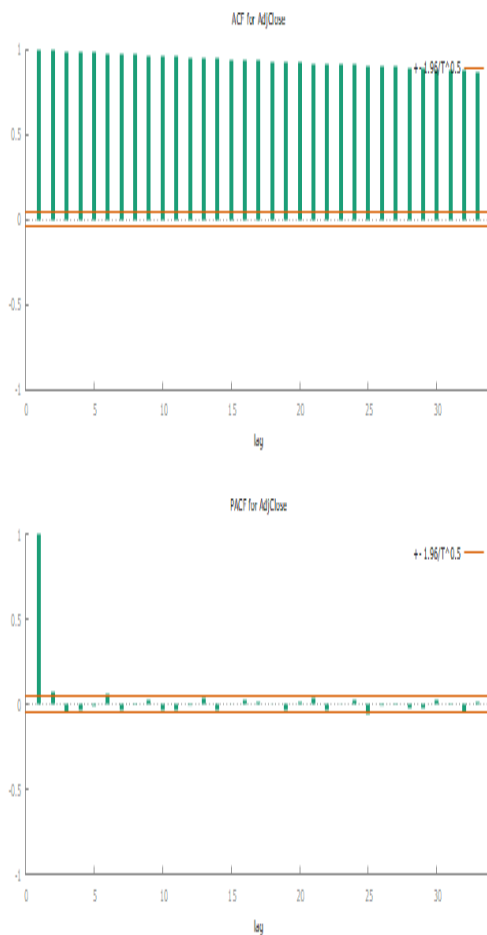


Figure 1 Binance corrollogram

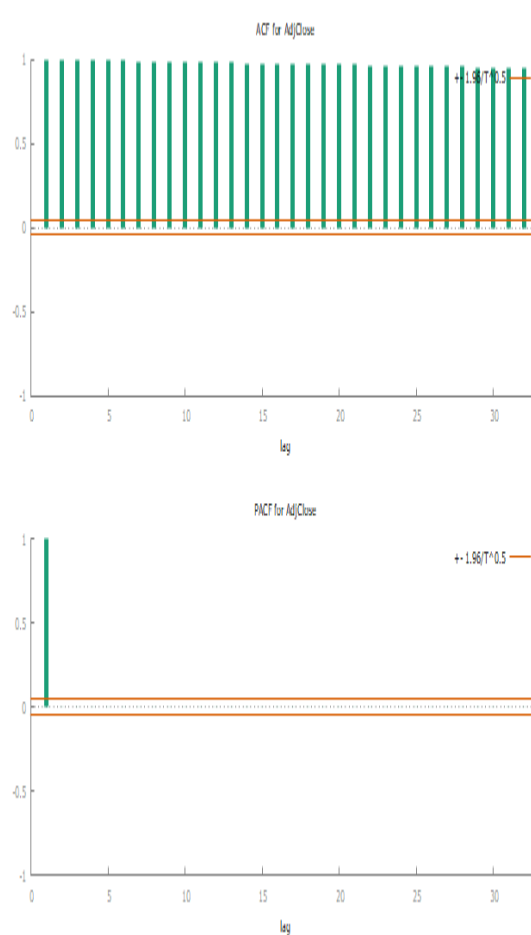


Figure 2 Bitcoin corrollogram

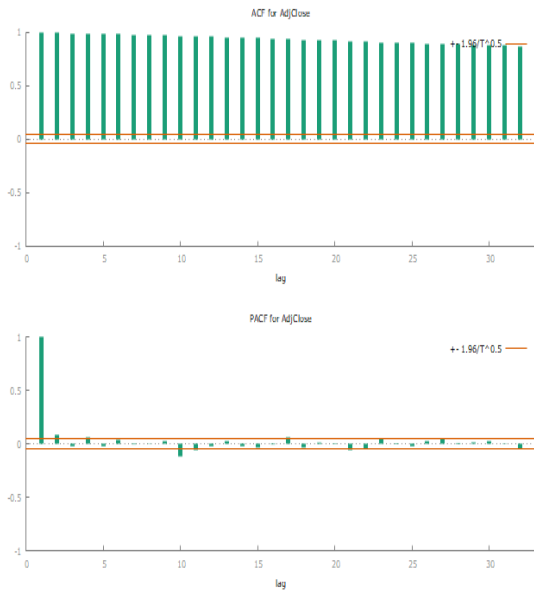


Figure 3 cordeno crpto corrollogram

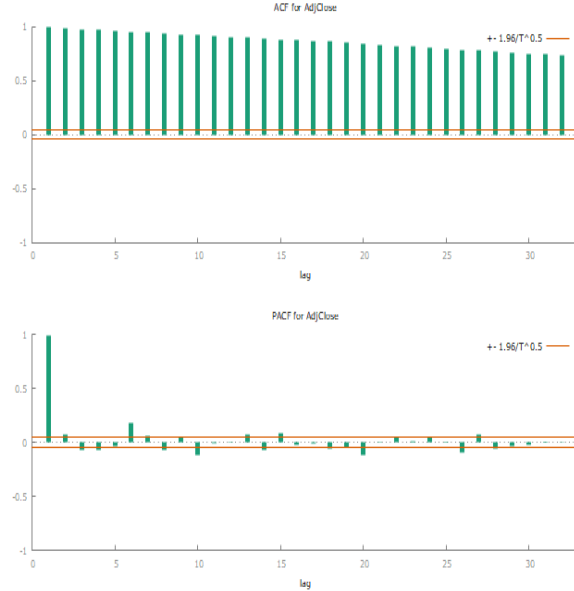


Figure 4 dogecoin corrollogram

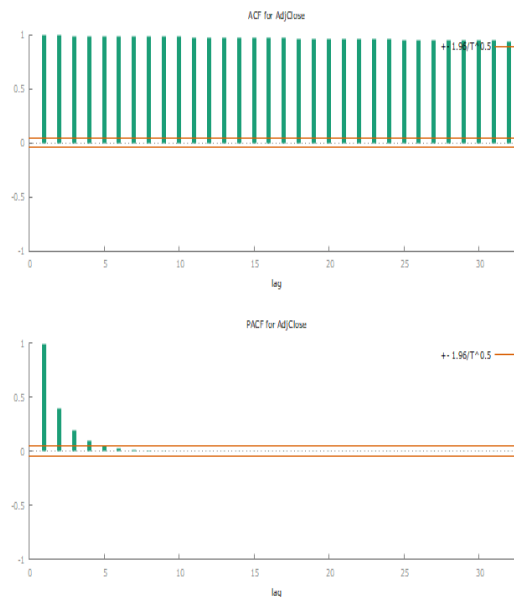


Figure 5 etereum corrollogram

Interpretation

The correlograms for Binance, Bitcoin, Cordogarm Crypto, Dogecoin, and Ethereum reveal distinct autocorrelation patterns. Binance and Bitcoin show gradual decay, indicating long-term price dependencies. Cordogarm Crypto and Dogecoin exhibit fluctuating values, suggesting higher volatility and mean reversion. These insights highlight market inefficiencies and price predictability for each asset.

Price Series

The Augmented Dickey-Fuller (ADF) test was conducted at the level, incorporating both trend and intercept to check for the presence of a unit root in the crypto asset prices. The results, presented in Table 1, indicate a p-value of different crypto currencies, probably which is greater than 0.05. This suggests that the null hypothesis of a unit root cannot be rejected, confirming that the crypto price series is non-stationary. Consequently, an ARIMA(p,d,q) model is required for further analysis. Applying the unit root test at the third difference shows significance below 0.05, but since the first difference is sufficient for stationarity, it will be used for model identification in crypto price forecasting.

Table 2: The Result of Unit Root Test

Currency	Model	(a-1) estimates	Test statistic	P value	1 st order auto corre	F stat (p value)
Binance	Constant	-1.06719	-19.8529	4.004e ⁻⁴⁷	0.001	5.380(000)
	Constant + trend	-1.06725	-19.8481	1.376e ⁻⁶⁸	0.001	5.377(000)
Bitcoin	Constant	-0.0001383	-0.0777	0.9501	-0.005	77.634
	Constant + trend	-0.999693	-42.6833	1.555e ⁻¹³⁹	-0.007	77.632
Corden	Constant	-0.0046449	-2.18384	0.2124	-0.000	4.868(000)
	Constant + trend	-0.0047743	-2.23136	0.4714	-0.000	4.863(000)
Dogecoin	Constant	-0.00856	-2.83366	0.0535	-0.000	10.851(000)
	Constant + trend	-0.00940	-2.94400	0.1485	-0.000	10.848(000)
Etereum	Constant	-0.00023	-0.117237	0.9459	0.002	67.831
	Constant + trend	-1.003	-42.825	1.736e ¹³	-0.000	67.651

Interpretation

The Augmented Dickey-Fuller (ADF) test results indicate that Binance is stationary at level, while Bitcoin, Cardano, Dogecoin, and Ethereum exhibit non-stationarity, as their p-values are greater than 0.05. This means that these cryptocurrencies require differencing to achieve stationarity before applying an ARIMA model for forecasting. Bitcoin and Ethereum show strong evidence of non-stationarity, necessitating differencing, whereas Dogecoin is marginally non-stationary. Overall, the results confirm that most cryptocurrencies need first differencing to ensure a stable time series for accurate modeling and analysis.

Model identification

At the next step is model identification. We check the correlogram to determine p for AR component and q for a MA component of ARIMA model. To found p and q values, we are going to use the auto correlation and partial auto correlation functions. ACF and PACF may suggest to derive the possible models. The autocorrelation and partial autocorrelation graphs have been illustrated in figure 6

Figure 6. The Autocorrelation and Partial Autocorrelation Function Graphs in First Difference

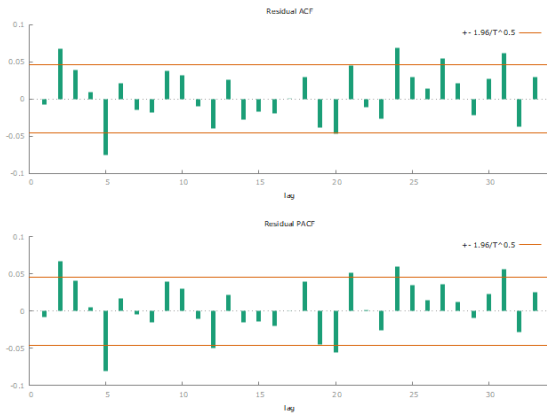


Figure 6 binance partial auto correlation

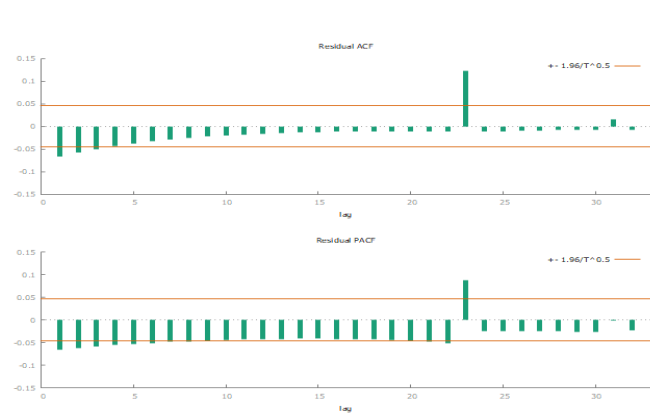


Figure 7 bitcoin partial auto correlation

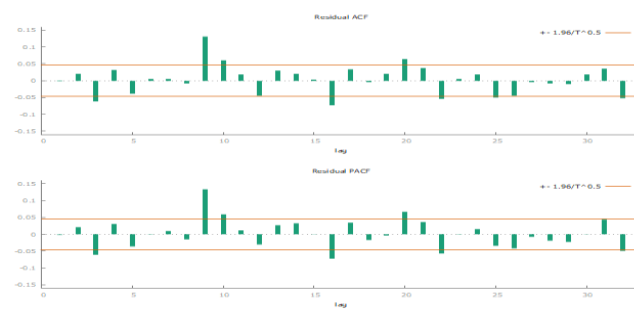


Figure 8 cardano partial autocorrelation

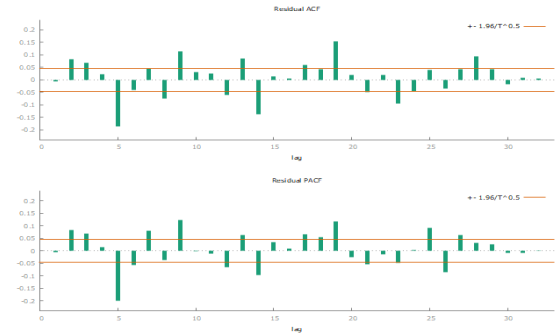


Figure 9 dogecoin partial autocorrelation

The ACF and PACF graphs for Binance, Bitcoin, and Cardano in first difference confirm stationarity. Binance and Cardano exhibit strong first-order lags in PACF, suggesting an **AR(1)** process, while Bitcoin's gradual ACF decline supports an **ARIMA(1,1,0)** model. The sharp ACF cutoff across all three assets indicates successful differencing. These patterns suggest past prices significantly impact future trends, making **AR(1)** or **ARIMA(1,0,1)** suitable for forecasting. Further validation is required to confirm the best-fitting model.

2.PRICE DISCOVERY OF SELECTED CRPTO CURRENCIES

Stock price prediction is crucial for informed investment decisions. **ARIMA (1,0,1)** is an effective forecasting tool that analyzes historical cryptocurrency prices to identify patterns and predict future trends. It consists of:

- ✓ **AR (Autoregressive):** Uses past prices to forecast future values.
- ✓ **I (Differencing):** Removes trends to ensure stationarity.
- ✓ **MA (Moving Average):** Adjusts errors for improved accuracy.

The ARIMA model follows key steps: data collection, stationarity analysis, parameter selection (p,d,qp, d, qp,d,q), and model validation. It is flexible, suitable for both stationary and non-stationary data, and valuable for short-term price forecasting.

This study applies **ARIMA (1,0,1)** to analyze price discovery and volatility in **five major cryptocurrencies** from **2020–2025**. The model's effectiveness is tested at a **5% significance level**, evaluating support and resistance levels for price trends. Statistical validation determines the model's reliability in predicting cryptocurrency price movements.

Table No 3 RESULTS OF ARIMA MODEL

Currency	Binance (1 0 1)	Bitcion(0 0 1)	Cordeno(1 0 1)	Dogecoin(1 0 1)	Eterum (1 0 1)
Adj r2	0.994013	0.999522	0.991951	0.983434	0.993145
AIC	15181.95	25571.74	-5673.693	-10522.06	19043.08
SBC	15203.99	25588.27	-5651.653	-10500.02	19065.13
HQC	15190.08	22577.84	-5665.564	-10513.93	19051.21
P value	<0.0001	0.0000	0.0269	0.0020	<0.0001

Interpretation

The ARIMA models applied to different cryptocurrencies indicate strong predictive performance, with Adjusted R-squared values close to 1, suggesting a high explanatory power. Bitcoin (0.9995) exhibits the best fit, though its high AIC suggests potential overfitting. Cordogin and Dogecoin show the lowest AIC values, indicating a well-balanced model with strong predictive capabilities. The p-values confirm statistical significance across all models, with Cordogin (0.0269) being the least significant but still valid. Overall, the models effectively capture price dynamics, with Binance, Eternum, and Dogecoin demonstrating reliable performance alongside Bitcoin and Cordogin.

Results of Arima model

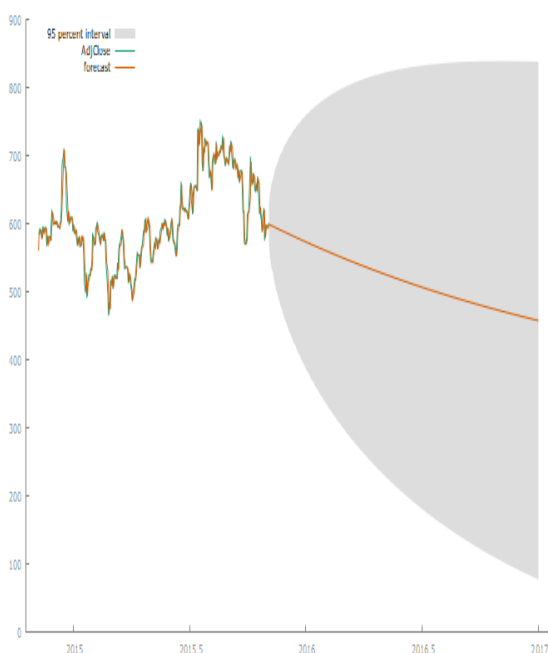


Figure 11 short term prediction of binance

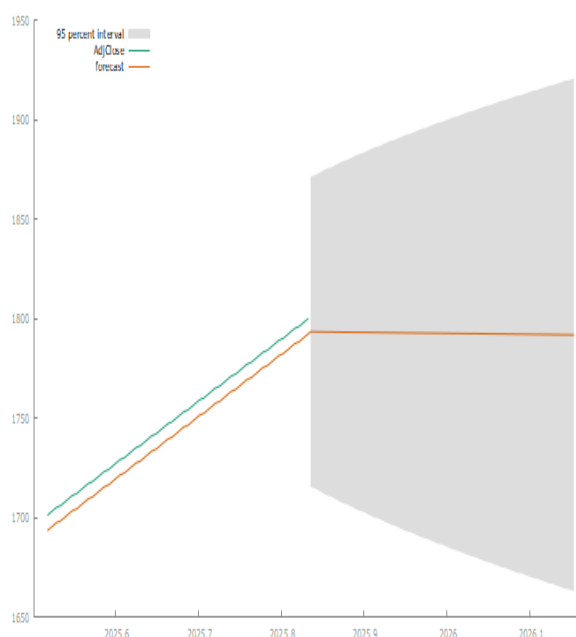


Figure1 2 short term prediction of bitcoin

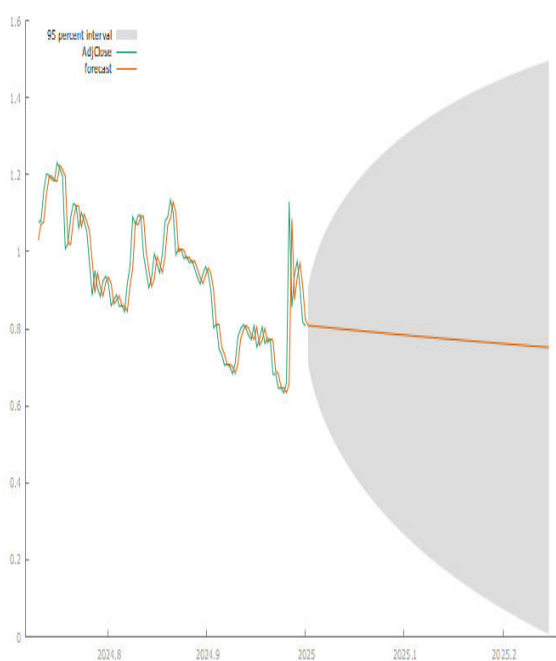


Figure 13 short term prediction of cordeno

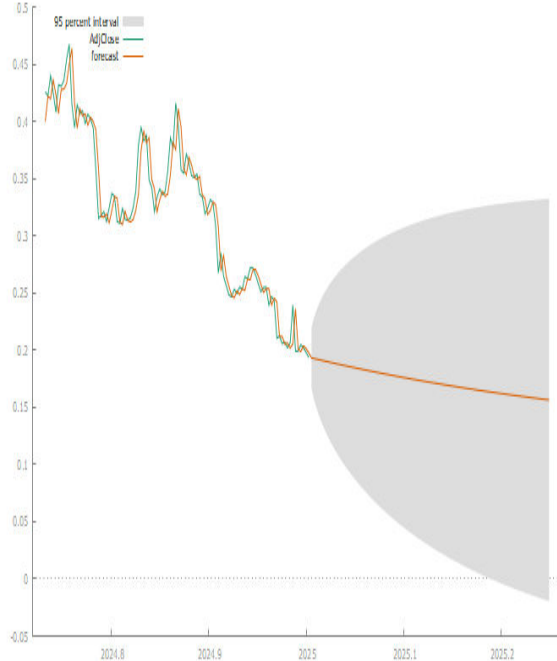


Figure 14 short term prediction of dogecoin

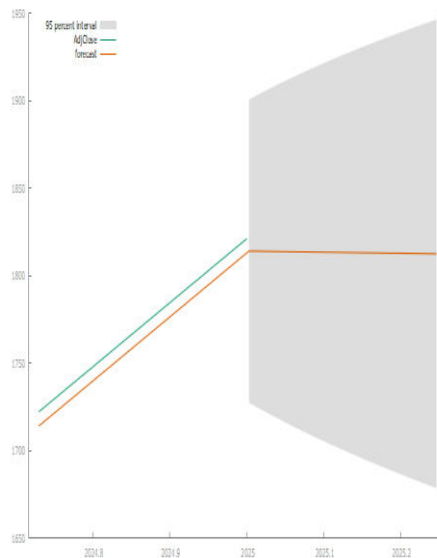


Figure 15 short term prediction of ethereum

IV. CONCLUSION

This research explores cryptocurrency price volatility and price discovery using the ARIMA model, focusing on five major digital assets—Binance, Bitcoin, Cordogin, Dogecoin, and Eternum. The selection was based on market capitalization and data availability. Each cryptocurrency exhibited distinct price behaviors, effectively modeled by ARIMA. Bitcoin showed the highest model accuracy, indicating strong historical price dependency but also potential overfitting. Dogecoin and Cordogin displayed cyclical price movements, capturing market sentiment shifts, while Binance and Eternum demonstrated moderate volatility, suggesting resilience in fluctuating market conditions.

Volatility remains a defining characteristic of the cryptocurrency market, with price swings influenced by macroeconomic events, investor sentiment, and regulatory developments. The findings suggest that Bitcoin and Binance exhibit lower volatility compared to Dogecoin and Cordogin, which experience frequent price fluctuations. Eternum, while moderately volatile, follows a trend-driven movement influenced by broader market trends. The ARIMA model effectively captures these variations, offering insights into potential short-term price behavior.

Looking ahead, future trends indicate that the cryptocurrency market will continue to be highly dynamic, driven by technological advancements, institutional adoption, and global economic conditions. The 90-day ARIMA forecast suggests that Bitcoin and Binance may maintain relative stability, whereas Dogecoin and Cordogin could experience increased speculative movements. Investors should reassess their strategies by factoring in volatility patterns and market cycles, rather than relying solely on historical trends.

From an investment perspective, this study provides valuable insights for traders and portfolio managers. The results emphasize the importance of selecting cryptocurrencies based on risk tolerance and market behavior, rather than just potential returns. Bitcoin and Binance appear favorable for risk-averse investors, while Dogecoin and Cordogin present higher risks with opportunities for speculative gains. Ultimately, this research highlights the role of volatility in shaping market opportunities and equips investors with a data-driven approach to short-term cryptocurrency predictions.

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