



## **Price, Trade Volume and Return in the Ethereum Market: An ARDL Model**

Osama Liaqat<sup>1</sup>, Kehkashan Nizam<sup>2</sup>, Jahanzaib Alvi<sup>3</sup>, Arbab Muhammad Jehandad<sup>4</sup>

<sup>1</sup> PhD Scholar, Department of Business Administration, IQRA University, Karachi, Pakistan.  
Email: osama.60032@iqra.edu.pk

<sup>2</sup> PhD Scholar, Department of Business Administration, IQRA University, Karachi, Pakistan.  
Email: Kehkashan.60003@iqra.edu.pk

<sup>3</sup> Department of Business Administration, IQRA University, Karachi, Pakistan.  
Email: jahanzaib.52655@iqra.edu.pk

<sup>4</sup> Lecturer in Economics, Department of Economics, University of Balochistan, Quetta, Pakistan.  
Email: arbab.jehandad@gmail.com

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### **ABSTRACT**

This research analyzes the price-setting behaviors of Ethereum, a digital currency and alternative payment system that has gained significant attention from investors. By employing symmetric and asymmetric causality tests, the study identifies the link between Ethereum's return, price, and volume from August 7, 2015, to November 30, 2020. The data obtained from CoinMarketCap.com consists of 1,940 observations suitable for analysis. The research employs ARDL, ARDL bound tests, and VECM to achieve its objectives. The findings indicate a significant and positive association between Ethereum's return, price, and trading volume in the short and long run. This suggests that as Ethereum's price and trading volume increase, it attracts more investors and leads to higher returns.



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**Corresponding Author's Email:** [Kehkashan.60003@iqra.edu.pk](mailto:Kehkashan.60003@iqra.edu.pk)

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## **1. Introduction**

Cryptocurrencies have gained significant attention in recent years, particularly Bitcoin and Ethereum. While some argue that cryptocurrency markets do not provide exploitable opportunities (El Alaoui, Bouri, & Roubaud, 2019), others have observed that the Bitcoin price has a substantial impact on trading activity (Gemici & Polat, 2019). Understanding the dynamics of cryptocurrency markets is crucial for evaluating the potential usefulness of trading strategies (El Alaoui et al., 2019).

However, it have often been viewed as speculative assets other than traditional investments, as they do not generate cash flow like well-managed corporations (Akbulaev & Salihova, 2019). The volatile nature of cryptocurrencies, including significant price fluctuations, further highlights the speculative nature of these digital assets (Tejaswi, Chauhan, Lakshmi, Swetha, & Sri, 2022).

The term "cryptocurrency" derives from the encryption techniques used to secure these digital currencies. The concept of anonymous cryptographic electronic cash was introduced in the 1980s Chaum (1990), followed by proposals for cryptographic electronic payment systems in the 1990s (Requiem, 2020). Satoshi Nakamoto's creation of Bitcoin in 2009 marked a significant milestone in the development of cryptocurrencies (Nakamoto, 2009a).

Despite their growing popularity, cryptocurrencies face challenges related to stability, reliability, accountability, and consumer trust. The threat of hacking attacks poses a significant risk to the adoption and acceptance of cryptocurrencies (Aydin Korpes, 2021). Central banks and governments are also closely monitoring the its development, with some expressing skepticism about their future as currencies (CoinMarketCap, 2020).

Currently, there are thousands of cryptocurrencies available for trading, with Bitcoin being the most prominent (CoinMarketCap, 2021). Ethereum, introduced by Vitalik Buterin in 2013, has also gained significant attention in the crypto space (Blog, 2021). However, Ethereum faced challenges in its early years, such as the hacking incident involving The DAO project (Financial Times). Nevertheless, Ethereum has continued to evolve with the introduction of Ethereum 2.0, aimed at improving scalability and transaction throughput (Ethereum, 2021).

The objective of this research is to analyze the long and short run relationship between the trading price, volume, and returns of Ethereum. Understanding these dynamics will aid investors and professionals in making informed decisions regarding Ethereum investments. The study will review existing literature, provide a theoretical framework, conduct a scientific analysis, and present the findings in a mathematical interpretation. Ultimately, this research aims to enhance our understanding of Ethereum's price dynamics and provide valuable insights for market participants.

Despite the growing popularity and importance, there is still a significant research gap in understanding the dynamics of cryptocurrency markets, particularly regarding Ethereum (BC & BS, 2022). While some studies have explored the relationship between trading price, returns, and volume, there is a need for further research specifically focused on Ethereum. The existing literature provides limited insights into the short-term and long-term linkages between these variables in the context of Ethereum. Additionally, there is limited studies that integrate theoretical frameworks, scientific analysis, and mathematical interpretations to shed light on the underlying dynamics of Ethereum's price behavior. Filling this research gap will contributes to understanding that is better for Ethereum's market dynamics and provide valuable insights for investors and professionals in the cryptocurrency space (Min & Cai, 2022).

The problem addressed in this research is the limited understanding of the relationship between the trading price, volume, and returns of Ethereum (Vaishali, 2023). While cryptocurrencies have gained significant attention and have become a subject of speculation, their underlying dynamics and the impact of these variables on Ethereum's market behavior remain insufficiently explored (Alahmad, Alfouderi, Alonaizi, & Aldhamen, 2023). The lack of comprehensive studies integrating theoretical frameworks, scientific analysis, and mathematical interpretations hinders our ability to comprehend Ethereum's price dynamics and make informed investment decisions (Song & Zhang, 2023). Therefore, the problem is to bridge this knowledge gap by conducting a comprehensive analysis that investigates the short-term and long-term linkages between the trading price, volume, and returns of Ethereum. The findings of this

research will provide valuable insights for investors and professionals in understanding Ethereum's market behavior and its implications for investment strategies.

Rest of the study is divided in the following sections. Section 2 covers theoretical foundation of the research along with recent related studies, section 3 would be covering the methodology in placed to conduct this research, section 4 will be explaining the results obtained by statistical derivations which would also comply research objectives of the study, and section 5 would be covering discussion, conclusion, recommendation and future directions of the study.

## **2. Literature Review**

### **2.1. Theoretical Foundation**

The theory of pricing was proposed by Bliss (1988) states that the price of a product or service is determined by the relationship between supply and demand (Eichner, 2023). In the context of cryptocurrencies, economic fundamentals can theoretically influence their pricing, as evidenced by historical data. However, a closer analysis reveals that many Bitcoin users hold cryptocurrencies as investments rather than actively participating in transactions (Rajasa, Manap, Ardana, Yusuf, & Harizahayu, 2023). By studying the microdata of individual transactions, we can gain insights into cryptocurrency usage patterns and how they evolve over time.

Whereas, Conventional theory assumes consistent returns across all trading and non-trading periods, but evidence suggests that return sequences may vary during closed periods of organized markets (Oldfield & Rogalski, 1980). Cryptocurrency prices, for instance, fluctuate based on trading activity during open market hours, while adjustments and important news are often announced after market closure. Additionally, the presence of irrational investor behavior driven by emotions can contribute to dramatic price changes and market uncertainty in the cryptocurrency space.

### **2.2. Empirical Review**

Several studies have examined the relation among the price and volume. Gemici and Polat (2019) focused on the period from January 2012 to April 2018, using Bitcoin price and trading volume as variables. They found co-integration between Bitcoin's trading volume and price in the long term, with a larger influence of Bitcoin price on trading volume. They concluded that as Bitcoin prices rise, it attracts more investors and leads to an increase in trading volume.

Sapuric, Kokkinaki, and Georgiou (2022) investigated the relationship between Bitcoin returns, volatility, and volume, along with six other currencies representing various markets and economies. They used an asymmetric GARCH model and found significant relationships between Bitcoin returns, volatility, and trading volume. They emphasized the importance of understanding these variables for forecasting and risk management in the Bitcoin market. They also noted that the correlations between variables may change over time, requiring further research in different periods.

Sami and Abdallah (2021) examined the impact of the crypto market on stock market performance in the MENA region. They considered variables such as cryptocurrency volume, cryptocurrency returns, stock returns, real GDP, oil production, and financial transactions index. Their study focused on the period from 2014 to 2018 and revealed a substantial link between the Bitcoin market and stock market performance in the MENA region. They found that changes in cryptocurrency returns had different effects on stock market performance in Gulf and non-Gulf countries.

Caporale and Plastun (2019) analyzed market overreactions in cryptocurrencies, specifically focusing on Ripple, Dash, Bitcoin, and Litecoin. They examined abnormal price behavior and market reactions using various statistical tests. Their findings indicated that overreactions in the cryptocurrency market did not present good profit opportunities. They emphasized the importance of transaction costs and scale in manipulating statistically significant deviations.

Felix and von Eije (2019) analyzed under-pricing in initial coin offerings (ICOs) and compared them to initial public offerings (IPOs). They considered variables such as trading volume, rating, issue size, coins sold ratio, sentiment, and bonus scheme. Their study included ICOs from September 2015 to January 2018 and concluded that ICO under-pricing could be reduced by considering the issuer's characteristics and problem sizes. They highlighted the potential benefits for both issuers and investors in understanding the under-pricing phenomenon.

El Alaoui et al. (2019) focused on the price-volume cross-correlation in the Bitcoin market. They analyzed Bitcoin prices and trade volume, finding a nonlinear relationship and multi-fractality. Their findings provided insights into the effectiveness of trading technologies in the Bitcoin market and suggested inefficiencies in the market.

Cagli (2019) investigated the rapid prices of Bitcoin and seven other Altcoins. They considered variables such as market capitalization, value, and circulating supply. Their study covered the period from April 2013 to January 2018 and revealed explosive behaviors and significant bilateral coexplosive relationships among the cryptocurrencies analyzed.

Akbulaev and Salihova (2019) examined the relationship between Bitcoin exchange rates and trade volume using Granger causality analysis. Their study covered the period from December 27, 2013, to February 1, 2018, and found a one-sided causal relationship between market shifts and transaction changes. They concluded that delayed volume changes affect price increases, while delayed price changes have an impact on transaction volume.

Mensi, Al-Yahyaee, and Kang (2019) investigated the effects of structural fractures on Bitcoin and Ethereum pricing returns' dual long memory levels. They used four autoregressive heteroscedasticity models and found dual long memory qualities in Bitcoin and Ethereum markets. They highlighted the importance of understanding long memory patterns and structural fractures for risk management and asset pricing.

Corbet and Katsiampa (2020) conducted a study on the asymmetric mean reversion of Bitcoin price returns. They utilized data from July 20, 2010, to February 22, 2018, to analyze time-varying mean reversion using different data frequencies. Their analysis employed the ANAR model, and regardless of the data frequency, they found evidence of asymmetric reversal tendencies in Bitcoin price returns. Specifically, they observed a greater reverting activity in negative price returns compared to positive returns, although the reverting trend became more symmetrical at lower data frequencies.

Corbet, Lucey, and Yarovaya (2018) explored date stamping the Bitcoin and Ethereum bubbles. Their study focused on the period between January 9, 2009, and November 9, 2017, for Bitcoin, and August 7, 2015, to November 9, 2017, for Ethereum. They employed the ADF (GSADF) approach and the recurrent reverse regression approach to identify and timestamp bubbles within the data. The study did not find significant evidence of a widespread bubble in the Bitcoin and Ethereum markets. However, they did find support for the view that Bitcoin experienced a genuine bubble phase, particularly with price increases over \$1,000.

Geuder, Kinateder, and Wagner (2019) investigated cryptocurrencies as financial bubbles, focusing on Bitcoin. They analyzed Bitcoin daily closing prices from March 19, 2016, to

September 19, 2018. Using the LPPL model, they identified bubble cycles in the Bitcoin price series and observed a good fit with the LPPL model.

They studied the multifractal behavior of price and volume changes in dynamics until the bubble burst on December 6, 2017. They found that the Bitcoin price exhibited faster than exponential acceleration, suggesting the presence of bubble activity. However, after December 2017, no further bubble activity was detected using the LPPL or PSY model.

Stosic, Stosic, Ludermir, and Stosic (2019) analyzed the cryptocurrency market. They analyzed daily closing prices and exchange values of a subset of the top 100 cryptocurrencies from late 2013 to the end of 2017. Using the MF-DFA approach, they found that price shifts were more complex than volume changes, with major and minor variations influencing the multifractal behavior of price and volume, respectively. The study also highlighted the absence of price shift associations and the presence of long-term anti-persistent correlations in volume changes.

Cheng and Yen (2020) investigated the relationship between economic policy uncertainty (EPU) and the cryptocurrency market, specifically focusing on China, the US, Japan, and Korea. They collected cryptocurrency data, including Bitcoin, Ripple, Ethereum, and Litecoin, from the Coin Market Cap database. The study period ranged from February 2014 to June 2019. They found that China's EPU index could predict Bitcoin returns, while the EPU indexes of the other countries did not exhibit the same predictive ability. The study also observed a change in China's cryptocurrency trading strategy in September 2017, which further enhanced the EPU's predictive capacity for Bitcoin returns.

Nasir, Huynh, Nguyen, and Duong (2019) investigated the forecasting of cryptocurrency volumes and search engine returns, focusing on Bitcoin. They used Bitcoin returns, Google search values, and trade volumes as variables. The data spanned from the first week of 2014 to the last week of 2017, obtained from Google Trends and Coinmarketcap. The study found that Google search values, particularly in the short term, had a significant impact on Bitcoin returns. However, the impact on cryptocurrency trading volumes was not statistically significant. The researchers suggested including other factors such as emotion and risk aversion in future studies to improve the accuracy of cryptocurrency return prediction models.

The literature review reveals various research gaps and potential areas for further exploration in the field of cryptocurrencies. Investigating the efficiency of markets, interconnections with traditional financial markets, market anomalies, bubbles, cross-correlations, long-term memory patterns, external factors, and prediction models can contribute to a deeper understanding of cryptocurrency dynamics and inform investment strategies and policy decisions.

### **3. Methodology**

The purpose of this study is to provide an explanatory analysis of the relationship between the return, price, and volume of Ethereum from its inception on August 7, 2015, to November 30, 2020, on a global scale. As this topic has not been extensively researched before, an explanatory analysis is conducted to establish research objectives, develop conceptual frameworks, and propose a model that can be further investigated. The explanatory analysis is a strategic approach to designing studies that focuses on illustrating the components of the research. The researcher employs a comprehensive premise and analysis strategy to address future challenges.

Quantitative analysis techniques are utilized in this study. There are several reasons for choosing a quantitative research method: firstly, because the assumptions have not been tested, the study adopts an explanatory approach to examine and test ideas through quantitative analysis. Additionally, the data obtained is presented in percentages, which further justifies the

use of quantitative analysis methods. Throughout the period from August 7, 2015, to November 30, 2020, a correlational study design is employed to analyze the short-term dynamics and long-term relationship between Ethereum's trade price, volume, and return. Correlation analysis is a research methodology that examines the relationship between two variables to establish a statistically significant link. The goal of correlation analysis is to classify variables in a manner that demonstrates that a change in one variable causes a change in the other.

The data for this research is obtained from coinmarketcap.com. CoinMarketCap, founded in 2013, provides comprehensive market information and real-time updates. The platform collects data from various exchanges every minute to ensure data accuracy, and multiple data cleaning and verification algorithms are applied. For this study, data is collected from August 7, 2015, to November 30, 2020, as Ethereum was launched in 2015. The values of Ethereum's trade volume are divided by one hundred million (100,000,000) to simplify the data interpretation, meaning that one unit of trade volume represents one hundred million (100,000,000) dollars.

The research model of this study is as follows:

$$ER_t = \alpha_0 + \beta_1 ETV_t + \beta_2 EP_t + e_t \quad (1)$$

Whereas  $\alpha$  is constant, ER represents Ethereum return, ETV Ethereum trade volume, EP Ethereum prices and, t is time series data,  $\beta$  is coefficients and e is error term. The hypotheses of this research is,

H1: There is a significant relationship between Ethereum trade volume and Ethereum return.

H2: There is a significant relationship between Ethereum prices and Ethereum return.

We apply the autoregressive distributed lag approach designed for joint integration to investigate long-term interactions between targeted variables by Pesaran, Shin, and Smith (2000). ARDL preferred over other co-integration methods as ARDL may be employed irrespective of if selected variables are stationary to I (0), I (1). For small sample characteristics, the ARDL process was better approximated; (Basher, 2015) Even in the ARDL procedure the estimates can be made independent of the explanatory variable.

$$\Delta ER_t = \psi_0 + \psi_1 \sum_{i=1}^p \Delta EP_{t-i} + \psi_2 \sum_{i=1}^p \Delta ETV_{t-i} + \gamma_1 EP_{t-1} + \gamma_2 ETV_{t-1} + \mu_t \quad (2)$$

Where  $\mu$  indicates error terms and dynamics of error correction are shown by a summation sign,  $\psi$  represents constant whilst the second part of the equation corresponds to the long-term relationship. When identifying a cointegration relationship among the variables using the johansen test, a vector error correction model (VECM) has to be calculated. In this approach, all variables are considered dependent variables while the error correction model (ECM) is included, followed by an optimum lag length estimate. VECM is a vector self-representation model, the long-term association between variables in the VAR model, utilized by Engle and Granger.

$$\Delta ER_t = \phi_0 + \phi_1 \sum_{i=1}^p \Delta EP_{t-i} + \phi_2 \sum_{i=1}^p \Delta ETV_{t-i} + \eta ECT_{t-1} + \mu_t \quad (3)$$

Where  $\phi$  represent phi coefficient. Phi coefficient is used to measure association between two binary variables

### 3.1. Variable Definitions Ethereum prices

Ethereum prices is the price in which Ethereum sale in global market and its use in this article as an independent variable.

### Ethereum trade volume

Ethereum trade volume is the volume which show how much Ethereum trade in global market its use in this article as an independent variable.

### Ethereum return

Ethereum return is the profit or loss on Ethereum investment over the day its use in this article as a dependent variable.

## 4. Results and Analysis

### 4.1. Descriptive analysis

A descriptive analysis is the initial stage in carrying out statistical investigations. It offers you an insight into how the data is dispersed, helps discover outlines and errors, and enables you to discriminate between variables and prepare for deeper statistical analysis.

**Table 1**  
**Descriptive Analysis**

Descriptive	Volume	Price	Return
Mean	43.2	216.951	0.005
Median	17	177.34	0
Maximum	314	1396.42	0.51
Minimum	0.001	0.434	-0.728
Std. Dev.	57.2	227.742	0.065
Observations	1943	1943	1943

Note: 1 unit of volume is equal to one hundred million (100000000)

In this test we take 1943 observation in which volume have highest value of mean , median and also have maximum value and Std. Dev. in all variable which are 43.2 , 17 , 314 and 57.2 respectively whoever return have minimum value in all variables which is -0.728.

### 4.2. Stationary Analysis

Augmented Dickey Fuller (ADF) unit root tests assess the stationary qualities of a long-term relationship. The test serves to determine if the estimates are zero or not. The aggregate distribution of Augmented Dickey Fuller statistics is determined by this test. The variable is deemed to be stabilized if it is smaller than the critical values in the statistics table.

**Table 2**  
**Stationary Analysis**

Variables	Level		1 <sup>st</sup> Difference		Results
	t-statistic	P-values	t-statistic	P-values	
Price	2.480	0.120	6.967	0.000	Stationary at 1st Difference
Return	42.128	0.000			Stationary at Level
Volume	2.485	0.119	37.298	0.000	Stationary at 1st Difference

The following Table 2 shows the results, which show that both price and volume are non-stationary at level but stationary at 1st deference, and return is stationary at level. It means that at a critical level of 5%, all variables have no unit root problem and are stationary.

### 4.3. Auto Regressive Distributive Lag Model (ARDL)

ARDL co-integration approach is used to identify the long-lasting link between series with various integration orders. The re-parameterized result shows the short-term dynamics and the long-term link between the investigated variables. Although the approach of cointegration for ARDL requires no pre-testing of unit roots, a built-in stochastic pattern prevents the crash of the ARDL model. The null hypothesis of the ARDL test is that the variables are not co-integrated.

**Table 3**  
**ARDL Test**

Variable	Coefficient	Prob.
ER(-1)	0.068	0.001
ER(-2)	0.037	0.036
EP	0.001	0.000
EP(-1)	-0.002	0.000
EP(-2)	0.001	0.006
EV	0.000	0.000
EV(-1)	0.000	0.000
C	0.007	0.000
Prob(F-statistic)		0.000

This test show that the prob values of all test is less then critical values mean there is cointegration between variables mean there is long run relationship exist. The coefficient show that Ethereum retune in first leg and second leg have positive long run relation while Ethereum price in original and second leg have positive long run relation but in first leg have negative long run relation with variables also Ethereum volume in level have positive long run relation but in first leg have negative long run relation. We can say that Ethereum price and volume both in first leg have significant negative long run relation while all other variable has positive long run relation in this model. While Prob (F-statistic) value of this test is 0% which show that cumulative effect all independent variable on Ethereum return is significant.

### 4.4. ARDL Bound test

First of all, we must test the ARDL model to confirm the efficiency and optimum delays in defining the balance of variables. After these tests, bound test is carried out to find a co-integration effect or influence to determine the short- and long-term visibility which can reveal our doubt as to model efficiency and lastly, an error correction model test is carried out to establish balance of the long-term model relationship.

**Table 4**  
**ARDL Bound Test**

Test Statistic	Value	k
F-statistic	355.9284	2
	Critical Value Bound	
Significance	I0 Bound	I1 Bound
10%	3.17	4.14
5%	3.79	4.85
2.5%	4.41	5.52
1%	5.51	6.36

According to the Bound Test, selected cryptocurrency variables have a long run relationship, since the F-Statistic value is 355.928 more than the upper bound on Critical values (I1) at any significant level. Based on the results, the long run Cointegration is presented in the following table there is a positive long-term relationship between return, price and volume. Because when price of Ethereum changes it also change it trade volume like if its price going to decrees then people stope there trading new investor stope because of uncertainty and old



investor start to hold it and wait to increases in its price. Likewise, when its price increases people start trading.

#### 4.5. Vector Error Correction Model

The VECM is the resultant model's name. In order for deviations in this model to converge, the error term must be substantial and negative. It is expected that if the error term is not substantial or negative, the VECM does not perform effectively. In this analysis two variables have been employed in various models as dependent variables and the VECM approach for estimating the long-term coefficient between variable and the short-term corrective term for vector errors is employed.

**Table 5**  
**VECM**

Variable	Coefficient	Prob.
EP	0.002	0.000
EV	0.001	0.001
ECT(-1)	-0.961	0.000
C	-0.001	0.612
Adjusted R-squared		0.642
Prob(F-statistic)		0.000

The Table's error correction terms have negative and significant coefficients, showing that the error corrector mechanism of the model works correctly and that short-term variables in the long term do not return. This also shows the validity of the association between variables found for a long time. The error correction terms' coefficients suggest that 1% of variables changes signal negative convergence of 96,167% in return for the next day because cryptocurrency market is having very uncertainty in it like other trading market its change more frequently. Based on the long-term relationship between variables, it is discovered that a 1% increase in Bitcoin prices results in a 0.190 percent increase in Bitcoin return, while a 1% increase in Bitcoin volume results in a 0.001 percent increase in Bitcoin return. While Prob (F-statistic) value of this test is 0% which show that cumulative effect all independent variable on Ethereum return is significant and Adjusted R-squared value is 64.20% which how that Ethereum trade price and trade volume have 64.20% variance on Ethereum return.

#### 4.5. Discussion

Table 3 presents the results of the ARDL analysis, indicating that all variables exhibit a long-run relationship with statistical significance ( $P < 0.05$ ). ARDL tests are used to address situations where two or more non-stationary time series are integrated to prevent them from drifting away from equilibrium over time. These tests aim to determine the sensitivity of two variables over a specific timeframe, assuming a constant average price. Our findings suggest that deviations from equilibrium can occur over time, with trade price and volume having a significant impact on return. This relationship has been supported by previous studies such as (Bouraoui, 2020). Specifically, changes in Ethereum's price have an effect on its return, and an increase in trade volume indicates investor interest, potentially leading to higher returns. However, the effect of trade volume on return appears to be of shorter duration compared to the impact of trade price.

Table 5 presents the results of the VECM analysis, indicating that short-term variables do not converge in the long run, as evidenced by the negative error correction coefficients ( $P < 0.05$ ,  $\beta = -0.961670$ ). This finding is consistent with studies conducted by Bouraoui (2020); Gemici and Polat (2019); Pagnottoni and Dimpfl (2019). The reason behind this result is that changes in Ethereum's price and volume have an effect on its return in the short term, but this effect does not persist in the long run. The deviation between price and volume only remains for

a short period because Ethereum's price experiences daily fluctuations. Consequently, the effect of price on return also varies on a daily basis.

The ARDL analysis reveals a long-run relationship between the variables, with trade price and volume significantly impacting Ethereum's return. On the other hand, the VECM analysis suggests that the relationship between price, volume, and return is more pronounced in the short term, as deviations between these variables do not persist in the long run. These findings align with previous research conducted by Bouraoui (2020); Gemici and Polat (2019); Pagnottoni and Dimpfl (2019).

## **5. Conclusion**

Bitcoin, created by Nakamoto (2009b), has long been one of the most popular digital currencies. However, internal disagreements within the bitcoin community have led to recent divisions, resulting in the launch of bitcoin cash and the emergence of other decentralized currencies. In 2013, Vitalik Buterin, a programmer, proposed Ethereum. The network was utilized by The DAO, a third-party project, which went live on July 30, 2015, with 72 million premined coins. Unfortunately, the project suffered a security breach, resulting in the theft of 50 million Ether. The Ethereum community voted to reverse the fraudulent transaction on the blockchain, leading to the creation of the original Ethereum Classic chain (ETC).

Ethereum 2.0, also known as Eth2, is an ongoing open-source project that includes a shift to proof of stake and the use of sharding to enhance transaction scalability. The primary goal of Ethereum 2.0 is to significantly increase network transaction capacity from around 15 transactions per second to tens of thousands per second.

The objective of this study is to analyze the short-term dynamics of trading volume and returns in Ethereum. Specifically, it investigates the relationship between Ethereum pricing, trading volume, and return. The analysis begins with descriptive analysis followed by stationary analysis of Ethereum prices, trade volume, and returns. The results indicate that Ethereum prices, trade volume, and returns exhibit stationary properties.

Next, the study examines the cointegration relationship among Ethereum prices, trade volume, and returns, revealing that these variables are integrated in the long run. The study employs the VECM (Vector Error Correction Model) method to estimate long-term and short-term coefficients. The findings indicate that Ethereum prices and trade volume have a stronger impact on Ethereum returns. As Ethereum prices and trading volume increase, it attracts more investors, leading to a rise in Ethereum returns. Given that Ethereum is considered a high-risk investment, price increases offer greater profits for investors. However, a decrease in trade volume does not significantly affect returns, suggesting that it has little impact on the decline in returns. This could be attributed to investors being hesitant to trade when prices fall, as they expect Ethereum prices to rise further, resulting in a decrease in trade volume.

This study explores the dynamics of Ethereum trading volume, pricing, and returns. It finds that Ethereum prices and trade volume have a significant influence on returns. As prices and trading volume increase, investor interest grows, resulting in higher returns. However, a decrease in trade volume has a minimal effect on returns. This may be due to investors' reluctance to trade during price declines, anticipating future price increases.

### **5.1. Managerial Implications/Recommendations**

Ethereum and other cryptocurrencies are best explained in future currencies. Today, the methods of commerce is not widely acknowledged. There are substantial disadvantages preventing them from being fully functional currencies. This study helps us understand

Ethereum's behavior that will aid us in future. The question is also if cryptocurrencies are merely a symptom of a larger financial bubble. However, although dubious, it is feasible for them to be utilized more frequently in future as trading means. The potential uses of bitcoins block chain technology are also exciting. The technology may be utilized for additional applications, such legal, security and voting systems.

## 5.2. Future Recommendations

This research is limited to Ethereum for this study. Further research should add a wider range of cryptocurrency to make it possible to generalize the findings further effectively. Second, this study has only shown the relation between Ethereum price, trade volume and return may another factor also effect Ethereum return which are not mansion in it. Other researchers should investigate the factures and try to find a complete result which completely define how Ethereum return work in cryptocurrency market.

This study will help those Practitioners who are want to invest in Ethereum that how Ethereum price influence its trade volume. This will also help them to make their investment plan and help them to predict future potentials in Ethereum. This report will improve the understanding about Ethereum because Ethereum just launch in 2015 that's why there are so less research present which only conduct on Ethereum and its trade volume. Moreover, this article also helps in future researches to find the behave of Ethereum because in this reach I only try to find the relation between Ethereum price and its trade volume however there are also other factor ream to studies which effect Ethereum volume this research helps new researcher to find and study in those factures

## 5.3. Limitations and Delimitations

Firstly, the sample is limited to Ethereum for this study. Further detailed studies with a wider range of cryptocurrency make it possible to generalize the findings further effectively. Second, this study has only shown the relation between Ethereum price, trade volume and return may other factor also effect Ethereum trade volume which are not mansion in it. Furthermore, the generalizability of the results of present study are limited since other factures are not consider in it which also have effects on Ethereum trade volume. Other researchers should investigate the factures and try to find a complete result which completely define how Ethereum return work in cryptocurrency market. As far as delimitations are concerned, this research just focused on Ethereum. Secondly, the data is collected from only one exchange. Moreover, the study may contain biasness because the results are self-reported and respondents may have misquoted answers which may make the results less convincing.

### Authors Contribution

Osama Liaqat: Original Draft, Idea, Conceptual Framework, Methodology

Kehkashan Nizam: Editing, Formatting, Data Analysis

Jahanzaib Alvi: Proofreading, Literature Review

Arbab Muhammad Jehandad: Supervision and Direction

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