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Price of Ethereum Token Effect on the Non-Fungible Token User Trading Activities in the 2020s

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Abstract: This research investigates the relationship between the price of the Ethereum token and Non-Fungible Token (NFT) trading activities on the Ethereum blockchain in the 2020s. Through regression analysis and t-tests, the study explores how changes in Ethereum's price and price volatility influence NFT trading behaviors. The regression analysis reveals significant positive correlations between Ethereum's price and various NFT trading variables, indicating that an increase in Ethereum's price positively impacts sales volume, unique sellers, unique buyers, and average sales of NFTs. Conversely, Ethereum's price volatility demonstrates significant negative associations with NFT trading activities, suggesting that market uncertainty and risk aversion influence investor decisions. The findings provide valuable insights for practitioners, investors, and traders in the NFT market, offering guidance for decision-making strategies and market trends; however, the study also acknowledges limitations in establishing causal relationships and suggests future research directions. Understanding the dynamics between Ethereum's price and NFT trading activities is crucial in navigating the evolving landscape of blockchain-based assets and decentralized markets.

Keywords: blockchain, ethereum, non-fungible token

1. Introduction

In recent years, the advent of blockchain technology has revolutionized our traditional understanding of ownership, transactions, and the economy at large. Ethereum, a decentralized, open-source blockchain platform, has emerged as a pivotal player at the forefront of this revolution. Ethereum has facilitated an entirely new form of digital asset - the Non-Fungible Token (NFT). Unlike cryptocurrencies such as Bitcoin or Ethereum's native Ether, NFTs represent a unique, indivisible, and thus non-fungible asset, carving a significant niche within the broader digital economy. Through Ethereum's innovative smart contract functionality, NFTs encode ownership information on the blockchain, creating an immutable proof of ownership for digital or digitized assets, from artwork to real estate.

The majority of NFT transactions occur on the Ethereum blockchain and are powered by Ether, Ethereum's native cryptocurrency [1]. Ethereum's advanced smart contract capabilities have made it the blockchain of choice for NFT developers and marketplaces. When purchasing an NFT, a buyer typically pays in Ether, making it the default currency for NFT transactions. Ether serves as both a digital currency and a "fuel" for operating transactions on the Ethereum network. This dual role is particularly relevant in the NFT marketplace, where Ether not only serves as a medium of exchange

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but also powers the execution of the smart contracts that establish ownership of the NFTs. Thus, exploring if there exists a relationship between the price and price volatility of the Ethereum blockchain's native Token Ether and NFTs users' activities becomes worth investigating. The research question for this paper thus becomes: What relationship exists between the price of the Ethereum token and the NFT trading activities on the Ethereum blockchain? By conducting a study on this topic, we can shed further light on the connections and dependencies between the two markets that used to drive and are still driving some of the most significant topics of interest in the blockchain world.

2. Literature Review

Despite the transformative potential exhibited by blockchain technologies like Ethereum and novel digital assets such as Non-Fungible Tokens (NFTs), academic literature on these topics still remains nascent. Launched in 2015, Ethereum has rapidly ascended as a trailblazer in the world of decentralized applications and smart contracts. NFTs, gaining significant traction during the COVID-19 pandemic era, have created a seismic shift in the digital ownership landscape [2]. However, the novelty of these technologies and their relatively recent prominence suggests that the body of research is still in its formative stages. Therefore, this literature review aims to collate and synthesize the currently available scholarship on Ethereum and NFTs, while acknowledging the preliminary nature of these studies and the rapidly evolving contexts they seek to document and understand.

Many research studies aim to explore the relationship and differences between cryptocurrency and traditional investments. This is because people have yet to become familiar with cryptocurrency and its related areas, and a control group that has been extensively studied is necessary for comparison. Cryptocurrencies' returns are considered and tested as having low correlations with traditional investment products like the industry portfolio, market indices, the stock market, gold, and bonds [3][4]. The majority of Bitcoin users treat cryptocurrency less as a medium of exchange but as an asset to be traded with other cryptocurrencies and itself [5]. Other popular research topics are how cryptocurrencies' returns and volatilities are related to each other. An investment asset like cryptocurrency lacks diversification because of the high returns and volatilities spillover effects and high correlations to each other [6]. Studies have also shown that the trading volume of a specific cryptocurrency plays an essential role in predicting the cryptocurrency's returns [7][8]. The above preliminary studies about crypto returns, volatilities, trade volumes, and other aspects of cryptocurrencies were mainly conducted during the period when the web3 and blockchain topics were gaining popularity a few years before 2020. Most early-stage studies use Bitcoin as the main subject for their research, with some studies using Ethereum as a secondary subject for observation and comparison.

As the NFT market and the connected Ethereum gained much attention in 2021, there has been rapid growth in research in such fields. The study on NFT's rapidly growing markets and its fluctuation in pricing show an overall steady increase in value and are currently in a market inefficient stage [9]. Academia also shows interest in the financial correlation between NFT prices and the prices of cryptocurrencies. Major cryptocurrencies' lagged returns, especially Bitcoin and Ether, have shown some impact on the Decentraland LAND Token market, a secondary NFT market, but the price volatility connectedness between NFT and cryptocurrencies remains negligible [10]. A more detailed study on the financial connections between NFT and Ethereum finds interesting results: the return spillover effects from Ethereum to NFTs are more significant, and the price volatility spillover effects from Bitcoin to NFTs have shown to be more dominant, indicating that NFTs cannot be counted as an asset class that is separated from the Ethereum blockchain that they are traded in [11]. However, a study on whether NFTs can act as a safe haven for Cryptocurrency price and volatility fluctuations shows that during the Covid-19 and Russia-Ukraine war period, NFTs could act as a

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diversification investment in a portfolio to hedge against the risk of Ethereum fluctuations in the short term to the mid-term time period [12]. The financial aspects of NFTs and Ethereum are heavily studied and yield interesting and different results. However, a knowledge gap appears in connecting the financial aspects of the NFTs and Ether to user behavior.

Aside from the studies on the pricing, returns, and volatilities of the Crypto and NFT markets, researchers also conduct studies on the user sentiments towards the Crypto and NFT markets. One study indicated that investors had shown the opposite behavior toward investing in Bitcoins as opposed to investing in traditional financial products: they tend to enter the market and buy in Bitcoin when Bitcoin's prices are exceptionally high and tend to not enter the market when Bitcoin prices are low, making lots of crypto investors losing money during the process [13]. People are still adjusting and familiarizing themselves with the all of sudden popular notions of Web3, NFTs, and metaverse [14]. The study conducted by Tuba and others on user sentiments on NFTs showed that monetary value is only one of the factors that impact user buying, holding, and liking of NFTs, and other factors include the uniqueness of NFTs, the artistic value, the technology newness, or simply because the idea of NFT is fun [15].

In spite of the burgeoning academic interest in Ethereum, Non-Fungible Tokens (NFTs), and their consequential implications on the digital economy, there remains a notable knowledge gap. Specifically, empirical investigations assessing the correlation between Ether's price dynamics and user behavior concerning NFTs traded on the Ethereum blockchain are limited. Given the increasing prominence of NFTs and the extensive utilization of Ether as a medium of exchange in these transactions, understanding this relationship could yield significant insights. Such a study would illuminate the behavioral nuances of participants in the NFT market and the potential influence of Ether's price volatility on these behaviors. Furthermore, it could offer a more granular understanding of the underlying mechanisms that drive the digital asset market. Closing this knowledge gap has significant academic worth and provides crucial insights that can be useful in policy-making, investment strategies, and developing blockchain technology.

3. Methodology

3.1. Data

This study employs a mixed-methods approach to investigate the relationship between the daily price fluctuations of Ether and the user trading activities of Non-Fungible Tokens (NFTs). For the former, we sourced a comprehensive dataset from the open-source platform Dune Analytics. This dataset provides daily price tracking data for Ether. R will be used to calculate the rolling volatilities of the Ether daily price.

To understand NFT trading activities, we utilized data from CryptoSlam, an open-source data aggregator known for its reliable and comprehensive data on NFT sales and transactions. CryptoSlam provides a broad array of metrics, including sales volume, user metrics, and top-selling NFT projects, enabling a robust examination of NFT trading behavior. NFT data on the unique buyers, unique sellers, and sales (USD) that occur on the Ethereum blockchain will be utilized as three variables for the regression analysis. All data will have a starting date of 2021-01-01 and an ending date of 2023-06-30.

Figure 1 displays the daily tracking of key variables used for this study. A few key macroeconomic trends could be identified from the graph that impacted the price of Ethereum as well as the trading activities of NFT. After the price of Ethereum reached a peak of over $4,000, the price of the token gradually went down as consumer confidence dwindled in the market and the crypto market cooled. This trend is less evident for NFT trading activities but still noticeable. The most rapid drops in

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Ethereum daily price and NFT sales volume occurred around June 2022, which is now recognized as the “June Crypto Crash” by the broader market.

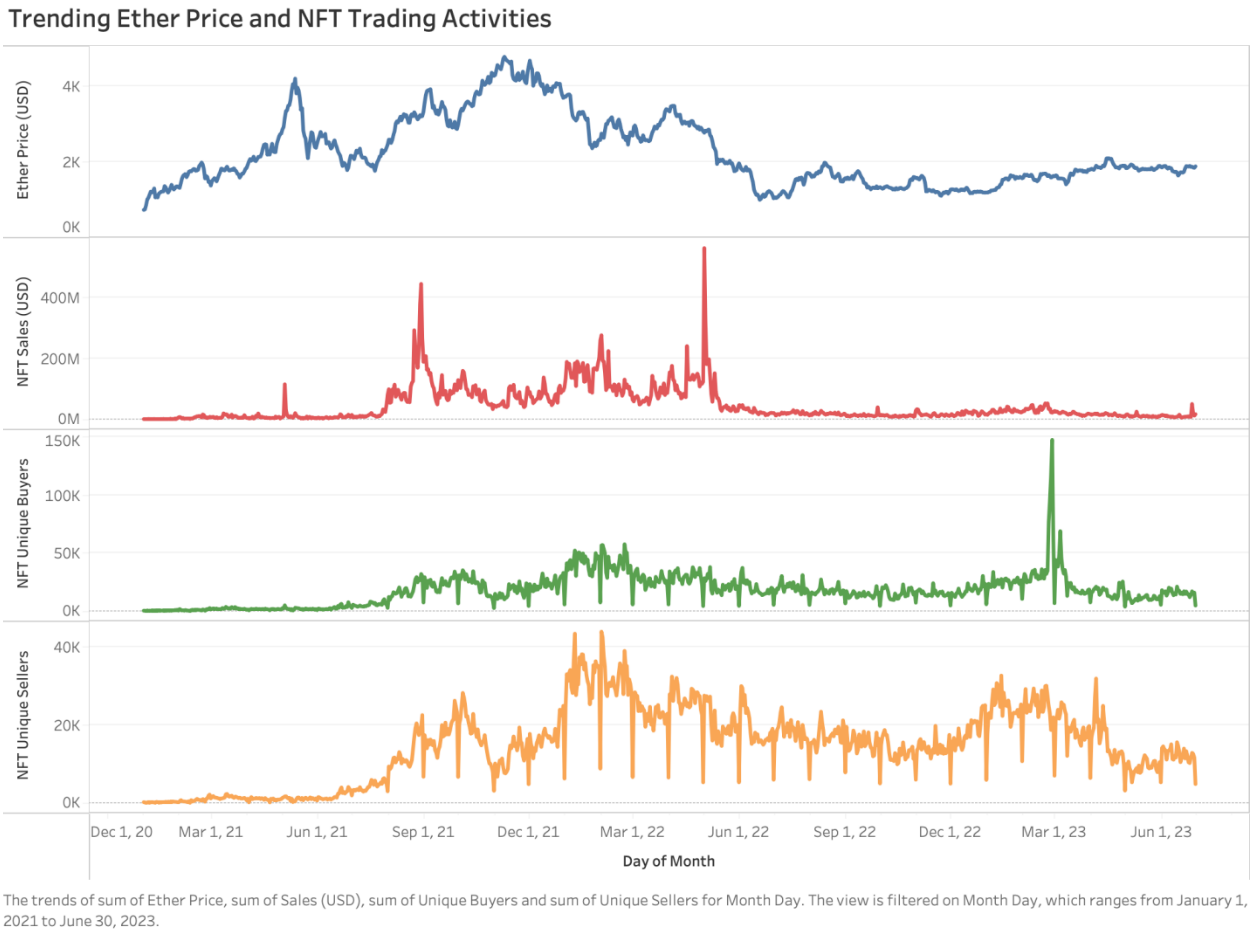

Figure 1: Trending line graph for Ethereum price, NFT sales, unique buyers, and unique sellers.

3.2. Method

The insights gleaned from Figure 1 provide valuable visual cues on the broader market trends of Ethereum price and NFT trading activities. As we observe the patterns and fluctuations in the graph, it becomes evident that there exists a complex interplay between the price movements of Ethereum and the trading volumes of NFTs. However, a more rigorous approach is required to delve deeper into understanding the underlying dynamics and statistical significance of these relationships.

This leads us to employ a robust statistical framework, comprising regression analysis and t-tests. By employing regression analysis, we seek to quantify the extent to which changes in Ethereum's price and its volatility impact the trading activities of NFTs. Additionally, we use t-tests to examine whether distinct periods of high and low Ethereum price and high and low volatility significantly influence NFT trading activity. By transitioning from the visual insights of Figure 1 to a statistical approach, we aim to unveil nuanced insights and establish empirical evidence that will contribute to a comprehensive understanding of the intricate relationship between Ethereum price, its volatility, and the vibrant world of Non-Fungible Tokens trading.

4. Results

First, Table 1 provides descriptive statistics on the data used for this study.

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Table 1: Descriptive statistics on the data.

Variable	Obs	Mean	Std. dev.	Min	Max
sales	911	4.44e+07	5.61e+07	179932.8	5.62e+08
unique_sel~r	911	14760.38	9519.556	248	43985
unique_buyer	911	17700.24	13425.98	272	147353
ave_sale	911	1144.773	1047.151	82.86	10328.02
ether_price	911	2252.273	929.4656	737.1415	4794.948
ether_sd	911	.0311451	.0172675	.0022433	.1126874

Table 1 reports the statistics of the relevant variable's mean, standard deviation, minimum, and maximum values. The first four rows depict the sales, unique sellers, unique buyers, and average sales of NFT daily, while the last two rows show the daily price and the rolling volatilities of the Ethereum token, respectively.

In recognition of the fact that the price change and the price volatility could both have a substantial correlation to the NFT trading activities with the assumptions that investors tend to react to both the price of an underlying cryptocurrency and the degree of volatility of the underlying cryptocurrency when trading NFT assets, the multiple regression analysis will have Ethereum price (ether_price) and Ethereum rolling volatility (ether_sd). To ensure uniformity in the units of measurement, we took the natural logarithm of the dependent variables sales, unique seller, unique buyer, and average daily sales. In summary, the regression equations are:

$$ln\_sales = \beta 0 + \beta 1 \text{ ether\_price} + \beta 2 \text{ ether\_sd} \tag{1}$$

$$ln\_seller = \beta 0 + \beta 1 \text{ ether\_price} + \beta 2 \text{ ether\_sd} \tag{2}$$

$$ln\_buyer = \beta 0 + \beta 1 \text{ ether\_price} + \beta 2 \text{ ether\_sd} \tag{3}$$

$$ln\_ave\_sale = \beta 0 + \beta 1 \text{ ether\_price} + \beta 2 \text{ ether\_sd} \tag{4}$$

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Table 2: Regression analysis of Ether price and volatility contribution on NFT trading activities.

Equation	Obs	Parms	RMSE	"R-sq"	F	P>F
ln_sales	911	3	1.023042	0.4156	322.9181	0.0000
ln_seller	911	3	1.110516	0.1596	86.21146	0.0000
ln_buyer	911	3	1.042074	0.1777	98.11674	0.0000
ln_ave_sale	911	3	.61045	0.5090	470.7323	0.0000

	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
ln_sales						
ether_price	.0008309	.0000365	22.76	0.000	.0007592	.0009026
ether_sd	-20.66613	1.965173	-10.52	0.000	-24.52294	-16.80932
_cons	15.65575	.1095608	142.90	0.000	15.44073	15.87077
ln_seller						
ether_price	.0001613	.0000396	4.07	0.000	.0000835	.000239
ether_sd	-26.31693	2.133203	-12.34	0.000	-30.50351	-22.13035
_cons	9.613721	.1189286	80.84	0.000	9.380314	9.847128
ln_buyer						
ether_price	.0002315	.0000372	6.23	0.000	.0001585	.0003045
ether_sd	-24.67474	2.001732	-12.33	0.000	-28.6033	-20.74618
_cons	9.595708	.111599	85.98	0.000	9.376686	9.81473
ln_ave_sale						
ether_price	.0006598	.0000218	30.29	0.000	.0006171	.0007026
ether_sd	6.977114	1.17262	5.95	0.000	4.675753	9.278475
_cons	4.976417	.065375	76.12	0.000	4.848113	5.104721

Table 2 displays the regression results and the estimated coefficients. In general, the regression findings indicate that there are significant positive correlations between the price of Ethereum and the variables that denote NFT trading activities. For a unit increase in the Ethereum price, the sales volume, unique sellers, unique buyers, and the average sales of NFTs ($\beta 1 > 0$, $p = 0.00$) will increase by 0.083%, 0.016%, 0.023%, 0.065%, respectively. On the other hand, the relationship between Ethereum price volatility and the NFT trading activities appears significantly negative except for Ethereum price volatility's effect on NFT average sales. This indicates that NFT investors react very strongly towards the volatility of the Ethereum price when making decisions to trade NFT. However, the opposite observation is derived for the Ethereum price volatility effect on NFT average sales amount. This can be further investigated with a t-test.

Building upon the regression analysis results presented in Table 1, we now turn our attention to the t-test analysis to further investigate the impact of distinct periods of high and low Ethereum price, as well as high and low Ethereum volatility, on NFT trading activities. By applying t-tests, we seek to explore whether these different market conditions significantly influence the variables denoting NFT trading activities. Specifically, we aim to compare the mean values of sales volume, unique sellers, unique buyers, and NFT average sales during periods of "high price" and "low price", as well as during periods of "high volatility" and "low volatility."

The t-test results presented in Appendix 1, Tables 3.1, 3.2, 4.1, 4.2, 5.1, 5.2, 6.1, and 6.2 provide valuable insights into the impact of both high and low Ethereum price and high and low Ethereum volatility on various NFT trading activities. Based on the t values and p values of the T-Tests, all NFT trading activities' differences between high and low Ethereum prices and high and low Ethereum price volatilities are significant ($p = 0.00$), with an exception for the difference in mean average NFT sales during high and low Ethereum price volatilities ($t = -0.425$, $p = 0.67$). Some key findings are revealed by the T-tests.

During periods of high Ethereum price (group 1), there are substantial increases in sales volume, unique sellers, unique buyers, and average sales for NFT. This corresponds to the regression analysis where all coefficients for Ethereum price (ether_price) are positive, indicating a positive relationship between Ethereum price and NFT trading activeness. During periods of high Ethereum price volatilities (group 1), there are substantial decreases in sales volume, unique sellers and unique buyers for NFT. This also corresponds to the regression analysis where all coefficients for Ethereum price volatility (ether_sd) are negative, indicating a negative relationship between Ethereum price volatility and NFT trading activeness.

5. Discussion

The empirical analysis aimed to explore the relationship between the price and price volatility of Ethereum's native token Ether and the activities of users in the Non-Fungible Tokens (NFT) market. The regression analysis revealed significant positive correlations between the price of Ethereum and various NFT trading activities, including sales volume, unique sellers, unique buyers, and average sales of NFTs. Conversely, the relationship between Ethereum price volatility and NFT trading activities showed significant negative associations. NFT investors demonstrated strong sensitivity to the volatility of the Ethereum price when making trading decisions. Notably, there was an interesting observation that Ethereum price volatility did not significantly impact NFT average sales amount, warranting further investigation. Figures must appear inside the designated margins.

The t-test analysis further examined the impact of distinct periods of high and low Ethereum price and volatility on NFT trading activities. The t-test results confirmed the significance of differences in NFT trading activities between high and low Ethereum prices and high and low Ethereum price volatilities, except for the mean average NFT sales during high and low Ethereum price volatilities. This finding connects interestingly with Dowling's finding that the price volatility of cryptocurrencies and the price of NFT have a neglectable connection (2022). In this study, the volatility of a specific type of cryptocurrency, Ethereum, impacts another factor of NFT, which is the trading activity.

The findings of this study directly address the research question by shedding light on the relationship between Ethereum's price, price volatility, and the trading activities in the NFT market on the Ethereum blockchain. These empirical findings provide strong evidence of the interconnectedness between Ethereum's dynamics and the vibrant NFT market, offering valuable insights for investors, traders, and policymakers seeking to navigate the rapidly evolving landscape of blockchain-based assets and decentralized markets.

Currently, there are no published studies on the relationship between Ether prices and NFT trading activeness. The findings of this study hold significant implications for both researchers and stakeholders in the NFT market. The price of Ethereum and NFT trading activities are connected, suggesting that Ethereum's price fluctuations influence market participants' behaviors. Therefore, investors and traders should keep a close eye on the movements of Ethereum's price, as it can serve as an indicator of heightened trading activity within the NFT market. On the other hand, the negative relationship between Ethereum price volatility and NFT trading activities suggests that heightened

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price volatility may lead to reduced trading activities, potentially due to increased market uncertainties and risk aversion among investors. Understanding this relationship can help NFT market participants strategize their trading decisions during periods of price instability.

The NFT market is influenced by Ethereum's dynamics and by broader market sentiment and external events. Market sentiment, investor psychology, and media coverage can significantly impact NFT trading behaviors. Furthermore, significant events such as regulatory changes, technological advancements, or major cryptocurrency market movements may drive shifts in NFT trading activities independently of Ethereum's price and volatility.

6. Conclusion

To summarize, the primary aim of this research was to investigate the relationship between the price of the Ethereum token and Non-Fungible Token (NFT) trading activities on the Ethereum blockchain. To achieve this, the study employed regression analysis and t-tests to explore how changes in Ethereum's price and price volatility influence NFT trading behaviors.

The key findings of the research provided valuable insights into the dynamics of the NFT market in relation to Ethereum's price and volatility. The regression analysis revealed significant positive correlations between Ethereum's price and various NFT trading variables, indicating that an increase in Ethereum's price positively impacts sales volume, unique sellers, unique buyers, and average sales of NFTs. Conversely, Ethereum's price volatility demonstrated significant negative associations with NFT trading activities, suggesting that market uncertainty and risk aversion influence investors' decisions.

These findings are directly relevant to the research question and objectives of this study, as they shed light on the interplay between Ethereum's dynamics and NFT trading activities. The results underscore the importance of Ethereum's price as a driver of NFT market activeness, while also highlighting the impact of price volatility on investor behaviors. This knowledge can be valuable for practitioners, investors, and traders in the NFT market, as it can inform decision-making strategies and provide insights into market trends.

Despite the valuable findings, this study has several limitations that should be acknowledged. The regression analysis identified correlations between Ethereum's dynamics and NFT trading activities. However, as with any observational study, causation cannot be definitively established, and other unobserved factors might drive these relationships. Secondly, the analysis might be subject to selection bias, as the data may include only specific NFT projects, platforms, or user groups. Different NFT ecosystems may have varying sensitivities to Ethereum's dynamics. For example, the behavior of NFT users may be influenced by blockchain and platform-specific features and user engagement strategies. Although this paper mainly focused on the NFT trading activities that happened in the Ethereum blockchain, other blockchains, such as Solana and Polygon, may attract distinct user communities with varying preferences and objectives, leading to differences in trading activities. Future studies can build upon this research by adopting a longitudinal approach, including additional control variables, and conducting qualitative research to gain deeper insights into user perspectives. Exploring the impact of external events and cross-currency comparisons could also enhance understanding of the dynamic NFT market.

The implications of this research extend to various stakeholders in the NFT ecosystem. Investors and traders can leverage the knowledge gained to make informed decisions and navigate the evolving market landscape. Policymakers can utilize these insights to implement measures that promote market stability and growth. Furthermore, future researchers can build upon this study's findings by addressing the identified limitations and exploring other dimensions of the relationship between the Ethereum's price and NFT trading activities.

In conclusion, this research contributes valuable empirical evidence to the understanding of the relationship between Ethereum's price and NFT trading activities. The findings provide critical guidance for stakeholders and offer another step for further exploration in the dynamic world of blockchain-based assets and decentralized markets. As the NFT market continues to evolve, ongoing research in this area will play a vital role in shaping the future of this emerging and transformative space.

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Appendix

Table 3.1: T-Test Results for Sales by High Ethereum Price.

Two-sample t test with equal variances

Group	Obs	Mean	Std. err.	Std. dev.	[95% conf.	interval]
0	557	1.59e+07	447802.8	1.06e+07	1.50e+07	1.68e+07
1	354	8.93e+07	3611662	6.80e+07	8.22e+07	9.64e+07
Combined	911	4.44e+07	1857045	5.61e+07	4.08e+07	4.81e+07
diff		-7.34e+07	2932672		-7.92e+07	-6.77e+07

diff = mean(0) - mean(1) t = -25.0362
H0: diff = 0 Degrees of freedom = 909

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
Pr(T < t) = 0.0000 Pr(|T| > |t|) = 0.0000 Pr(T > t) = 1.0000

Notes: Group 1 denotes higher average Ethereum prices, Group 2 denotes lower than average Ethereum price.

Table 3.2: T-Test Results for Sales by High Ethereum Volatility.

Two-sample t test with equal variances

Group	Obs	Mean	Std. err.	Std. dev.	[95% conf.	interval]
0	547	4.88e+07	2611459	6.11e+07	4.36e+07	5.39e+07
1	364	3.79e+07	2454731	4.68e+07	3.30e+07	4.27e+07
Combined	911	4.44e+07	1857045	5.61e+07	4.08e+07	4.81e+07
diff		1.09e+07	3776196		3486863	1.83e+07

diff = mean(0) - mean(1) t = 2.8860
H0: diff = 0 Degrees of freedom = 909

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
Pr(T < t) = 0.9980 Pr(|T| > |t|) = 0.0040 Pr(T > t) = 0.0020

Notes: Group 1 denotes higher average Ethereum volatility, Group 2 denotes lower than average Ethereum volatility.

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Table 4.1: T-Test Results for Unique Sellers by High Ethereum Price.

Two-sample t test with equal variances

Group	Obs	Mean	Std. err.	Std. dev.	[95% conf.	interval]
0	557	13153.61	347.5483	8202.435	12470.95	13836.28
1	354	17288.55	575.2931	10824.07	16157.11	18419.98
Combined	911	14760.38	315.397	9519.556	14141.39	15379.37
diff		-4134.931	632.7259		-5376.705	-2893.158

diff = mean(0) - mean(1) t = -6.5351

H0: diff = 0 Degrees of freedom = 909

Ha: diff < 0	Ha: diff != 0	Ha: diff > 0
Pr(T < t) = 0.0000	Pr(|T| > |t|) = 0.0000	Pr(T > t) = 1.0000

Notes: Group 1 denotes higher average Ethereum prices, Group 2 denotes lower than average Ethereum price.

Table 4.2: T-Test Results for Unique Sellers by High Ethereum Volatility.

Two-sample t test with equal variances

Group	Obs	Mean	Std. err.	Std. dev.	[95% conf.	interval]
0	547	16277.82	363.9973	8513.179	15562.82	16992.83
1	364	12480.05	548.4347	10463.47	11401.54	13558.56
Combined	911	14760.38	315.397	9519.556	14141.39	15379.37
diff		3797.77	631.8397		2557.736	5037.805

diff = mean(0) - mean(1) t = 6.0107

H0: diff = 0 Degrees of freedom = 909

Ha: diff < 0	Ha: diff != 0	Ha: diff > 0
Pr(T < t) = 1.0000	Pr(|T| > |t|) = 0.0000	Pr(T > t) = 0.0000

Notes: Group 1 denotes higher average Ethereum volatility, Group 2 denotes lower than average Ethereum volatility.

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Table 5.1: T-Test Results for Unique Buyers by High Ethereum Price.

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Two-sample t test with equal variances
```

Group	Obs	Mean	Std. err.	Std. dev.	[95% conf.	interval]
0	557	15069.6	536.8273	12669.58	14015.15	16124.06
1	354	21839.42	720.4766	13555.69	20422.45	23256.38
Combined	911	17700.24	444.8225	13425.98	16827.25	18573.24
diff		-6769.812	885.0532		-8506.797	-5032.827

```
    diff = mean(0) - mean(1)                                      t =  -7.6490
H0: diff = 0                                     Degrees of freedom =      909

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 1.0000
```

Notes: Group 1 denotes higher average Ethereum prices, Group 2 denotes lower than average Ethereum price.

Table 5.2: T-Test Results for Unique Buyers by High Ethereum Volatility.

```
Two-sample t test with equal variances
```

Group	Obs	Mean	Std. err.	Std. dev.	[95% conf.	interval]
0	547	19707.35	577.6188	13509.37	18572.73	20841.98
1	364	14684.07	667.4995	12735.08	13371.41	15996.72
Combined	911	17700.24	444.8225	13425.98	16827.25	18573.24
diff		5023.287	893.2505		3270.214	6776.36

```
    diff = mean(0) - mean(1)                                      t =   5.6236
H0: diff = 0                                     Degrees of freedom =      909

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

Notes: Group 1 denotes higher average Ethereum volatility, Group 2 denotes lower than average Ethereum volatility.

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Table 6.1: T-Test Results for Average Sales by High Ethereum Price.

Two-sample t test with equal variances

Group	Obs	Mean	Std. err.	Std. dev.	[95% conf.	interval]
0	557	667.0669	32.41928	765.1224	603.3877	730.7461
1	354	1896.417	52.56199	988.948	1793.043	1999.791
Combined	911	1144.773	34.69366	1047.151	1076.684	1212.861
diff		-1229.35	58.38776		-1343.94	-1114.759

diff = mean(0) - mean(1)　　t = -21.0549

H0: diff = 0　　Degrees of freedom = 909

Ha: diff < 0	Ha: diff != 0	Ha: diff > 0
Pr(T < t) = 0.0000	Pr(|T| > |t|) = 0.0000	Pr(T > t) = 1.0000

Notes: Group 1 denotes higher average Ethereum prices, Group 2 denotes lower than average Ethereum price.

Table 6.2: T-Test Results for Average Sales by High Ethereum Volatility.

Two-sample t test with equal variances

Group	Obs	Mean	Std. err.	Std. dev.	[95% conf.	interval]
0	547	1132.738	48.27651	1129.092	1037.908	1227.568
1	364	1162.858	47.77394	911.4687	1068.909	1256.806
Combined	911	1144.773	34.69366	1047.151	1076.684	1212.861
diff		-30.11966	70.86302		-169.1938	108.9545

diff = mean(0) - mean(1)　　t = -0.4250

H0: diff = 0　　Degrees of freedom = 909

Ha: diff < 0	Ha: diff != 0	Ha: diff > 0
Pr(T < t) = 0.3355	Pr(|T| > |t|) = 0.6709	Pr(T > t) = 0.6645

Notes: Group 1 denotes higher average Ethereum volatility, Group 2 denotes lower than average Ethereum volatility.