Trends and Triggers: Analyzing the Co-Movement of Cryptocurrency and NFT Prices

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Abstract: This paper aims to explore the complex interrelationships between the prices of cryptocurrency, specifically Ethereum (ETH), and five top Non-Fungible Token (NFT) collections: Bored Ape Yacht Club, Mutant Ape Yacht Club, Azuki, Moonbirds, and Otherdeed. Motivated by the intertwining dynamics of these digital assets and the unexplored nature of their interdependencies, this study employs a Vector Autoregressive (VAR) model and utilizes Granger Causality to dissect the multifaceted interactions. The analysis period ranges from April 2021 to January 2023, a critical window of exponential growth and fluctuation in the digital asset market. The results demonstrate a statistically significant impact of ETH prices on NFT collection prices, but not vice versa, revealing the strong dependence of the NFT market on cryptocurrency volatility. Specifically, the research finds that changes in ETH's value are predictive of shifts in NFT prices, whereas NFT price fluctuations lack predictive power for ETH prices. In conclusion, this research represents an advancement in understanding price dynamics in the rapidly evolving digital economy. By innovatively analyzing the co-movement of cryptocurrencies and NFTs, it not only enriches existing knowledge but also paves the way for further exploration, offering practical insights for diverse stakeholders navigating this exciting, ever-changing field.

Keywords: Cryptocurrency, Non-Fungible Token, Price Co-movement, Vector Autogressive Model, Granger Causality

1. Introduction

The rise of cryptocurrencies and non-fungible tokens (NFTs) has garnered significant attention in recent years. These digital assets have redefined the perspective and interaction towards conventional currency and collectible paradigms. In the current digital economy, understanding underlying mechanisms of cryptocurrencies and NFTs is becoming increasingly important. On one hand, cryptocurrencies are digitally or virtually instantiated currencies that leverage cryptographic technologies to ensure secure transactions over a decentralized network, typically referred to as blockchain [1]. Every transaction is recorded in a public ledger through blockchain, thereby fostering transparency, security, and immutability. The inaugural cryptocurrency, Bitcoin, was instituted by an unidentified consortium termed Satoshi Nakamoto in 2009 [2]. Cryptocurrencies provide several advantages, including expedited, secure transactions devoid of intermediaries such as banking institutions or government bodies. Furthermore, cryptocurrencies enable financial inclusion by granting individuals with internet connectivity the opportunity to engage in global financial

transactions [3]. However, challenges including scalability dilemmas and the energy expenditure associated with cryptocurrency mining still persist when popularizing the prevalence of cryptocurrency.

On the other hand, Non-Fungible Tokens (NFTs) are unique digital assets that are non-interchangeable due to their inherent distinctive attributes [4]. In contrast to cryptocurrencies, which can be segmented into smaller units like cents or satoshis, NFTs signify ownership rights over a particular item or content. NFTs are also fabricated leveraging blockchain technology; they can be acquired, sold, and exchanged on a variety of platforms utilizing smart contracts of Ethereum [5]. In addition, the creator of NFTs stands to receive royalties at each instance of a successful transaction, whether through an NFT market or by direct peer-to-peer exchange. Although fundamentally constituted by mere code, the value ascribed to NFTs by a buyer stems from the relative scarcity of the digital object they represent. This perspective amplifies the perceived security of selling prices for IP-related products, creating a valuation paradigm that previously may have seemed inconceivable for non-fungible virtual assets.

Both cryptocurrencies and NFTs have attracted substantial interest owing to multiple factors. Firstly, the decentralized nature of cryptocurrencies appeals to those seeking financial sovereignty, free from the constraints of traditional financial institutions [3]. Recent advances such as increased institutional adoption and the formulation of regulatory frameworks are facilitating widespread acceptance. Cryptocurrencies have significantly restructured global financial transactions by enabling secure peer-to-peer transactions devoid of intermediaries [1]. This has the potential to transform traditional banking and remittance services while advocating financial inclusion for unbanked populations worldwide.

Secondly, the influence of NFTs transcends beyond finance into various industries such as art, music, gaming, and beyond. Artists can now appeal to a global audience without solely relying on physical galleries or record labels. Moreover, NFTs provide verifiable proof of authenticity and provenance for digital artworks or collectibles [6]. A surge in popularity of NFTs among artists, musicians, and content creators, who can now directly monetize their digital creations via tokenized ownership, has been observed [4]. The distinctness of each token imparts value to NFTs within sectors such as art, music, and gaming, with notable transactions including the sale of Beeple's artwork "Everydays: The First 5000 Days" for $69 million [7]. Furthermore, notable endeavors such as NBA Top Shot, which enables fans to possess unique basketball highlight clips as NFTs, have further enhanced interest in these digital assets [8].

However, the relationship between cryptocurrency prices and the value of NFT objects presents an intriguing area for exploration. Price fluctuations in cryptocurrencies may affect the demand for NFTs as investors seek alternative investments during periods of market volatility [9]. When cryptocurrency prices witness a surge, individuals may seek to diversify their portfolio by investing in NFTs or vice versa when cryptocurrency prices decline. In particular, several crucial factors influence both cryptocurrency prices and the value of NFT objects. Primarily, market sentiment plays an instrumental role in determining investment behavior within these realms. Positive news concerning regulatory developments or innovative applications can enhance investor confidence leading to increased adoption of both cryptocurrencies and NFTs [9]. Secondly, technological advancements such as scalability improvements in blockchain networks can amplify transaction speed and minimize costs associated with trading cryptocurrencies and NFTs, thereby positively impacting their prices [10]. Furthermore, the relationship between cryptocurrency prices and the value of Non-Fungible Token (NFT) assets can be complex, and it is intricately tied to broader economic conditions and variables. The prices of cryptocurrencies can be sensitive to macroeconomic factors, such as economic instability or recession. In periods of economic downturn or significant uncertainty, some investors might turn to cryptocurrencies as a form of safe haven investment. This

behavior is motivated by the perception that cryptocurrencies, by virtue of their decentralized and global nature, can act as a hedge against risks that are inherent to traditional financial markets, including inflation risk, geopolitical risk, and even systemic risk in extreme cases [11]. In this context, a safe haven asset is one that is expected to retain or increase in value during times of market turbulence. When investors perceive an increased risk in traditional markets, the demand for such safe haven assets often rises, leading to an increase in their prices. Therefore, during periods of economic instability or recession, we might see a surge in the demand for cryptocurrencies, leading to a rise in their prices.

In this paper, we aim to investigate the relationship and concurrent movement between cryptocurrency prices and NFT objects for a thorough understanding of these digital assets. Given that cryptocurrencies have revolutionized financial systems while NFTs have unveiled new pathways for ownership and provenance in the digital domain, price fluctuations in cryptocurrencies may influence the demand for NFTs owing to investor behavior during market volatility. The value of NFTs might be impacted indirectly by changes in cryptocurrency prices. For example, when cryptocurrency prices rise significantly, cryptocurrency owners experience an increase in their wealth (on paper, at least). Some of these owners might choose to diversify their portfolio by investing in other types of digital assets, such as NFTs, thereby driving up demand and prices for NFTs. Conversely, when cryptocurrency prices fall, investors may seek to liquidate their NFT holdings in order to cover losses or to invest in cryptocurrencies that they perceive as undervalued. This could potentially put downward pressure on NFT prices. It is also possible that a decline in cryptocurrency prices might reduce the purchasing power or investment capacity of prospective NFT buyers, especially if they primarily hold cryptocurrencies. This could, in turn, lead to decreased demand and lower prices for NFTs. Furthermore, changes in NFT values could also have an impact on cryptocurrency prices. If NFTs become highly desirable and attract significant interest from investors, there could be an increased demand for cryptocurrencies that are commonly used to buy and sell NFTs. For instance, if a particular type of NFT that is bought and sold using Ethereum becomes very popular, the demand for Ethereum could rise, leading to an increase in its price.

As such, we leverage the full price history of five top NFT collection categories by sales [12]: Azuki, Bored Ape Yacht Club, Moonbirds, Mutant Ape Yacht Club, and Otherdeed and identify their comovement patterns with the cryptocurrency Ethereum for its prevalent acceptance in NFT transactions. We construct the multivariate time series of prices of NFT collections and Ethereum (ETH) and employ the Vector Autoregressive (VAR) model and Granger Causality to explore their cross-correlations. The results show that ETH price has statistically significant impact on prices of NFT collections but not vice versa, implying the strong dependence of NFT market on the volatility of cryptocurrency.

Overall, this paper sets out to explore the uncharted waters of the co-movement of cryptocurrency and NFT prices, motivated by the need to understand these novel and complex relationships. The introduction of the VAR model and Granger Causality serves as a sophisticated tool capable of capturing the multifaceted dynamics of these digital assets. By bridging the gap between traditional financial modeling and the unique characteristics of digital economy, this research promises to shed new light on a rapidly evolving area, enriching the existing body of knowledge and paving the way for future studies in this exciting and ever-changing field.

2. Literature Review

The emergence of cryptocurrencies and Non-Fungible Tokens (NFTs) has sparked a wealth of research exploring various aspects of these novel digital assets. This literature review aims to provide a comprehensive overview of the existing body of knowledge on cryptocurrency market dynamics,

NFT market trends, the co-movement of financial assets, and the use of Vector Autoregressive (VAR) and Granger Causality models in financial research.

2.1. Cryptocurrency Market Dynamics

The dynamics of cryptocurrency markets [13] have been a topic of intense research interest. [2] introduced Bitcoin, the first cryptocurrency, as a decentralized peer-to-peer payment system. Since then, thousands of cryptocurrencies have been launched, with Ethereum (ETH) being one of the most prominent due to its smart contract functionality [14]. The price dynamics of cryptocurrencies have been found to be influenced by a variety of factors. [15] argued that the fundamental value of Bitcoin is zero, suggesting that its price is driven by speculative demand [16]. found that cryptocurrencies exhibit unique volatility dynamics, with sudden and extreme price changes being common. [17] found that cryptocurrency returns are influenced by global economic factors, investor attention, and regulatory news. [18] proposes the presence of herding behavior in the cryptocurrency market, tends to occur as uncertainty increases.

2.2. NFT Market Trends

The NFT market, while newer than the cryptocurrency market, has also attracted significant research attention. NFTs represent a unique asset class that allows for the tokenization of digital and physical assets on the blockchain [5]. Research on the NFT market is still in its infancy, but early studies have focused on understanding the factors driving NFT prices and the dynamics of the NFT market. For instance, [19, 20] report the relationships between Bitcoin and cryptocurrency and point out that Ether price shocks reduce the number of active NFT wallets. It has been found that the rarity and historical significance of an NFT, as well as the reputation of the creator, significantly influence its price. The NFT market has seen explosive growth, with sales[1] reaching billions of dollars in 2021. The value of NFTs has been found to be influenced by a variety of factors, including the reputation of the creator, the uniqueness of the asset, and the overall sentiment in the cryptocurrency market [21]. However, the NFT market is also characterized by high volatility and speculation, with significant price fluctuations being common [22].

2.3. Co-Movement of Financial Assets

The co-movement of financial assets is a well-studied phenomenon in the financial literature. [23] showed that financial asset prices often move together due to shared economic factors, investor sentiment, and market contagion effects. [24] found that correlations between asset prices increase during periods of market turbulence. The relationship between cryptocurrency and traditional financial assets has also been explored. [25] found that cryptocurrencies can provide diversification benefits due to their low correlation with traditional asset classes. However, [26] examined the financial asset capabilities of bitcoin and explored the financial properties of Bitcoin, finding that it shares characteristics with both gold and the dollar, acting as a medium of exchange and a store of value. [27] found that Bitcoin exhibits some characteristics of a traditional financial asset, behaving like gold in terms of hedging capabilities. Several studies have investigated the co-movement of cryptocurrencies with other financial assets. In a study by Liu [28], it was found that during periods of market stress, cryptocurrencies tend to exhibit higher co-movement with traditional asset classes, reducing their effectiveness as a diversification tool.

In particular, mixed evidences have been reported regarding the co-movement between NFTs and cryptocurrencies reflecting the market's recent emergence. [20] investigates the intersection between

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[1] https://www.nonfungible.com/

cryptocurrency and NFT market participants in year 2021. The study's findings underscore the existing complexity associated with purchasing NFTs using cryptocurrencies and highlight limited spillover between cryptocurrencies and NFT markets. These findings were echoed by a study conducted by the Blockchain Research Lab in June of the same year [29]. Their research posits that a decline in cryptocurrency value can depress the NFT market, while an appreciation might encourage investors to explore NFTs, particularly in the context of ETH, the common denomination for NFTs.

It is crucial to note, however, that both of these studies were published prior to the significant expansion of the NFT market in the latter half of 2021. Recent data suggests that the correlation between cryptocurrencies and NFTs may be more nuanced, necessitating further research and analysis to elucidate the dynamic interplay between these digital assets.

2.4. VAR Models and Granger Causality in Financial Time Series Research

The Vector Autoregressive (VAR) model is a popular tool in financial research for studying the dynamic relationships between multiple time series variables. [30] introduced the VAR model as a way to capture the dynamic interdependencies between economic variables without requiring strong theoretical assumptions. VAR models have been used extensively in the analysis of financial markets [31]. For instance, [32] used a VAR model to study the interactions between stock and bond returns. More recently, VAR models have been applied to the cryptocurrency market. For example, [33] used a VAR model to analyze the volatility of Bitcoin. In the literature of time series modeling, many similar techniques are also proposed. For instance, the Autoregressive Integrated Moving Average (ARIMA) model, as described by [34, 35], uses regression on functions of a multivariate variable where the data values have been transformed by differencing them with their preceding values. This transformation is used to address non-stationarity in the data. The autoregressive model has also extended the traditional AR model by incorporating deep learning techniques [36], allowing for the capture of potential non-linear relationships and complex dynamics [37].

Meanwhile, Granger causality is a statistical concept used to determine whether one time series is useful in forecasting another and it has been used extensively in finance research to infer causal relationship among time series within complex financial systems [38]. Some application research include: 1) investigation of risks in financial networks such as financial contagion [39-41]; 2) exploration of role of financial development in driving the economic growth of countries [42, 43], and 3) the inter-relationship between financial instruments [44, 45].

2.5. Summary

In conclusion, while there is a growing body of literature on the dynamics of the cryptocurrency and NFT markets, the relationship between these two markets is still not well understood. The use of VAR models in studying the relationship between cryptocurrency and NFT prices is still a relatively unexplored area. This study aims to contribute to this emerging field by applying a Deep VAR model to analyze the co-movement of ETH and NFT prices. This study aims to fill this gap by providing a comprehensive analysis of the co-movement of cryptocurrency and NFT prices using a Deep VAR model that we propose in this manuscript.

3. Methodology

In this section, we introduce both Vector Autoregressive (VAR) model and Granger Causality method to analyze the relationship between cryptocurrency (ETH) price and NFT prices over time.

3.1. VAR model specification

The VAR model, a multivariate time series model, serves as a critical tool for understanding relationships and predicting patterns within economic and financial time series. Extending the univariate autoregressive (AR) model, the VAR approach treats all variables as endogenous, allowing them to depend on their lagged values as well as the lagged values of other variables in the system.

Formally, a reduced-form bivariate VAR (1) model can be described as

$$y_{1,t}^{(1)} = b_{1,0} - b_{1,2}y_{2,t} + \phi_{1,1}y_{1,t-1} + \phi_{1,2}y_{2,t-1} + \epsilon_{1,t} \tag{1}$$

$$y_{2,t}^{(1)} = b_{2,0} - b_{2,1}y_{1,t} + \phi_{2,1}y_{1,t-1} + \phi_{2,2}y_{2,t-1} + \epsilon_{2,t} \tag{2}$$

where $y_{1,t}$ represents the crypto price at time t, $y_{2,t}$ represents the NFT price at time t, $b_{i,j}$ and $\phi_{i,j}$ are parameters to be estimated, and $\epsilon_{i,t}$ is the error term.

Empirically, the reduced-form VAR (1) calculates the target value at time t

$$y_t = a_0 - A_1 y_{t-1} + u_t. \tag{3}$$

Let us assume that the process is weakly stationary and taking the expectation of y_t, we have

$$E[y_t] = a_0 - A_1 E[y_{t-1}], \tag{4}$$

where $E[u_t] = 0$. If we let $\tilde{y}_t = y_t - \mu$ be the mean-corrected time series, we can write the model as

$$\tilde{y}_t = A_1 \tilde{y}_{t-1} + u_t. \tag{5}$$

Substituting $\tilde{y}_{t-1} = A_1 \tilde{y}_{t-2} + u_{t-1}$, we get

$$\tilde{y}_t = A_1(A_1 \tilde{y}_{t-2} + u_{t-1}) + u_t. \tag{6}$$

If we keep iterating, we eventually get

$$y_t = \mu + \sum_{i=1}^{\infty} A_1^i u_{t-1} + u_t. \tag{7}$$

Letting $\Theta_i = A_1^i$, we get the VMA infinite representation

$$y_t = \mu + \sum_{i=1}^{\infty} \Theta_i u_{t-1} + u_t. \tag{8}$$

where y_t represents the target value at time t. In the context of your study, this could be the price of a cryptocurrency or an NFT at time t. a_0 is a constant term in the model. A_1 is the coefficient of the lagged value of the target variable. It measures the impact of the target value at time $t - 1$ on the target value at time t. u_t represents the error term at time t. It captures the influence of all other factors not included in the model that affect the target value at time t. $E[y_t]$ is the expected value (or mean) of the target variable at time t. $\tilde{y}_t$ is the mean-corrected time series, obtained by subtracting the mean (μ) from the target value at time t. Θ_i is the coefficient of the error term at time $t - i$ in the infinite Vector Moving Average (VMA) representation of the model. It measures the impact of the error term at time $t - i$ on the target value at time t. μ is the mean of the target variable.

We further generalize VAR (p) model to account for the lagged values of crytocurrency and NFT prices from the past p periods as:

$$y_t = a_0 + \sum_j^p \mathbf{A}_j \, y_{t-j} + u_t \tag{9}$$

where $\mathbf{y}_t$ is a $N \times 1$ vector containing N endogenous variables, $\mathbf{a}_0$ is a $N \times 1$ vector of constants, $\mathbf{A}_1, \mathbf{A}_2, \ldots, \mathbf{A}_p$ are the p $N \times N$ matrices of autoregressive coefficients, and $\mathbf{u}_t$ is a $N \times 1$ vector of white noise disturbances.

3.2. Granger Causality

Granger Causality is a statistical concept used to investigate causal relationships between time series. This methodology relies on lagged values of time series data to ascertain whether past values of one variable can be utilized to predict future values of another. Essentially, if a variable Y is causally affecting X, then past values of Y should contain information that helps predict X beyond the information contained in past values of X alone.

Formally, given a stationary stochastic process A_t, let $\overline{A}_t$ denote the set of past values A_{t-j}, $j = 1, 2, \ldots, \infty$, and $\overline{\overline{A}}_t$ represent the set of past and present values A_{t-j}, $j = 0, 1, \ldots, \infty$. Further, let $\overline{A}(k)$ represent the set A_{t-j}, $j = k, k+1, \ldots, \infty$. Given U_t as all the information in the universe gathered since time $t - 1$, $U_t - Y_t$ represents all this information excluding the specified series Y_t, a stationary time series distinct from X_t.

We can define Granger Causality through the following relationship: $\sigma^2(X|U) < \sigma^2\left(X|\overline{U-Y}\right)$ Under this condition, we affirm that Y is causing X, symbolized by $Y_t \Rightarrow X_t$. This means that Y_t "Granger-causes" X_t if X_t is better predicted using all accessible information than when the information excluding Y_t is utilized. Similarly, if $\sigma^2(Y|U) < \sigma^2\left(Y|\overline{U-Y}\right)$, we affirm a feedback causality, i.e., X is causing Y, which is denoted by $Y_t \Leftrightarrow X_t$. Additionally, if $Y_t \Rightarrow X_t$, we define the (integer) causality lag m to be the least value of k such that $\sigma^2\left(X|U - Y(k)\right) < \sigma^2\left(X|U - Y(k+1)\right)$. This implies that the knowledge of values Y_{t-j}, $j = 0, 1, \ldots, m-1$ doesn't enhance the prediction of X_t.

4. Results

4.1. Data Description

I collected the historical NFT prices from Desights NFT Price Analysis competitior [2], which is a data challenge that involves data scientists, analysts, and NFT enthusiasts to develop data analytics reports and machine learning models that can assist in forecasting the floor price of NFTs. It contains 37 dimensions of features for five major NFT collections: Bored Ape Yacht Club, Mutant Ape Yacht Club, Azuki, Moonbirds, and Otherdeed spanning from April 2021 to March 2023. According to [12], these five collections together represent the top 5 NFT categories in terms of sales volume in year 2022, reaching $5.26 billion in total. We also merge this time series data with the ETH prices at daily level. Some important features used are listed below, from which we use the evolutions of NFT and ETH prices through time only. Therefore, other variables such as quantity are not used.

- **indexer_id**: Unique identifier for the NFT sale or collection.
- **__confirmed**: Flag indicating whether the transfer has been confirmed.
- **timestamp**: The timestamp of the NFT sale (in ISO-8601 format).
- **aggregator_name**: The name of the aggregator used in the NFT sale (null if no aggregator was used).

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[2] https://desights.ai/shared/challenge/6?utm_source=nft&utm_medium=nft&utm_campaign=nft

- **token_id**: The token ID of the NFT that was sold or the NFT.
- **is_multi_token_sale**: Whether the sale is a multi-token sale, including more than one unique NFT for the given payment.
- **multi_token_sale_index**: The index of the sale within the multi-token sale (will be 0 if not a multi-token sale).
- **price**: The total value of this sale in the payment token (in Wei).
- **usd_price**: The total value of this sale in USD.
- **eth_price**: The total value of this sale in ETH.
- **native_price**: The total value of this sale in the native token (ETH).
- **quantity**: The quantity of tokens sold (will only be greater than 1 for ERC-1155 NFTs).
- **royalty_fee**: The decimal-adjusted royalty fee paid to the creator of the NFT.
- **platform_fee**: The decimal-adjusted platform fee paid to the exchange that facilitated the NFT sale.
- **minted_timestamp**: The NFT's mint timestamp (in ISO-8601 format) or the collection's timestamp of creation.
- **supply**: The NFT's supply (0 if NFT has been burned)

4.2. Stationarity Check

Before applying the VAR model, it is crucial to ensure that the time series data is stationary. A stationary time series is one whose statistical properties such as mean, variance, and autocorrelation are all constant over time. Most statistical forecasting methods are designed to work on a stationary time series. The reason being, a stationary series is relatively easy to predict as it reverts to the mean, and variations around the mean have a constant amplitude and a constant frequency. Non-stationary series, on the other hand, are unpredictable as they are affected by the randomness of the root cause, making them difficult to model. They can have trends, varying variances, or even cyclic behavior.

To check for stationarity, we use unit root tests such as the Augmented Dickey-Fuller (ADF) test, which is a type of statistical test called a unit root test. The intuition behind a unit root test is that it determines how strongly a time series is defined by a trend. It uses an autoregressive model and optimizes an information criterion across multiple different lag values. The null hypothesis of the test is that the time series can be represented by a unit root, that it is not stationary (has some time-dependent structure). The alternate hypothesis (rejecting the null hypothesis) is that the time series is stationary. After the stationary checking, we apply differencing as a method of transforming a time series dataset to remove the temporal dependence of the dataset, such as trends and seasonality.

A differenced series is the change between consecutive observations in the original time series, and can be written as:

$$\Delta y_t = y_t - y_{t-1} \tag{10}$$

where Δy_t is the differenced series, y_t is the original series at time t, and y_{t-1} is the original series at time $t-1$. In some cases, the first difference is not enough to make the series stationary, and we may need to take the second difference, or even higher orders of difference. The second difference is simply the difference of the first difference series, and can be written as:

$$\Delta^2 y_t = \Delta y_t - \Delta y_{t-1} \tag{11}$$

where $\Delta^2 y_t$ is the second differenced series, and Δy_t and Δy_{t-1} are the first differenced series at time t and $t-1$, respectively. After differencing, we should check for stationarity again. As the resultant differenced series is stationary, we proceed with fitting the VAR model.

4.3. Explorative Data Analysis

First, we investigate the price evolution of ETH along with five NFT collections, as depicted in Figure 1. This illustration encompasses the mean price data between April 2021 and April 2023. Notably, BoredApeYachtClub stands out as the predominant contributor to the monthly mean price. Upon examination, correlations are evident among the ETH prices of the different collections, with all of them reaching a peak around March 2022 before subsequently declining. Given that BoredApeYachtClub starts from April 2021 and the other NFT collections start later, we obtain a right-censored data.
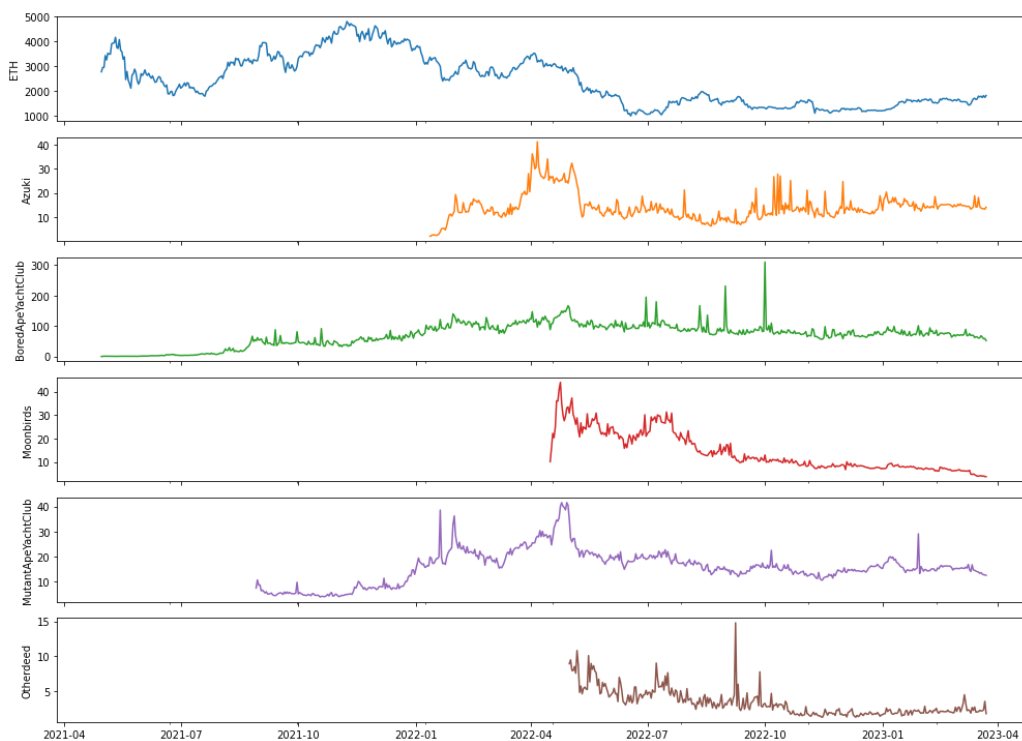

Figure 1: Time series of prices of ETH and five NFT collections (Azuki, BoredApeYachtClub, Moonbirds, MutantApeYachtClub, Otherdeed.

Second, se run the stationary check on the data using Augmented Dickey-Fuller Test (ADF Test), which is commonly used to test for a unit root in a univariate process in the presence of serial correlation. Figure 2 shows the test statistics and p-values for each asset. The interpretation of the results are shown in the following. Some time series are not stationary, so we perform the differencing until they meet the stationary requirement of less than 1% of test statistics and less than 0.01 of p-value.

	Azuki	BoredApeYachtClub	Moonbirds	MutantApeYachtClub	Otherdeed	ETH
Test statistic	-3.5123	-2.3323	-1.4104	-2.1995	-3.1614	-1.6916
p-value	0.0077	0.1618	0.5773	0.2064	0.0223	0.4354
Critical value - 1%	-3.4455	-3.4399	-3.4498	-3.4421	-3.4509	-3.4399
Critical value - 5%	-2.8682	-2.8658	-2.8701	-2.8667	-2.8706	-2.8658
Critical value - 10%	-2.5703	-2.5690	-2.5713	-2.5695	-2.5716	-2.5690

Figure 2: Stationarity check for ETH and NFT prices using ADF test.

- Azuki:

Test Statistic: -3.5123, which is less than the critical value at the 1% level (-3.4455). p-value: 0.0077, which is less than 0.01. Interpretation: Strong evidence against the null hypothesis of a unit root, suggesting that the series is stationary at the 1% significance level.

- BoredApeYachtClub:

Test Statistic: -2.3323, which is greater than the critical values at all significance levels. p-value: 0.1618, which is greater than 0.10. Interpretation: Insufficient evidence to reject the null hypothesis of a unit root, suggesting that the series is likely non-stationary.

- Moonbirds:

Test Statistic: -1.4104, which is greater than the critical values at all significance levels. p-value: 0.5773, which is greater than 0.10. Interpretation: Insufficient evidence to reject the null hypothesis of a unit root, suggesting that the series is likely non-stationary.

- MutantApeYachtClub:

Test Statistic: -2.1995, which is greater than the critical values at all significance levels. p-value: 0.2064, which is greater than 0.10. Interpretation: Insufficient evidence to reject the null hypothesis of a unit root, suggesting that the series is likely non-stationary.

- Otherdeed:

Test Statistic: -3.1614, which is less than the critical value at the 5% level (-2.8682) but greater than the critical value at the 1% level (-3.4509). p-value: 0.0223, which is less than 0.05. Interpretation: Evidence against the null hypothesis of a unit root, suggesting that the series is stationary at the 5% significance level but not at the 1% level.

- ETH:

Test Statistic: -1.6916, which is greater than the critical values at all significance levels. p-value: 0.4354, which is greater than 0.10. Interpretation: Insufficient evidence to reject the null hypothesis of a unit root, suggesting that the series is likely non-stationary.

After we perform first-order difference on non-stationary assets, we visualize the time series in Figure 3 and verify their stationarity using ADF test again. As Figure 4 shows, all time series has achieved stationarity after the differencing.
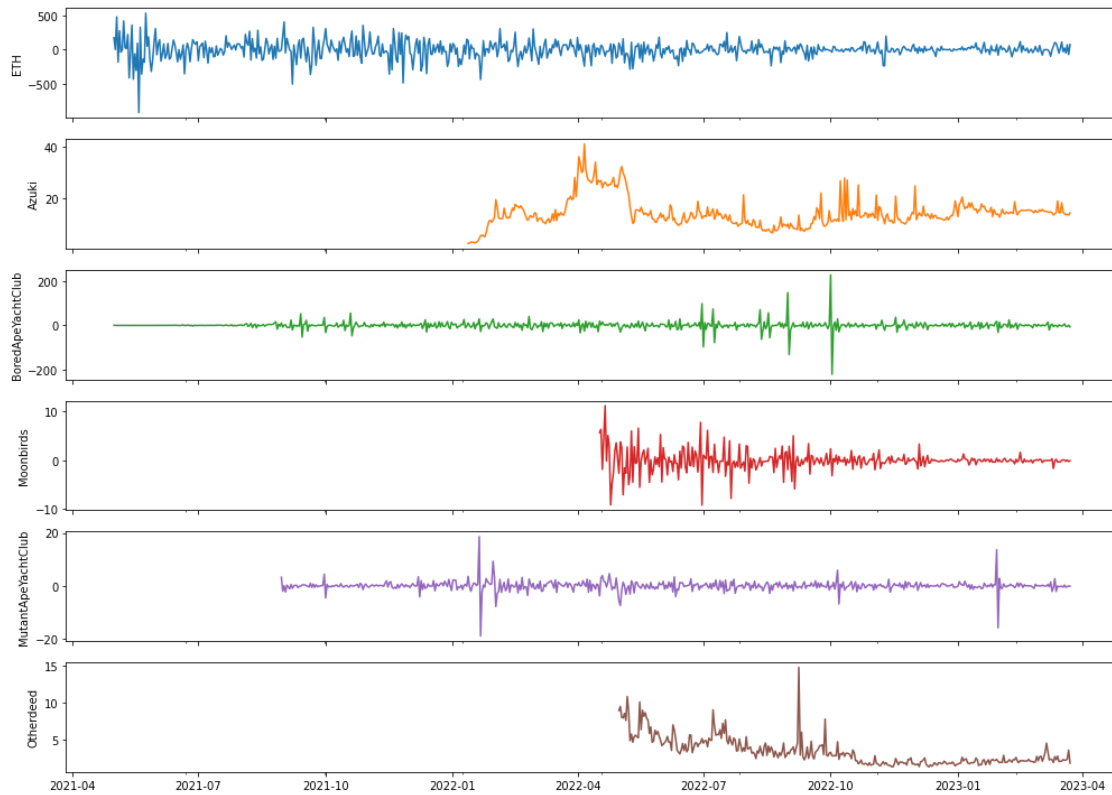
Figure 3: Stationarized time series of prices of ETH and five NFT collections (Azuki, BoredApeYachtClub, Moonbirds, MutantApeYachtClub, Otherdeed.

	Azuki	BoredApeYachtClub	Moonbirds	MutantApeYachtClub	Otherdeed	ETH
Test statistic	-3.5123	-18.5895	-5.5994	-7.7903	-3.1614	-10.4241
p-value	0.0077	0.0000	0.0000	0.0000	0.0223	0.0000
Critical value - 1%	-3.4455	-3.4399	-3.4506	-3.4421	-3.4509	-3.4399
Critical value - 5%	-2.8682	-2.8658	-2.8704	-2.8667	-2.8706	-2.8658
Critical value - 10%	-2.5703	-2.5690	-2.5715	-2.5695	-2.5716	-2.5690

Figure 4: Stationarity check for ETH and NFT prices using ADF test after differencing. All timesereis become stationary given its statistical significance of the test.

4.4. Forecasting Analysis

We conduct a hyperparameter study to determine the optimal number of lags p for the VAR models by comparing different models using various information criteria. The optimal lag order is an essential hyperparameter in time series modeling, as it can significantly impact the model's performance. By selecting the lag order that minimizes the information criteria, including AIC, BIC, HQIC and FPE, with the aim of choosing a model that balances goodness of fit with model complexity, aiming to avoid both underfitting and overfitting. In the context of the VAR model for BoredApeYachtClub, the lag order p refers to how many previous time steps (or "lags") the model considers when predicting the current value of the time series. By analyzing different lag orders, we can find the one that best captures the underlying temporal dependencies in the data. We find BIC and HQIC to be lowest at 4, and we also observe an elbow in the plots for AIC, and FPE, so we choose the number of

lags to be 4, as shown in Figure 5. The choices of number of lags for other NFT collections follow the same process.
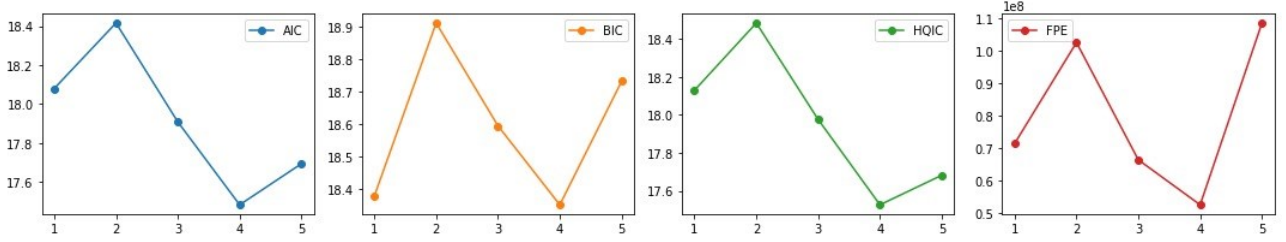

Figure 5: The information criteria over different lags for BoredApeYachtClub

Next, we perform the final forecasting experiment. We divide the dataset into training, validation, and test set. The training set consists of the time series from April 2021 to October 2022, the validation set consists of the time series from November 2022 to December 2022, and the test set consists of the time series since January 2023. We use the VAR models to forecast the future close price of ETH and floor price of five NFT collections. For comparison purpose, the forecasting results are evaluated using both VAR models and ARIMA models. Table 1 reports the mean absolute error (MAE) and mean squared error (MSE) for all NFT collections and ETH prices. We find that except Otherdeed, VAR models yield consistently lower error for all other four NFT collections and ETH prices, showing its better forecasting performance.

Table 1: Performance comparisons (the lower the better), between VAR model and ARIMA model for ETH and five NFT collections.

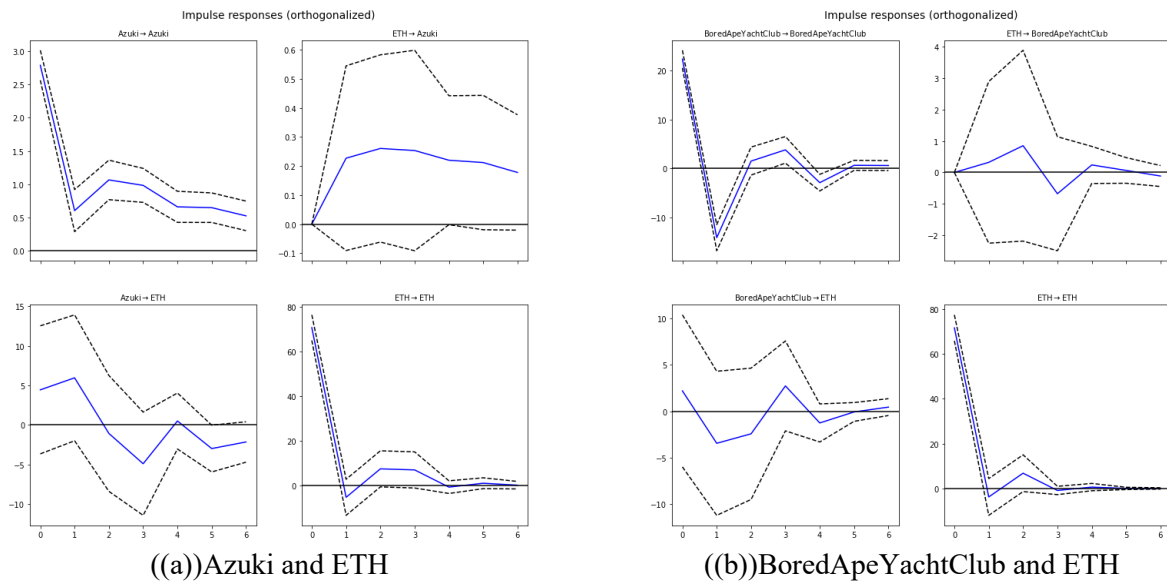|	MAE	MSE
Azuki-VAR	0.819941	1.231603
Azuki-ARIMA	1.004494	1.642900
BoredApeYachtClub-VAR	4.413774	41.464032
BoredApeYachtClub-ARIMA	4.974641	48.748520
Moonbirds-VAR	0.230183	0.136069
Moonbirds-ARIMA	0.298951	0.153773
MutantApeYachtClub-VAR	0.530950	0.784391
MutantApeYachtClub-ARIMA	0.546762	0.802751
Otherdeed-VAR	0.373560	0.367504
Otherdeed-ARIMA	0.372335	0.320895
ETH-VAR	37.691778	2514.413403
ETH-ARIMA	55.555686	4922.421081

4.5. Structural VAR Analysis

4.5.1. Impulse Response Function (IRF) in Analyzing ETH and NFT Prices

Given that VAR models have become an essential tool for understanding the complex dynamics between various financial and economic variables. When studying the relationship between ETH and NFT prices, the Impulse Response Function (IRF) plays a crucial role in deciphering the structural connections and the underlying economic mechanisms for two reasons [46]. First, the coefficients of a VAR model themselves can be intricate and challenging to interpret. The IRF provides an intuitive way to visualize the temporal effects of unexpected shocks (or innovations) in one variable (e.g., ETH prices) on another variable (e.g., NFT prices). Second, the IRF traces out the response of NFT prices to shocks in ETH prices (and vice versa), capturing the time path of these effects. This dynamic

response offers insights into how an abrupt change in ETH prices might influence the NFT market over time, or how NFT market fluctuations might feed back into ETH prices.

More specifically, the IRF represents the response of one variable to a one-time "shock" or "impulse" in another variable. Essentially, it traces the effects of a one-unit increase in an error term on current and future values of the endogenous variables. We perform pairwise orthogonalized IRF analysis between price of ETH and the price of each of the five NFT collections, because orthogonalized IRFs, which take into account the correlations between the shocks, may be used to provide a more accurate interpretation [47].

Figure 6 illustrates the Impulse Response Function (IRF) between the prices of Ethereum (ETH) and five notable NFT collections over six distinct time periods. The analysis reveals a consistent positive relationship between fluctuations in ETH prices and the corresponding changes in these NFT collections. Specifically, an increase by a value of one standard deviation in ETH prices has led to a proportionate rise in the value of the NFT collections, thereby affirming the positive effect of ETH on NFT prices. However, this relationship is nuanced by the rather wide confidence intervals depicted in the IRF, highlighting a significant level of uncertainty in the exact magnitude of this impact. Intriguingly, the analysis further disentangles the nuanced dependencies of different NFT collections on ETH prices, such as Azuki, Otherdeed, Moonbirds, MutantApeYachtClub, and BoredApeYachtClub. These dependencies are inversely correlated with their respective sales volumes in 2022, suggesting that NFT collections with lower sales are more susceptible to the volatility of the cryptocurrency market. This correlation may provide insights into the underlying dynamics of the crypto market and present valuable information for investors, policymakers, and NFT collectors, especially in understanding how market trends and investment in one area (such as ETH) can have far-reaching implications on other related assets (such as various NFT collections). It also prompts further exploration into the factors that may drive these complex interactions, as well as the potential strategies to mitigate undue risk or leverage these relationships for investment or policy decisions.
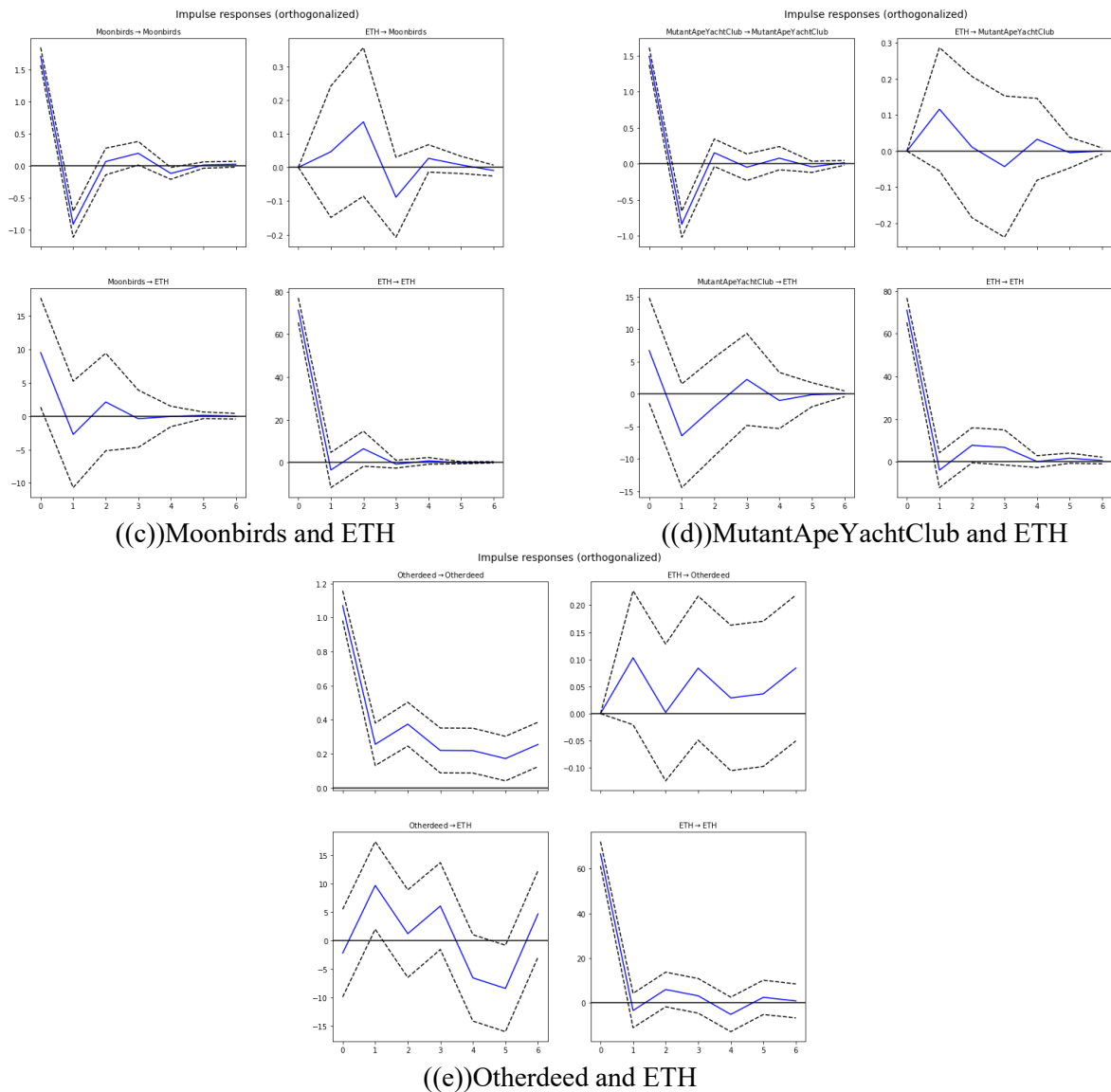

((a))Azuki and ETH ((b))BoredApeYachtClub and ETH

((c))Moonbirds and ETH

((d))MutantApeYachtClub and ETH

((e))Otherdeed and ETH

Figure 6: Impulse Response Function (IRF) in Analyzing ETH and NFT Prices

4.5.2. Forecast Error Variance Decomposition (FEVD) in Analyzing ETH and NFT Prices

In our study, the interpretative power of the model is further examined through a detailed analysis of the forecast error, as depicted in Figure 7, utilizing the method of Forecast Error Variance Decomposition (FEVD). FEVD serves as a tool that quantifies the proportion of information that each variable contributes to the forecast error variance of the other variables within the Vector Autoregressive (VAR) system. While Impulse Response Functions (IRFs) are instrumental in tracing the time-bound impacts of shocks within one variable onto others, FEVD adds another dimension by systematically disaggregating the variance in an endogenous variable into distinct component shocks within the VAR system.

Our findings reveal interesting dynamics specific to the interaction between NFT collections and ETH prices. For example, in the case of the NFT collection BoredApeYachtClub, the variance in price is primarily attributed to exogenous shocks to itself, and this contribution decreases over time. This pattern signals that BoredApeYachtClub's pricing movements may be relatively autonomous and chiefly self-driven, minimally influenced by external variables in the model. The diminishing

effect over time may allude to a delayed or gradual influence from other market forces or slowly unfolding internal dynamics.

Conversely, for the close price of ETH, the variance appears largely unexplained by exogenous shocks to itself, but intriguingly, this unexplained variance increases over time. Initially, like NFTs, ETH's price appears predominantly influenced by its intrinsic factors. However, as time progresses, this pattern evolves, potentially revealing a delayed or cumulative effect wherein changes within the NFT market gradually permeate and influence ETH prices.

The results derived from the FEVD analysis extend beyond mere statistical inference. They paint a rich picture of the complex interdependencies and intricate relationships that characterize the cryptocurrency market, particularly between emerging assets like NFT collections and established cryptocurrencies like ETH.
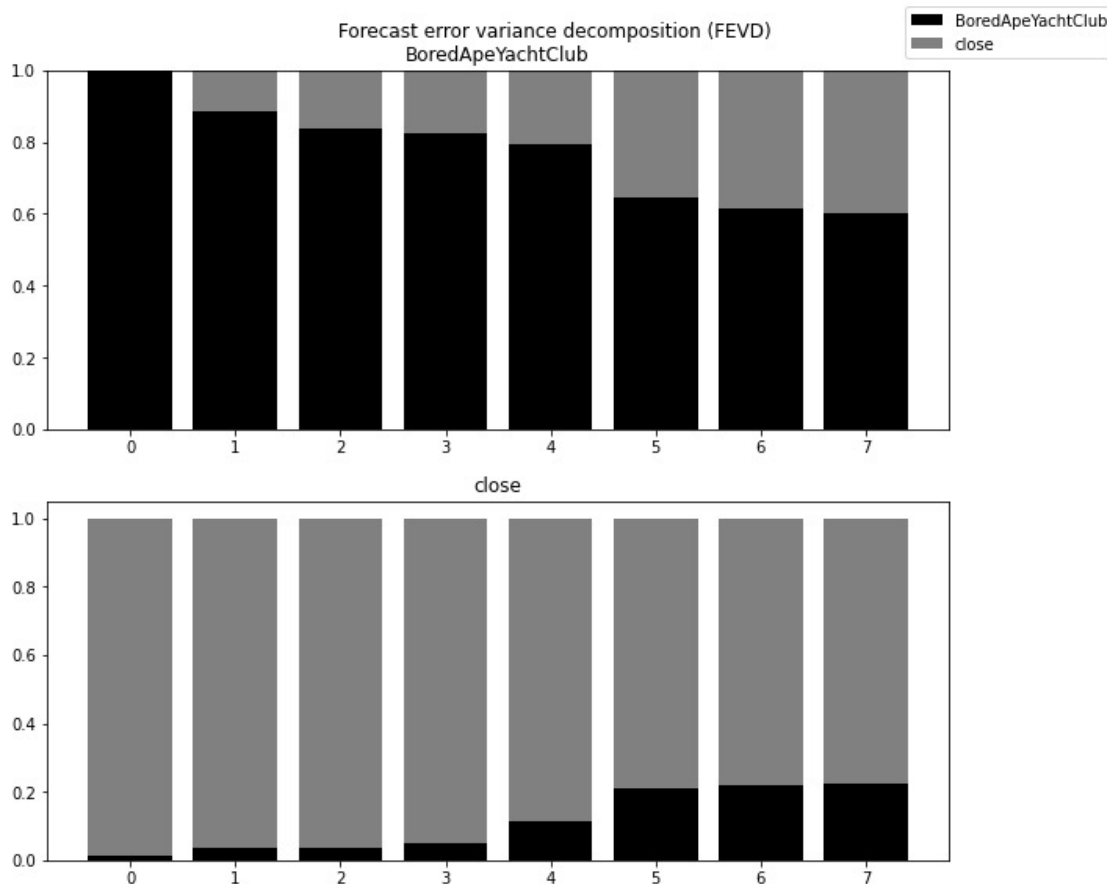

Figure 7: FEVD between ETH and BoredApeYachtClub

4.6. Granger Causality

In our analysis, we aim to determine whether there is a causal relationship between the prices of ETH and various NFT collections. We employ the Granger causality test to examine this relationship, which involves formulating a Null Hypothesis that states that the coefficients of the corresponding past values of ETH are zero. To simply put, this Null Hypothesis asserts that there is no relationship between the historical prices of ETH and the future values of the NFT collections, thus suggesting that fluctuations in ETH prices do not lead to changes in NFT prices.

As summarized in Table 2, the analysis reports P-Values for the effect of ETH prices on NFT collections. These P-Values allow us to test the Null Hypothesis. To clarify which variable is

considered the predictor ('X') and which is the response ('Y'), columns of the dataframe are suffixed with _x and the rows are suffixed with _y. If a P-Value is less than a predetermined significance level (commonly 0.05), we can reject the Null Hypothesis, which means that there is evidence of a causal relationship. In this case, we find that ETH consistently rejects the Null Hypothesis for the chosen NFT collections, implying that the price of ETH does indeed have an influence on these NFT collection prices. Consequently, changes in ETH's value could be considered predictive of subsequent alterations in the prices of these NFTs.

Table 2: Granger Causality P-Values between NFT collections and ETH

	Azuki_x	BoredApeYachtClub_x	Moonbirds_x	MutantApe YachtClub_x	ETH_x
Azuki_y	1.00	-	-	-	0.035
BoredApe YachtClub_y	-	1.00	-	-	0.034
Moonbirds_y	-	-	1.00	-	0.0001
MutantApe YachtClub_y	-	-	-	1.00	0.043
ETH_y	0.203	0.3612	0.125	0.065	1.00

Interestingly, the reverse Granger causality relationship, wherein the NFT collection prices would predict the ETH price, is not observed in our analysis. This one-sided causality underlines the more vulnerable nature of NFT prices to the turbulence of the ETH market. It emphasizes that although variations in ETH price can signal future changes in NFT prices, alterations in the value of NFT collections themselves do not present predictive indications for the ETH market. This outcome could carry significant implications for traders, investors, and market analysts who navigate both the burgeoning NFT market and the broader cryptocurrency landscape.

5.   Conclusion

This study aims to explore the relationship and concurrent movement between cryptocurrency prices and Non-Fungible Token (NFT) objects, focusing on Ethereum (ETH) and top NFT collections like Bored Ape Yacht Club, Mutant Ape Yacht Club, Azuki, Moonbirds, and Otherdeed. Recognizing the way cryptocurrencies have revolutionized financial systems and NFTs have created new paradigms for digital ownership, this research aimed to understand how price fluctuations in cryptocurrencies might influence the NFT market.

Using both VAR and Granger Causality analysis allows to facilitate the capture of potential nonlinear relationships and complex dynamics between these digital assets for a nuanced examination of the co-movement between ETH and NFT prices. The data, collected from the NFT Price Analysis Dataset and covering a full timespan from the beginning of NFT market through a set of analysis, including stationarity check, statistical analysis, and forecasting.

The findings unveiled a statistically significant impact of ETH prices on NFT collections but not vice versa. It revealed the strong dependence of the NFT market on cryptocurrency volatility and the influence of investor behavior during market fluctuations. These insights hold substantial implications for investors looking to navigate these intricate dynamics, as well as policymakers contemplating regulation within these emergent markets.

However, this study is not without limitations. The specific data only covers the floor price of the whole collection and thus may restrict the model's broader applicability, necessitating further validation and exploration of other digital assets, variables, or financial contexts.

In closing, this research marks an understanding of the price dynamics within the digital economy. By probing the co-movement of cryptocurrencies and NFTs through a multivariate time-series approach, it enriches existing knowledge and beckons further exploration in this rapidly evolving field. It may also serves as a useful step for investors, regulators, and scholars for more comprehensive future studies. By bridging traditional financial modeling with the unique characteristics of the digital economy, it provides multifaceted interactions of these novel assets and promises to shape investment strategies, policy decisions, and academic pursuits in this exciting and ever-changing domain.

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