Determinants of Non-Fungible Tokens Collection Market Activity in the Post-Pandemic Period

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Structured Abstract

Purpose

As an emerging technological and financial asset, non-fungible tokens (NFT) have yet to be completely understood and, owing to bubble-like behavior along with pandemic effects, literature has mostly focused on pricing mechanisms and spillover effects between cryptocurrency and NFTs. This work aims to determine the significant determinants of trading activity in NFT collections quantified by the number of transactions as a means to characterize NFTs investors behaviours.

Design/methodology/approach

NFTs collection-week data from the Ethereum blockchain were scraped. Together with collection-specific features, we employ factor analysis and rich regression estimation to identify the factors that are significantly correlated to trading activity.

Findings

Our results, consistent across the different models and methodologies, indicate that the historical transaction and pricing as well as Ethereum market activity are the important determinants of NFTs trading activity. Certain collection-specific properties also show significant relationship with NFTs trading activities, such as age, size, creators commision, collection attention, and utility.

Research limitations/implications

Our work calls for more studies to fully understand the effect of wash trades and on NFT market activity.

Practical implications

Our results give recommendations to NFT investors and can guide them in performing sensible investment decisions at the level of selecting potential liquid and valuable collections. Given NFTs trading activity closely associate with NFTs market liquidity, understanding the determinants of NFTs trading provide important implications for preventing market failure.

Keywords

Non-fungible Tokens, Ethereum Market, NFTs investors behaviors

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1. INTRODUCTION

ride. Starting from $220 million on May 2021, total daily trading volume rose to $3.1 billion just three months later[1]. In the first quarter of year 2022, this value was down to $1.78 billion daily transaction volume, before the market gradually bled to volumes ten times smaller to approximately $200 million in June 2022. The NFT market value from then has remained mostly stable. Whereas many investors and even researchers remain skeptical about NFT as a market no thanks to its efficiency, NFT products and communities to develop, including but not limited to more utility functions of NFTs as well as motivating newer NFT and cryptocurrency technologies.

NFTs and cryptocurrencies are commonly believed to be strongly interconnected given that they are based on blockchain technology and that NFTs are traded using cryptocurrencies. Nevertheless, early research on NFTs found modest exposure of NFT markets to the variation of the cryptocurrency market (Borri et al., 2022) and low volatility transmission (or spillover effects) between the two markets (Dowling, 2022) The association between NFTs market and cryptocurrency even becomes less significant when the effects of the Covid-19 epidemic subsided (Boido & Aliano, 2023). The low correlations of NFTs with cryptocurrencies and the traditional financial market together with its high risk-return feature make NFTs appealing as an alternative asset class (Mazur, 2021). This work, using data from early 2022 to mid-2023 must then be taken in the context when the global enters the last phase of the global pandemic.

Financial literature on NFTs have so far focused on the pricing models of NFTs ((Horky et al., 2022) (Kong & Lin, 2021) ((Nadini et al., 2021a)) (Kireyev et al., 2021) and the spillover effects between blockchain markets and NFT markets(Ante, 2021) ((Boido & Aliano, 2023) (Umar et al., 2022) (Urom et al., 2022). Meanwhile, studies on the factors that generate or characterize NFT trading activity receive much less attention. Price and volume are “fundamental blocks of any theory of market reaction” (Lo Jiang Wang et al., 2000) and these two factors define market liquidity, which in turn, influences asset returns (Amihud & Mendelson, 1986). This is even more evident in studies on emerging and related markets like cryptocurrency or NFT markets, which have been observed to frequently display spillover effects between returns and volume (Balcilar et al., 2017)(Yousaf & Yarovaya, 2022) Returns have also been shown to be dependent and even predicted based on transactional volume (Yousaf & Yarovaya, 2022) (Fousekis & Tzaferi, 2021) In such emerging markets, the near-certain belief of being able to find a bigger fool fueled by the observation or manipulation of trading activity could keep the market profitable and liquid.

Our research fills the gap of previous literature by studying the determinants of NFTs collection trading activity using the cross sectional-time series of transactions from sixty-six NFT collections during post-covid-19 period. We found that trading activity of an NFT collection, denoted by its number of transaction, show significant correlation to its previous trading activity, the median price of the collection and its previous price volatility. Etherum market is found to have strong connection to NFTs trading activity, in which, a 10% increase in ETH/USD raises NFT sales by 1 or 2.6% depending on estimation model – this number is similar to the finding by Ante (2021b) on Etherum NFTs in the period before and during Covid-19, emphasizing the continuous effects of ETH valuation on the NFTs market. Interestingly, we found that investors seem to tradeoff investments in NFTs and ETHs, denoted by the negative relationship between NFTs trading activity and ETHs dollar trading volume. Our paper signify the importance of collections fixed-effects in determining its trading volume and expect futher literature on this topic. Moreover, the collections charateristics have been found to significantly correlated with higher sales of NFTs are greater in size, younger in age and more actively sought (denoted by Google search volume index). Other factors such as the percentage commision NFT creators receive from secondary sales, whether NFTs are utilized in games or if NFTs provide alternative potential financial earnings show mixed evidence in our testing models. In general, our study focus on NFTs collection charateristics in determining their sales by exploiting a rich dataset of transaction covering a large number of collections (whereas previous literature mainly focus on a few big collections or one specific category) and a numbers of NFT variables (which are collected through code or manually).To our knowledge, this is the first paper to study such a wide range of NFT types with details on each collection-specific characteristics.

In the next section, we present related literature review and variable constructions. Section III presents details on data collection and analysis employed in this study. The identified factors proven to be significant will be shown and discussed in Section IV. Section V provides the limitations of our study and some concluding remarks.

2. LITERATURE REVIEW AND VARIABLE CONSTRUCTION

Non-fungible tokens or NFTs, by their nature, is a divergent asset class compared to cryptocurrencies.

1 Data observations from Cryptoslam

Each NFT is non-fungible in that it is unique and not interchangeable with any other NFT in the same way a currency like Bitcoin can be. Individuals, then, can have at least one of the following motives when buying NFTs: (1) for their own personal pleasure, e.g. an accompanying item in their games, or (2) as a piece of online art, or (3) for (NFT) community, product, anmd technology development, by investing, minting in NFT or NFT-related products, or (4) for financial benefits through trading activities, among others Understanding the motives of transacting NFTs is essential in order to construct variables that determine NFT trading activities.

There exist various established measures of trading activity for stocks in financial literature. Notable examples include number of shares traded on the stock exchange (Gallant et al., 1992) (Amihud & Mendelson, 1986), dollar trading volume (James & edmister, 1983) share turnover (Lo Jiang Wang et al., 2000), number of trades (Conrad et. al, 1994), and bid-ask spread (Amihud & Mendelson, 1986). The non-fungible feature of NFTs make it the only "share" of itself and different from other "shares" in the same collection, thereby making the choice for measuring NFT trading activity somewhat limited. Studies on NFT mostly use dollar trading volume and number of trades to quantify NFT trading activity (Nadini et al., 2021b) (Boido & Aliano, 2023) (Anselmi & Petrella, 2023) (Wilkoff & Yildiz, 2023). Our paper uses the number of NFT transactions as a proxy for trading activity, for the fact that dollar trading volume, calculated by dollar price multiplied by number of trades, would give an incorrect picture of NFT market flows, because some assets are sold at enormously higher prices compared to others. In other words, the price of NFT assets are very skewed, even across NFTs in the same category or even in the same collection. We use both successful NFT transactions (having contract value greater than zero) and total transactions, including bidding and transfer transactions as two alternative measurements of NFT trading activity; the former creates a picture of which transactions are actually performed, while the latter can model the attractiveness of a collection as it involves all other activities of these assets. Wash trades, i.e. trades facilitated to artificially inflate the number of transactions or the price in order to false generate interest, or benefit from market-specific benefits awarded to tokens which reach a quota, distort the actual trading behaviour. Transactions that are doubted to be wash trades should be excluded from analysis. In this report, we employ a simple rule in order to examine if, at that level, differences in transactional behaviour can be observed.

In the stock market, trading activity and market liquidity are closely linked to each other, with activity having been used as determinant of market liquidity (Brennan & Subrahmanyam, 1996), (Camilleri & Galea, 2019). In times of crisis, however, panic traders push up the flow of the transactions but market liquidity remains low. In case of NFT's market, (Wilkoff & Yildiz, 2023) have found strong evidence of positive causation effects of trading activity (proxied by number of trades) on NFTs' market liquidity. Our study on the determinants of trading activity, hence, give partial predictability of NFT's market liquidity.

We now motivate the selection of the possible determinants of trading activity. Instead of monitoring the transactions of each token, we have chosen to analyze the attractivity of a collection instead. Aside from dropping the idea of token rarity within a collection – which is an established factor that drives pricing upward (Kong & Lin, 2001) an investor often begins to evaluate a token based on the investment potential of the collection in which the token belongs to. Indeed, it is possible that buyers in the primary market buy a token before the collection is minted, allowing them to purchase tokens at a lower price but obtain a token from the collection at random. Investors in general cannot also isolate a token from the characteristics of a collection, hence our targeted focus on collection attractivity. Based from literature based on NFT pricing and stock investments, we have chosen the following explanatory variables for investigation (also see the Appendix for some notes and the notation used for these variables):

Price

The price-volume relation has been a important debate since early finance literature because it gives implication in pricing speculation and future market, and provides insight of market structure (Karpoff, 1987). Although NFTs market structure are very different from stock markets (for example, a great proportion of NFTs are sold via descending auction with limited bidding time), the volume-price relation might still be quoted as the distinction between the expectation of market as a whole and expectations of individual investors (Beaver, 1968). Research have proposed a few theories regarding NFTs trading mechanism, such as: seller at NFTs auction set the price at suboptimal to secure the ability of succesful sales in auction and the buyers might wait for price to go down, or fastly buy the item before auction expires (Kireyev et al., 2021) ; or the intensity of trading are based on people belief's on price appreciation and NFTs attention (Gobet & Venegas, 2022). Our paper found non-linear correlation of price and trading activity, in particular, (logarithm of) number of NFTs transactions (include or exclude bidding) positvely related to quadratic terms of (logarithm of) collection price, marking the complexity of NFTs trading behaviour consistent with previous studies

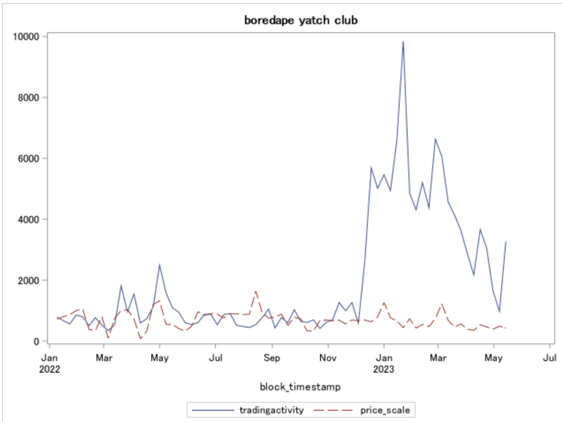

Figure 1 shows a time series plot showing trading activity and the price (rescaled) for a famous collection: Bored Ape Yacht Club.

Volatility

Our study includes the risk feature of NFTs, denoted by the fluctuation in NFT price in previous week. Higher volatility indicates the presence of investor uncertainties on NFTs' value and signify adverse selection problems which regularly occur in emerging markets. We have three assumptions regarding this variable: first, NFT trading activities might be negatively-correlated with volatility if investors are more risk-adverse, positively-correlated with volatility if NFT investors are risk-takers, and have no effects if buyers do not care about the fluctations in NFT price. Studies on the spillover effect of dollar trading volume and volatility on cryptocurrencies show insignificant effects of volatility on volume (Balcilar et.al, 2017) (Bouri et.al, 2019), but show strong asymmetric causal effect in NFT market (Yousaf and Yarovaya, 2022). The use of past volatility variable in our study is therefore, to avoid the bidirectional causality correlation between volume and volatility.

Collection Weekly return

Collection weekly return is calculated as the average return of all the tokens in that collection in a week. We hypothesize that higher past return motivates greater trading transactions.

Creator earnings

The number constitute the percentage of sales value that the creator of the NFT's collection will automatically generate in each occurance of secondary sales. Higher creator earnings percentage means less profit for traders, as a result, we suspect the negative relationship of creator eanings to trading activity.

Utility

Utility variable proxy for the additional financial benefits buyers enjoy when buying a NFT from specific collections. NFTs with utility would provide "their token holders certain perks, like passive income earning opportunities" Recently normal collectibles and art NFTs begin to be associated with one or more utility add-ons in order to keep up that keep up investors' NFT. Our paper categorize utility attached with NFT based on clear and certain assurance to give token holders a way to generate earnings besides trading NFTs. For example, access to private events within their communities are considered as leisure, rather utility because it does not provide clearly financial potential. Our paper define utility as one of the following categories: earning (P&E) capability in gaming industry, staking capability, NFT accompanied by real physical assets (real utility), virtual real estates functioned for lending, and passive income generating capability (e.g. revenue distribution).

Collection size

Collection size indicates the number of assets in that collection. A larger collection leads to more tokens to be transacted, but may suffer issues regarding rarity leading to lower pricing or even lower interest.

Gaming dummy

A gaming dummy variable indicates if the NFTs are gaming NFT or not. Until the end of 2018, 44% of transactions are reported in NFT gaming (Nadini.et.a1l, 2021).

Collection Attention

Literature have found significant positive effects of news and attention to token's price and blockchain market liquidity (Boido & Aliano, 2023; Kristoufek, 2013; Wilkoff & Yildiz, 2023). Following previous studies , we use Google Search Volume Index as measurement for NFTs Collection attention in a week.

Etherum Market Indicators

Ethereum market indicators include exchange rate ETH/USD and ETH dollar trading volume. Etherum remains a popular cryptocurrency for trading NFTs. Higher ETH/USD conversion translates to more expensive NFTs in USD, with verified sales around 2.5 times those in Bitcoin and 4 times the upcoming new cryptocurrency Solana[2]. On the other hand, a higher rate shows the value of the blockchain market. Previous literature have shown some degrees of comovement of cryptocurrencies on major NFT collections before and during Covid-19, e.g. increasing returns in Bitcoin and Etherum cause higher returns in herding NFTs (Bao et al., 2022) or increased NFT sales (Kraeussl & Tugnetti, 2022) However, peculiar dynamics are observed after Covid-19 (Boido & Aliano, 2023)). Figure 2 shows trading activity of several collections over time along with the ETH-USD exchange rate.

NFT market indicators

NFT market indicators include the NFT/USD exchange rate and NFT dollar trading volume (or spill-over effects), as an alternative measure of NFT and cryptocurrency activity.

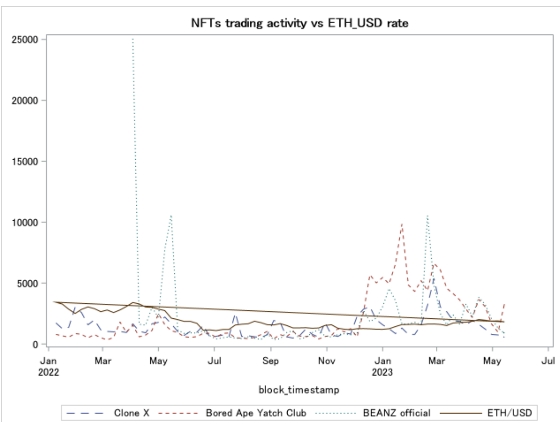

Figure 2: NFT trading activity (number of transactions) for select collections and the ETH-USD exchange rate.

3. METHODOLOGY

3.1 Data Collection

A list of collections from the Ethereum blockchain was obtained from www.crypto.com. During the time that data was downloaded (May 18, 2023) 198 collections were posted in their website. The top 70 collections in terms of total transaction volume were chosen in order to ensure that there are enough transactions to analyze. The contract addresses were individually verified via opensea.io and etherscan.io. All transactions from these collections dated from Jan 3, 2022 to May 14, 2023 (72 weeks) were scraped from the Ethereum blockchain using API endpoints provided by moralis.io. Collection details such as collection size, creator earnings, presence of utility, category, and date of initial offering were manually obtained from opensea.io, the collection's official website, and news regarding the specific NFT collection. Utility, in particular, has been hard-coded based on the number of benefits provided (0 for none, 1 for 1 and 2 for 2 or more benefits). Collections that have multiple addresses associated or cannot be easily determined have been removed from the list. In the end, a total of 66 collections are included in this study. The historical ETH-USD and NFT-USD conversion rates and volume details were obtained from www.yahoo.com. The Google historical search index values were obtained from publicly available Google data.

A total of 3,654,318 unique transactions concerning 763,103 unique tokens were downloaded from the blockchain. After aggregating data into weeks and accounting for a lag variable, we have a total of 3,566 data points. Other values such as the age of a collection, volatility and weekly returns are calculated during aggregation. Since we are taking the logarithm for some variables and accounting for null values, this dataset further decreases to 2,600 collection-week entries.

Our dependent variable (Trading Activity) will be largely subject to wash trading – an action considered unethical by the NFT community wherein NFT tokens are passed back and forth two or more wallets, usually at elevated prices, in order to artificially create an illusion of market activity, or to gain market-specific rewards given to exceptionally-active tokens. In

[2] Data from cryptoslam.com. Total sales including washtrades traced by Cryptoslam's algorithm almost doubles the ratios indicated.

order to determine the extent of wash trading activity in our dataset and minimize its effect, we employed a simple and minimal rule to flag wash trading activity. At first, following (Das et al., 2022), we define transactions belongs to two wallets that have total exchange transactions of at least ten times, then we rule out the possibility of two mutual interested traders by deleting the only transactions that contain at least one token being tossed at least once between two wallet. A total of 13,283 suspected wash trades were removed, resulting in 2,595 collection-week data points. We will work on two datasets, the full or entire dataset, and the *validated* dataset wherein suspected wash trades are removed.

3.2 Exploratory Factor Analysis

Before performing various regression methods, we wish to confirm which variables introduce the required variation in our dataset and actually manifest in transactions, and which ones likely have weaker or no influence at all. The variables indicated in the discussion above were then normalized using Python's Standard Scaler and were subjected to an Exploratory Factor Analysis using the Factor Analyzer package. The results reported in this paper use the MINRES fitting method with an oblique promax rotation owing to correlation between variables within the resulting factors. Nevertheless, using the alternative rotations, e.g., varimax method, does not change which indicators become significant, although the ordering of the factors may differ and other individual variables may occasionally be included.

3.3. Regression

While EFA provides exploratory structure of data and serves as primiraly guidance for variables selections, we keep skeptism in variables selection in our regression model- acknowldging the existence of variables which do not show significant results in EFA- might still give meaningful implications in our hypotheis or which relationships with NFTs trading volume have been demonstrated in previous literature. We cautiously conducted different regression settings with all of the variables, but report only the set with significant variables.

The introduction the lag of the Trading Activity cause the burden of possible biased estimators in our dynamic panel model. The second concern regarding modelling NFTs is the diverse values of between-collections characteristics that might cause insufficient estimators. In order to obtain meaningful results, we use different estimation methods on our baseline regressions on the selected variables as following:

$$TradingActivity_{i,t} = \beta_0 + TradingActivity_{i,t-1} + \beta_x X_{it} + \pi_{jt} + \nu_i + \varepsilon_{i,t}$$

where the equation provides a constant β_0 and an autocorrelated term of the dependent variable; X_{it} are set of continuous collection variables including Collection price, Volatility (Lag), Collection Age, and Collection Attention; ν_i denotes time-invariant characteristics of an NFT collection including collection size, utility, creator earnings and the gaming dummy (denoted if that collection NFT is gaming or not); and π_{jt} denotes information on the ETH market including ETH/USD and ETH dollar trading volume. Appendix A together with the introductory material above provides a more detailed definition of relevant variables.

The regression incorporates the ETH market as the main indicator for blockchain market (and dropping the correlated NFT cryptocurrency market) because of two main reasons: firstly, we want to update the possible effects of cryptocurrencies on trading by individual NFT collections on the period of post Covid-19 (see more discussion on above literature review). Secondly, possible correlation between NFT trading and ETH trading might introduce interesting implication on blockchain investors' behavior: positive correlation might show accumulative excitement over different blockchain assets class while negative correlation might suggest possible *substitute effect* when investors switch their investment from ETH to NFT or vice versa in order to limit their exposure to blockchain market. We remark that the Factor Analysis in this study categorizes ETH-USD and NFT-USD indicators in the same factor, confirming strong correlation between these two.

We estimate our baseline regression using fixed-effects model to remove unobserved heterogeneity that is present in the different collections in our dataset. This method corrects possible omitted variable bias which is caused by failing to include unobserved time-invariant explanatory variables, but on the other hands dropping collection fixed effects that our study might be interested in. Cluster robust standard error relaxes the assumption of unobserved heterogeneity and accounts for with-in collection correlation and heteroskedasticity which might account for variation in NFTs' transaction volume. We also use clustered based on collection price and volume, and obtain similar results on main exploratory variables.

Another standard approach is to use instrumental variables in Generalized Method of Moments (GMM) developed by Arellano and Bond (1991) and later Blundell and Bond (1998) (called System GMM). Instead of using one previous value as an instrumental variable for the lag of the dependent variable, Arellena and Bond (1991) use previous values of the difference equations in the instrument matrix to predict the present values[3]. GMM helps mitigate the problem of unobserved heterogeneity in dynamic panel data, preserving the time-invariant variables in our model while providing robust standard error. Besides, the rich instrument matrix gives it an advantage in working with quadratic terms and non-linearity model[4]. The result for our baseline model using GMM estimation is reported at table () and (). The test for autocorrelation shows significance at lag (1) but not lag(2). Sargan-Hansen tests of over-identification do not reject the validity of our instruments in all test settings.

4 RESULTS AND DISCUSSION

4.1 Summary Statistics

Table 1 reports summary statistics for all factors/regressors relevant to our testing model. All variables have been checked for seasonality. In the sample with wash trade detected (validated dataset), the entries show an average of 1,017 transactions (including bidding, token transfering and nonzero-value transactions) per collection in a week, with a peak of 147,955 transactions. Among all transactions, transactions with nonzero trading value accounts for 36%, ranging from zero to a maximum of nearly 20,000 transactions. Our median collection price (meaning median price of assets in one collection) have an average of around 612 million trillion wei (equalling 6.1 ETH or roughly of $109,000) and a median around 138 million trillion wei (1.3 ETH or $23,000). Collection volatility is calculated by the weighted-average of all assets' price volatility in one collection in a week (refer to Appendix A for variable definition). The statistics show a mean value of collection volatilty of around 577 million trillion wei (5.7 ETH), ranging from zero (meaning no transaction or only one nonzero-value transaction of each NFT in the collection occured in that week) to around

[3] Since Arellano & Bond GMM and system GMM designs for situation of large N, small T panel data, which do not desribe well our data of large T, our paper used version of restricted GMM with the number of lagged variables as instruments reduced to two (T-2). Such restricted GMM have been proven to minimize bias and still produce substaintial efficiency. (Judson & Owen, 1996)

[4] Fixed effects model could produce mis-specification when working with quadratic term of explanatory variables, since the quadratic term could bring group mean backs to equation (Mcintosh & Schlenker, 2006). For that reasons, we do not include collection price squared in fixed efffects model**.**

Table 1: Summary statistics of the weekly-aggregated dataset

	Number of Obs.	Mean	Min	Max	Skewness	Median
NFTs Collection Variables (Validated dataset - detected washtrades)						
Trading activity_All	3566	1017.07	0	147955	23.19	370.5
Trading activity_Nonzero-value	3566	363.22	0	19465	9.32	107
Collection Price	3566	6.13E+18	0	2.48E+20	6.49	1.38E+18
Collection Size	3566	13121.01	420	100000	4.26	9999
Collection Age / Age In Weeks	3566	52.77	7	300.57	0.89	42.57
Volatility	3566	5.77E+18	0	8.84E+20	15.17	1.47E+17
Creator Earnings	3566	0.05	0	0.1	-0.05	0.05
Utility	3566	0.69	0	2	0.58	1
Gaming dummy / Category - Gaming	3566	0.04	0	1	4.82	0
PFPs dummy / Category – ProfilePics	3566	0.79	0	1	-1.42	1
Collection Attention	3566	4.06	0	100	4.40	0.5
Blockchain Market Variables (Absolute Value)						
NFT/USD (conversion)	3566	0.04	5.71E-07	0.20	1.74	0.02
NFT/USD dollar volume	3566	116343.05	34	914664.71	2.3169942	4354
ETH/USD (conversion)	3566	1803.58	1100.65	3423.88	1.19	1628.91
ETH/USD dollar volume	3566	1.30E+10	3.71E+09	3.11E+10	0.64	1.35E+10
Log-transformed Variables						
Log(Trading Activity_all)	3554	5.8738	0.0000	11.9047	-0.4771	5.9283
Log(Trading Activity_nonzero)	3491	4.7321	0.0000	9.8764	-0.0646	4.7005
Log(Collection price)	3491	41.9599	34.1677	46.9606	0.1070	41.7972
Log(Collection size)	3566	9.1491	6.0403	11.5129	-1.2482	9.2102
Log (Volatility)	2914	40.3479	29.4258	48.2311	-0.1192	40.3978
Log(ETH/USD dollar trading volume)	3566	7.4497	7.0037	8.1385	0.7021	7.3957
Log(NFT/USD)	3566	23.1931	22.0344	24.1612	-0.3886	23.3233
Log(NFT/USD dollar trading volume)	3566	9.1277	3.5264	13.7263	0.1876	8.3789
NFTs Collection Variables (Undected washtrade dataset)						
Trading activity_All	3566	1024.77	0	147997	23.04	376
Trading activity_Nonzero-value	3566	369.38	0	19465	9.26	108
Collection Price	3566	6.73E+18	6.90E+14	2.48E+20	6.01	1.43E+18
Volatility	3566	1.29E+19	0	5.94E+21	33.33	2.57E+17
Weekly Returns	3556	1.63E+17	-2.59E+19	3.49E+19	5.17	3.65E+15

884,00 million trillion wei (884 ETH). While statistics on trading activity and median price do not differ much between the full and validated dataset, the former displays an average value of volatility almost double that of the latter, signaling the problems of price manipulation by wash trading in NFT markets.
Collection age variable ranges from 0 week (indicating the occurance of first sale) to more than 300 weeks age by May 14, 2023, with the median at 42 weeks. Creator of NFTs, on average, take 5% of profit in secondary sales of NFTs with a range from 0 to 10%. Regarding collection category dummies, our statistics show that 79% of our collections are labeled as profile pictures according to their Open Sea profile. Note that NFTs' utility can change in time. For instance, they can start as profile pictures and eventually add play-to-earn opportunities, staking mechanisms, or attached to physical merchandise; our paper uses the category listed in the Opensea marketplace for the dummies, but develops our own NFTs categorization based on their financial utility (Please refer to Appendix 2 for more details). The average utility for NFTs collection in our sample is 0.6. NFTs with zero financial utility (e.g. NFT arts or collectibles) account for about nearly half of our sample and NFTs with two or more financial utility accounts for around 20% of our collections (see Figure 3). We observe high skewness in value of many variables in our dataset, and as a result, logarithmic transformations are taken with values reported in table 1 below. More information on variable construction and definition are provided the in previous section and in Appendix 1.
Pearson Correlation shows high linearly correlation are the pairs of trading activity and its lag, rate ETH/USD and NFT/USD. Besides, modest correlation are found between Weekly Return and Lag(volatility) and between size and volume. We conduct but not report here tests for multicollinearity and obtain all VIF no more than 2, indicating the merely multicollinearity.

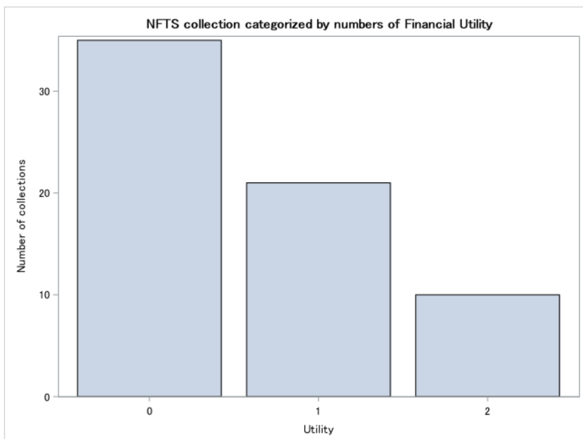

Figure 3: NFTs collection categorized by numbers of Financial utilty
Exploratory Factor Analysis (EFA)

4.2 Factor Analysis

We theorize and test whether the variables described above will affect the attractiveness of tokens in a collection as an investment, which is measured by Trading Activity. Bartlett's test of sphericity results in significant p-values and the KMO score (above 0.5) shows that the standardized data are suitable for factor analysis and possible dimensionality reduction for all cases: whether or not the dataset are validated (no wash trading transactions), and whether or not Trading Activity includes transfers and bids (all transactions, including zero-value ones) or limited to actual trades. Table 2 reports these results and the appendix provides further details on the eigenvalues.

Using the Kaiser criterion, a total of six factors are deemed to be relevant, explaining around 2/3 of the variance of the dataset. There is a minimal advantage of using the validated dataset in as far as variance is concerned. The factor loading matrices for the different cases are provided in the appendix, although we highlight similarities and stress the importance and significance of the variables as determinants of trading activity based on these.
The factor loadings (see Appendix C) showed positive values in most significant variables and, in all cases, are consistent in highlighting the 3 most significant factors. The numbering here are reported according to the convention of case 4 (validated dataset, non-zero trading activity):
Factor 1: Collection Price_log, Collection Price_log_squared, Volatility_lag_log
Factor 2: Trading Activity_log (dependent variable), Trading Activity_lag_log
Factor 3: the conversion rate between ETH-USD and NFT-USD

The next 3 factors are almost consistent across all four cases, differing only in
Factor 4: NFT-USD Volume_log, ETH-USD Volume_log
Factor 5: Utility
Factor 6: Category-gaming, Category-ProfilePics (negative)

Using alternative rotations may result in changes in ordering of factors and occasionally, having the other variables as the 6^{th} factor, but using the promax rotation is appropriate because of significant correlations between variables in the same factor.

The factor analysis above sheds light on which variables are potentially most significant in affecting the financial choices of NFT investors. Factor 1 is clearly about the pricing mechanism (including the role of volatility due to high-value transactions and possible speculation). Factor 2 is the obvious autocorrelation effect of the lag on the dependent variable. Factors 3 and 4 confirm the spillover effect of cryptocurrency to NFTs, although the conversion rate and volume have separate effects. Factor 5 shows the preference of investors to trade tokens with additional financial opportunities, and Factor 6 shows a preference for gaming-related tokens and less for mere profile pictures. Both factors 5 and 6 are collection-specific time-independent properties. The role of the variables as determinants to our variable will be further examined via regression methods.

Table 2: Summary results of EFA

Case	**Dataset**	**Trading Activity**	**Number of factors n (eig>1)**	**Bartlett's test of sphericity p-value**	**KMO score**	**Cumulative variance (n factors)**
1	Full	All transactions	6	0.0000	0.6200	0.6500
2	Full	Actual trades	6	0.0000	0.6335	0.6477
3	Validated (no washtrades)	All transactions	6	0.0000	0.6449	0.6664
4	Validated	Actual trades	6	0.0000	0.6297	0.6651

Relationship	Est. Std	Std. Err	p-value
η~F1	−0.0315	0.0105	0.0000
η~F2	0.2858	0.0234	0
η~F3	0.1296	0.0331	0.0021
η~F4	−0.1658	0.0447	0.0001
η~F5	−0.3662	0.0221	0
η~F6	0.2724	0.0142	0
TradingActivity~η	0.5838	−	−

Fit indices	Value
Degrees of freedom	26
Chi squared	934.2268
Chi squared p-value	0.0000
CFI	0.9706
GFI	0.9698
AGFI	0.9234
NFI	0.9698
TLI	0.9254
RMSEA	0.1160

4.3 Regressions

Tables 4 and 5 show consistent autocorrelation of NFT trading activity at lag(1) with highly significant t-test results. Other variables that show significance with large magnitudes are ETH/USD (positively loaded), ETH Dollar Volume (negatively loaded), the median of Collection Price (positively loaded) and Collection age (negatively loaded). Except for Age in Weeks valued in absolute term, the other variables above have been transformed in natural logs, which can be interpreted as follows. Using all transactions, a 10% increase in price of ETH/USD increases NFTs' total numbers of trades by 1% (using fixed efffects model) or 2.6% (using clustering standard errors); using only the nonzero-value transactions, the increase is 2% (using fixed efffects model) or 3.3% (using clustering standard errors). Collections that aged ten-week older decrease the total number of trades by 4% (using fixed-effects model) or 2% (using clustering standard error). A negative correlation between ETH Dollar trading volume and NFT total number of trades suggest substitute effect when investors tradeoff between ETH and NFT to maintain their proportion of blockchain assets in their portfolio. The tests show that a 10% reduction in ETH-USD trading increases the number of actual NFT sales to 2.1% (fixed-effects model) or 1.1% (in clusterting standard error). Collection size shows positive correlation with number of trades (in both samples of all transactions and nonzero-value transactions) can be understood that bigger collecions give traders more options to choose between the different tokens, leading to higher number of transactions. The results suggest that collections having 10% more asset have 2.7% more transactions. Our fixed-effects estimation gives an R-squared of nearly 70%, suggesting strong explanatory capability of our model[5].

Tables 6 and 7 shows the results using fixed effect estimation and cluster standard adjusted error on sample with nonzero-value transactions, where we observe higher t-statistics and greater-magnitude in almost coefficient estimates of the nonzero-value transactions using the validated dataset. The factor Lag(Volatility) shows negative and significant

[5] Pooling OLS gives a R-squared of around 30%. The significant rising in R-squared by fixed-effect model might suggest that further time-invariant explanatory variables should be explored in future papers.

correlation to NFTs trading volume when only actual trades are considered, indicating investors' risk adversion in the
- all transactions

necessity of detecting washtrades when conducting study on NFTs.

The results of GMM for the actual trades (reported in table 8) show results that are mostly consistent and similar in magnitude as in the tworevious regression models; this is true for ETH/USD, ETH Dollar Volume, the median of Collection Price, Lag(Volatility), Collection Age, and Collection Size, but not for ETH/USD and number of NFT trades. Tests for actual trades show significant correlations of gaming dummy (positive load), collection attention (positive load) , creator earnings (negative) , suggesting higher volume transactions are association with gaming NFTs, NFTs with more Google searches, and NFTs that give less royalty to its creators. Utility shows an intriguing negative relationship with the sales of NFT (which is consistent with our Exploratoty Factor Analysis), implying investors' choice of NFTs rather based on pleasure than financial utility. This result might also be explained by the fact that 70% of NFTs in our sample are originally profile pictures.

So far we have not discuss two important explanatory variables that contribute to Factor 1 in our Factor Analysis: the (logarithm of) collection price and its square. Firstly, when we test for individual effect of collection price, the price and number of trades show positive and highly significant relationship in all estimation models.However, this changed when we include both the (logarithm of the) collection price and its square into our baseline model. The quadratic term of the collection price is found to be significantly and positively correlated with trading volume in all samples. The coefficient of the quadratic term is small in magnitude and positive while the coefficient of price is larger and negative. Since we are testings on the logarithm of the number of trade and that of the price, then the actual relationship between trading quantity and price in absolute value is (insert equation here based on numbers from the table) a concave curve, which displays a dramatic decrease to a tu rning point given a small increase in price value and have very stiff upward sloping but almost horizontal tail. In effect, investors quickly lose their interest as the price of NFTs interest and at some point the trading of NFTs continues but becomes irrelevant of the price. This behavior could explain the downtrend for NFTs that have established certain prestige and value over time, and the frequent appearance of new NFTs collections.

Table 5 : Regression results using the fixed-effects model and clustering model for all transactions (including zero- .

	Wash trade detected		Wash trade undetected	
	Fixed-effects	Clustering	Fixed-effects	Clustering
Lag(Trading Activity)	0.55***	0.80***	0.50***	0.80***
	(37.17)	(30.13)	(29.49)	(31.24)
ETH/USD	0.26***	0.11***	0.26***	0.10***
	(6.13)	(3.7)	(5.32)	(3.55)
ETH Dollar Volume	-0.21***	-0.14***	-0.24***	-0.14***
	(-6.76)	(-6.05)	(-6.58)	(-6.14)
Collection Price	0.15***	0.07***	0.17***	0.07***
	(9.93)	(4.23)	(9.84)	(4.32)
Lag(Volatility)	0.001	-0.01	-0.01	-0.01*
	0.17	-1.52	(-0.12)	(-1.69)
Collection Size	-	0.24***	-	0.23***
	-	(6.77)	-	(6.73)
Age in Weeks	-0.004***	-0.002***	-0.01***	-0.002***
	(-5.4)	(-3.22)	(-16.93)	(-3.08)
Collection Attention	0.003	0.001	0.003	0.01
	1.23	1.12	1.11	(1.01)
Utility	-	-0.01	-	-0.006
	-	-0.61	-	(-0.35)
Gaming dummy	-	-0.07*	-	-0.07**
	-	(-1.87)	-	(-2.06)
Creator Earnings	1	-0.87	-	-1.09**
	0	(-0.91)	-	(-2.48)
R-squared	77.8%	NA	74.68%	NA

Table 6 : **-** **-zero**

	Wash trade detected		Wash trade undetected	
	Fixed-effects	Clustering	Fixed-effects	Clustering
Lag(Trading Activity)	0.51***	0.79***	0.51***	0.80***
	(32.28)	(37.8)	(32.03)	(34.14)
ETH/USD	0.33***	0.20***	0.33***	0.25***
	(6.75)	(5.35)	(6.82)	(5.25)
ETH Dollar Volume	-0.21***	-0.11***	-0.21***	-0.10***
	(-6.02)	(-4.46)	(-5.84)	(-4.42)
Collection Price	0.18***	0.07***	0.19***	0.08***
	(10.7)	(3.83)	(11.45)	(4.09)
Lag(Volatility)	-0.02***	-0.03***	-0.02***	-0.03***
	(-2.63)	(-3.06)	(-2.66)	(-3.08)
Collection Size	-	0.27***	-	0.27***
	-	(7.18)	-	(7.22)
Age in Weeks	-0.009***	-0.002***	-0.01***	-0.003***
	(-9.3)	(-3.31)	(-9.31)	(-3.29)
Collection Attention	0.004	0.0012	0.004	0.001
	(1.29)	(1.37)	(1.23)	(1.32)
Utility	-	-0.003	-	-0.004
	-	(-0.17)	-	(-0.21)
Gaming dummy	-	-0.05	-	-0.05
	-	(-1.44)	-	(-1.63)
Creator Earnings	0.41	-1.06	-	-0.83
	0	(-0.76)	-	(_0.73)

Table 7: Results of the GMM. P-values for Sargan-statistic (test of overidentifying restrictions) are obtained
-

	Washtrade Detected		Washtrade Undetected	
	Model 1	Model 2	Model 1	Model 2
Lag(trading volume)	0.62***	0.62***	0.61***	0.61***
	(28.51)	(29.61)	(44.16)	(27.54)
ETH/USD	0.10	0.07	0.14**	0.13**
	(1.33)	(1.15)	(2.36)	(2.28)
ETH Dollar Volume	-0.25***	-0.14***	-0.21***	-0.17***
	(-7.64)	(-4.94)	(-8.21)	(-7.65)
Collection Price	0.13***	-0.20***	0.10***	-0.13**
	(4.85)	(-3.46)	(6.67)	(-2.03)
Collection Price_squared		0.01***		0.004***
		(5.49)		(4.12)
Lag(Volatility)	-0.01	-0.02	-0.002	-0.01
	(-0.96)	(-1.59)	(-0.22)	(-1)
Collection Size	0.29***	0.51***	0.25***	0.41***
	(5.82)	(5.88)	(5.64)	(4.52)
Age in Weeks	-0.002***	-0.00	-0.002**	-0.001
	(-2.69)	(-0.67)	(-2.34)	(-1.47)
Collection Attention	0.01**	0.01	0.004	0.006
	(2.29)	(1.57)	(0.88)	(1.18)
Utility	-0.09	-0.10	-0.12	-0.13*
	(-1.48)	(-1.1)	(-1.4)	(-1.74)
Gamming dummy	0.11	0.19	-0.34	0.06
	(0.27)	(0.51)	(-1.34)	(0.19)
CreatorEarnings	-1.49	3.4	-4.7*	3.46
	(-0.53)	1.21	(-1.8)	(1.12)
Sargan test (prob>chisq)	0.295	0.2411	0.2216	0.2326
AR (1) Pr>statistic	<0.0001	<0.0001	<0.0001	<0.0001
AR(2) Pr>Statistic	0.7123	0.8746	0.5122	0.6186

Table 8: Results of the GMM. P- -

dataset, and are strongly significant in various

	Washtrade Detected		Washtrade Undetected	
	Model 1	Model 2	Model 1	Model 2
Lag(trading volume)	0.53***	0.54***	0.56***	0.61***
	(24.29)	(29.61)	(18.95)	(27.54)
ETH/USD	0.34***	0.27***	0.28***	0.13**
	(4.97)	(4.36)	(3.2)	(2.28)
ETH Dollar Volume	-0.23***	-0.13***	-0.22***	-0.17***
	(-9.23)	(-4.15)	(-8.16)	(-7.65)
Collection Price	0.10***	-0.20***	0.136***	-0.13**
	(4.59)	(-2.63)	(4.49)	(-2.03)
Collection Price_squared		0.005***		0.004***
		(5.49)		(4.12)
Lag(Volatility)	-0.06***	-0.05***	-0.005***	-0.01
	(-3.15)	(-3.93)	(-4.26)	(-1)
Collection Size	0.48***	0.66***	0.25***	0.46***
	(7.03)	(5.99)	(5.64)	(6.12)
Age in Weeks	-0.006***	-0.004***	-0.002**	-0.005***
	(-3.34)	(-3.2)	(-2.34)	(-4.26)
Collection Attention	0.02***	0.019***	0.004	0.02***
	(3.51)	(3.55)	(0.88)	(2.86)
Utility	-0.40***	-0.38***	-0.12	-0.49***
	(-3.21)	(-3.17)	(-1.4)	(-3.48)
Gamming dummy	0.87**	0.71**	-0.34	1.25**
	(1.98)	(2.44)	(-1.34)	(1.98)
CreatorEarnings	-10.78***	-5.53	-4.7*	-16.89***
	(-3.78	(-1.62)	(-1.8)	(-4.82)
Sargan test (prob>chisq)	0.3172	0.1944	0.2216	0.3711
AR (1) Pr>statistic	<0.0001	<0.0001	<0.0001	<0.0001
AR(2) Pr>Statistic	0.2725	0.3079	0.5122	3765

5. CONCLUSION AND FURTHER DISCUSSION

Our work shows that the trading activity of tokens in a collection, in this case the number of transactions, can be estimated based on different indicators. The primary determinants are the price and price volatility of tokens in the collections, previous trading activity of the collection, and the economic activity of cryptocurrency market. These components also comprise the top three factors that explain the variance of all variables in our regression models.

Other factors, such as collection attention, its alternative financial utilities, the NFT category dummy and creator earnings appear significant in some cases of the regression models, consistent in it being secondary factors in the factor analysis. These remain influential in guiding investors' choices although individual preferences and sensitivity, or lack thereof, to these factors may perhaps provide variability in these components.

Collection size and the age of the collection initially do not show up as significant in the factor analyses, appear highly significant in all regression settings. As mentioned above, larger collections do offer wider choices for investors, but this is counter to the rarity aspect of NFTs, potentially driving prices lower and indirectly, attractiveness of these tokens as investment opportunities. The regressions show negative correlation between activity and age, implying that as collections

investments, rather than betting on new collections. The non-inclusion of Collection Age might be related to the fact that recently, alternative blockchains that boast of lower gas fees (transaction fees) are on the rise, and our data does not currently include this effect.

This work also shows that, aside from quantitative differences, the behaviour of transaction are, mostly, qualitatively similar when considering all transactions, or only successful trades. Volatility, as shown in the GMM model, however is more significant when only actual trades are considered, hence the need to still consider this special case especially when accounting for the risks entertained by an investor. While bids and transfers may inflate data volume as well as potentially alter price medians, what determines collection attractivity and consequently, activity, remain mostly the same.

The factor analysis does not show large differences between using the full or validated dataset, aside from minor differences in the order of the factors. This could be attributed to the rather simple methodology employed in this study to rule out wash trades. Many alternative and more complex rules and algorithms have been employed to flag suspicious (Das et al., 2022) (Serneels, 2023)but the decentralized, anonymous, and unexplained nature of blockchain transactions prevents any method to detect all wash trades without error. Nevertheless, validating the dataset results in some unusual results in the regression which deserves more scrutiny in subsequent studies. Aside from influencing and tricking investors into inflated prices, wash trades induce security issues for the NFT community by becoming a source of unexplained error in studies of the market. Unfortunately, many investors do not find the practice unethical as it provides financial benefit to the perpetrators[6].

Wash trading is a serious concern that affects the entire NFT market. Our work utilized a very simple method to rule out wash trading activity, but the authors are aware that wash trading is more prevalent, serious, and complex. Though strenuous, it is not impossible to create a large network of wallets and systematically or even (semi-) automatically perform transactions, losing hundreds of dollars in gas fees only to prey on a fool who gets hooked into paying thousands of dollars higher than the market price of that token. It would be interesting to study how trading activity is affected and how its determinants and their importance will differ when more suspicious transactions are eliminated.

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7. APPENDIX

Collection Price_log	The median price of all non-zero-value transactions; transformed to logarithmic form
Collection Price_log_squared	The square of the median price of all non-zero-value transactions; transformed to logarithmic form
Volatility_lag_log	Collection volatility is computed as the weighted average of standard deviation of all tokens' price in that collection in a week. For example, collection A consists of x% Token X and y% Token Y, then Price volatility of A equals x%multiplied by standard deviation of prices of X plus y% multiplied by standard deviation of prices of Y in a specific week.
Trading Activity_log	The number of transactions of a collection; transformed to logarithmic form (Note: All transactions include zero-value transfers and bids but trading activity limits this to the number of non-zero-value transactions)
Trading Activity_lag_log	The lag of the trading activity; transformed to logarithmic form
NFT-USD Conversion	The exchange rate between the cryptocurrency NFT to USD (Note: this is not transformed because it is not extremely skewed.)
ETH-USD Conversion_log	The exchange rate between the cryptocurrency NFT to USD; transformed to logarithmic form
NFT-USD Volume_log	The volume of NFT-USD transactions; transformed to logarithmic form
ETH-USD Volume_log	The volume of ETH-USD transactions; transformed to logarithmic form
Collection Size	The number of tokens in a collection. Some collections expand over time or released tokens at specified schedules and we just use the maximum desired number or largest number at the time of the data collection, whichever is higher.
Utility	Indicated 0 for no known utility, 1 for 1 known *financial* utility (e.g. airdrop of new tokens, play-to-earn option, etc.), 2 for two or more utilities.
Gaming-dummy / Category-gaming	1 for self-rated gaming NFTs (Opensea.io); 0 otherwise
PFP-dummy / Category-ProfilePics	1 for self-rated profile picture NFTs (Opensea.io); 0 otherwise
Creator Earnings	Percentage receive by original NFT owner from secondary sales (Opensea.io)
Collection Age / Age In Weeks	The age of a collection from its 1st mint date (in weeks)
Collection Attention_log	Google trend search history as proxy for collection popularity relative to all other collections in this study
Weekly Return	Denote the average return of all tokens in that week. We calculate return of one token as the percentage change from the first price to the last price of that token in a week

A2: Details on the eigenvalue and variances explained from the EFA

Dataset	**Transaction**		**F1**	**F2**	**F3**	**F4**	**F5**	**F6**	**F7**
Full	All	eig	3.4382	2.428	1.8515	1.5006	1.2883	1.038	0.9586
		cum var	0.1661	0.2901	0.4116	0.4931	0.5739	0.65	0.7231
Full	Trading activity	eig	3.2928	2.3835	1.9955	1.5102	1.2596	1.0421	0.9602
		cum var	0.1725	0.2924	0.4085	0.4903	0.5712	0.6477	0.7115
Validated	All	eig	3.5588	2.458	1.8802	1.5029	1.2589	1.0217	0.8866
		cum var	0.1715	0.3126	0.4262	0.5077	0.5889	0.6664	0.7381
Validated	Trading activity	eig	3.3727	2.41	2.0673	1.5112	1.2351	1.0272	0.9308
		cum var	0.1773	0.3114	0.4233	0.5053	0.5868	0.6651	0.7324

A3: Factor loadings for the full dataset, all transactions

Variable	F1	F2	F3	F4	F5	F6	F7
Collection Price_log	1.0392	-0.1054	-0.0203	-0.0101	-0.0199	-0.0151	-0.0794
Collection Price_log_squared	1.0373	-0.1055	-0.0189	-0.0075	-0.017	-0.0163	-0.0818
Volatility_lag_log	0.5675	-0.0423	0.3544	-0.0787	0.0068	0.0097	-0.0587
Trading Activity_log	0.0824	0.0507	0.8229	-0.0739	-0.0436	-0.0063	0.0916
Trading Activity_lag_log	-0.0279	0.0349	1.0267	0.0151	0.0027	0.0177	0.1496
NFT-USD Conversion	-0.1296	1.091	0.0197	-0.1092	-0.0005	-0.0217	-0.0286
ETH-USD Conversion_log	-0.1154	0.8552	0.0801	0.0628	-0.0125	0.0082	-0.0374
NFT-USD Volume_log	-0.0413	0.0305	-0.0582	0.6063	-0.014	-0.0169	-0.0105
ETH-USD Volume_log	-0.0074	-0.0823	-0.0075	0.9236	-0.0094	0.0203	0.036
Utility	-0.0966	-0.0726	-0.0643	-0.0652	1.076	0.0685	0.1697
Category-gaming	0.1175	-0.0505	-0.166	-0.0305	0.0903	0.9566	0.1749
Category-ProfilePics	0.097	-0.0245	-0.1149	-0.0187	0.0252	-0.5392	0.1473
Creator Earnings	-0.2861	-0.088	0.0402	-0.1534	0.0801	-0.056	0.8966
Age In Weeks	-0.034	0	-0.1657	-0.1479	-0.0104	-0.0032	-0.4612
Collection Attention_log	0.1395	0.0901	0.034	0.0598	0.3418	-0.0442	-0.131
Returns_log	0.0703	0.0462	-0.0388	-0.0017	-0.0102	0.0089	0.0653

A4: Factor loadings for the full dataset, non-zero transactions

Variable	F1	F2	F3	F4	F5	F6	F7
Collection Price_log	1.0563	-0.0785	-0.093	-0.0369	-0.0086	-0.0077	-0.0243
Collection Price_log_squared	1.0543	-0.0788	-0.0912	-0.0341	-0.006	-0.0089	-0.0274
Volatility_lag_log	0.6056	-0.0537	0.3098	-0.0112	-0.1156	0.0063	-0.0902
Trading Activity_log	0.0258	0.0363	0.7902	-0.0313	-0.038	-0.0059	0.0991
Trading Activity_lag_log	-0.0691	0.0105	1.0096	0.0161	0.0026	0.01	0.1106
NFT-USD Conversion	-0.1188	1.0751	0.0209	-0.0075	-0.1071	-0.0192	0.0034
ETH-USD Conversion_log	-0.0861	0.8472	0.0316	-0.0321	0.0547	0.0091	-0.0322

NFT-USD Volume_log	-0.0519	0.0182	-0.0353	-0.0144	0.6411	-0.0145	-0.0147
ETH-USD Volume_log	-0.0154	-0.0682	-0.0034	-0.0152	0.8964	0.0192	0.0164
Utility	-0.1263	-0.0859	-0.0481	1.0835	-0.0704	0.0634	0.1464
Category-gaming	0.1092	-0.0313	-0.1824	0.0873	-0.0176	0.9593	0.2214
Category-ProfilePics	0.0858	-0.0153	-0.1249	0.0283	-0.0127	-0.543	0.172
Creator Earnings	-0.2795	-0.0796	0.0116	0.0455	-0.1502	-0.0438	0.7961
Age In Weeks	-0.0274	0.0309	-0.2082	-0.0154	-0.1365	0.0048	-0.4747
Collection Attention_log	0.1346	0.0797	0.0457	0.3446	0.0593	-0.0449	-0.1416
Returns_log	0.0589	0.0426	-0.0181	-0.0025	0.0051	0.0086	0.0883

A5: Factor loadings for the validated dataset, all transactions

Variable	F1	F2	F3	F4	F5	F6	F7
Collection Price_log	1.0761	-0.1419	-0.0308	-0.0251	0.0399	0.0017	-0.0203
Collection Price_log_squared	1.0725	-0.1388	-0.0312	-0.0206	0.042	0.0002	-0.0227
Volatility_lag_log	0.4901	0.3318	-0.0286	0.0399	-0.0473	0.0063	-0.0381
Trading Activity_log	-0.0654	0.9066	-0.0111	-0.0089	-0.0116	-0.0222	0.0402
Trading Activity_lag_log	-0.178	1.0662	-0.0387	0.0325	0.0822	-0.0066	0.0608
NFT-USD Conversion	-0.0357	-0.0722	1.0549	-0.0138	-0.1006	-0.0058	0.0256
ETH-USD Conversion_log	-0.0401	0.0182	0.8282	-0.0233	0.068	0.0187	0.0035
NFT-USD Volume_log	-0.001	-0.0235	0.0036	-0.0229	0.6762	-0.0144	-0.0306
ETH-USD Volume_log	0.0281	0.0108	-0.0302	-0.0155	0.8441	0.0149	0.0104
Utility	-0.0888	-0.0284	-0.0805	1.0786	-0.0903	0.0728	0.1445
Category-gaming	0.2072	-0.2496	0.011	0.0653	-0.0347	0.9752	0.1852
Category-ProfilePics	0.1312	-0.1393	-0.002	0.0106	-0.021	-0.5257	0.1397
Creator Earnings	-0.1844	-0.0403	-0.0162	0.0849	-0.1989	-0.0523	0.9431
Age In Weeks	-0.0954	-0.1224	-0.0372	0.0128	-0.1703	-0.0203	-0.4014
Collection Attention_log	0.1151	0.0486	0.0719	0.3495	0.0645	-0.0487	-0.1178
Returns_log	0.1778	0.2052	0.0206	-0.04	-0.1368	0.0088	-0.0016

A6: Factor loadings for the validated dataset, non-zero transactions

Variable	F1	F2	F3	F4	F5	F6	F7
Collection Price_log	1.0878	-0.192	-0.0148	0.0647	-0.0236	0.0099	-0.0033
Collection Price_log_squared	1.0845	-0.1893	-0.0152	0.0665	-0.0194	0.0082	-0.0063
Volatility_lag_log	0.5359	0.2788	-0.0367	-0.0754	0.0253	0.0028	-0.0729
Trading Activity_log	-0.0751	0.8649	0.0051	0.0176	-0.0073	-0.0144	0.0624
Trading Activity_lag_log	-0.1755	1.0439	-0.0238	0.0676	0.0356	-0.0052	0.0623
NFT-USD Conversion	-0.0397	-0.0231	1.0429	-0.0865	-0.007	-0.004	0.0315
ETH-USD Conversion_log	-0.0118	0.0014	0.8301	0.0628	-0.0346	0.0202	-0.0051
NFT-USD Volume_log	0.0042	0.0043	-0.0045	0.7129	-0.0307	-0.0112	-0.0493
ETH-USD Volume_log	0.0376	0.0292	-0.0117	0.8185	-0.0239	0.0154	-0.0084
Utility	-0.0891	-0.0228	-0.0771	-0.1046	1.0797	0.0707	0.1442
Category-gaming	0.2001	-0.2343	0.0276	-0.0133	0.0759	0.981	0.2207
Category-ProfilePics	0.1217	-0.1422	0.0067	-0.0117	0.019	-0.529	0.1669
Creator Earnings	-0.1539	-0.036	0.0049	-0.1863	0.0582	-0.0336	0.8725
Age In Weeks	-0.1079	-0.1992	-0.0189	-0.1707	-0.0001	-0.0155	-0.4281
Collection Attention_log	0.1142	0.0549	0.0649	0.0629	0.3477	-0.0493	-0.137
Returns_log	0.1975	0.1916	0.0115	-0.1557	-0.0428	0.0045	-0.0137