Understanding the Market of Digital Collectibles on the Ethereum Blockchain

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Blockchain-based platforms are gaining popularity as marketplaces for smart contracts and non-fungible tokens (NFT). However, little is known about consumer behavior in the context of the NFT-based assets traded on blockchains, and consumer willingness to pay for such assets and associated transaction costs given the volatility of crypto-currencies and transaction costs. In this paper, we study the phenomena in the context of CryptoKitties, an Ethereum blockchain-based game and an early adopter for smart contracts and NFT's. Our results indicate the presence of rational and speculative market processes. We find that consumers' willingness-to-pay for CryptoKitties is influenced by their rarity, and consumers are willing to pay higher transaction costs as the value of the digital collectible increases. However, as transaction costs increase, consumers are only willing to trade higher valued CryptoKitties, which subsequently leads to reduced trading volume.

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I. INTRODUCTION

Blockchain platforms utilize a distributed and shared public ledger, using cryptographic techniques to provide an immutable transaction record and allowing for transactions among parties without the need for a central trusted authority. A major difference between the Bitcoin and Ethereum platform, the second highest valued cryptocurrency in the world (CoinMarketCap, 2023), is the Ethereum platform's support for smart contract functionality. The platform uses Ether (ETH) crypto currency to compensate miners for performing smart contract computations and confirming transactions on the blockchain. Whereas Bitcoin transaction fees are primarily dependent on transaction size.

Like Bitcoin, the transaction fees (or the gas price in particular) for Ethereum users are a non-trivial cost, and are determined in an equilibrium between the system participants with contradictory fee attitudes (Huberman et al., 2021). Each Miner sets their own minimum fee in Gas price, which is measured in the unit of GWei. The swift surges in transaction fee might deter the cryptocurrency usage and prompt regular users to abandon or withhold transactions (Easley et al., 2019).

An unique feature of the Ethereum platform as compared to Bitcoin blockchain is its ability to execute smart contracts (Tapscott and Tapscott, 2016). Please note that in a smart contract, the terms of the contract between parties is encoded into a computer program and executed automatically when the terms are met. One of the earliest applications of blockchain-based smart contracts was in the gaming industry. CryptoKitties, a blockchain-based game introduced by Dapper Labs, uses Ethereum Smart Contracts to enable the purchase, collection, breeding, and selling of virtual cats by players. Released in 2017 and one of the earliest blockchain-based application for gaming and recreation, the CryptoKitty collectables represented as unique digital images of cats that appeal to game players, are non-fungible tokens (NFT) that are managed, protected, and authenticated by the Ethereum blockchain. One example of an expensive CryptoKitty collectible, Dragon, sold for 600 ETH—around $172,000 in Sep. 2018 (CryptoKitties, 2023a). The average sales price, however, is roughly $100 per kitten. Dapper Labs Inc. charges a 3.75% fee on trade (CryptoKitties, 2023b).

Each CryptoKitty is uniquely owned by the user, cannot be replicated, and is validated through the Ethereum blockchain. Owners may sell the CryptoKitty collectables via an auction for a price set in ETH, where another player can purchase to own this CryptoKitty or s/he can pay for breeding purposes. The transaction fee is paid by the initiator of the transaction. When a CryptoKitty is put up for auction by the seller, the seller pays a transaction fee by creating an auction contract. When a buyer initiates a transaction by offering a price for a CryptoKitty, the buyer pays the transaction fee. The value of a CryptoKitty can increase or decline based on market demand (Serada et al., 2020). Each CryptoKitty has a total of 12 attributes that describe various characteristics of the collectible. New Cryptokitties are created via smart contract, and they may inherit attributes from the parent CryptoKitties. Due to the limited number of attributes and attribute values, the rarity of a CryptoKitty can be determined by the combined rarity of the 12 cattributes. Thousands of players are actively engaged in the market since 2018 (Kittyhelper, 2023).

Given the popularity of the game and the availability of a large transaction dataset, the CryptoKitties digital collectibles and smart contracts provide a suitable environment to study consumer behavior in the context of the blockchain. Specifically, we focus our interest on buying/selling digital collectible smart contracts, and the related issues about buying customer and transaction cost. The characteristics of users in CryptoKitties are complex yet interesting. The users of CryptoKitties, whether buyers or sellers, are not necessarily pure investors of Ethereum, given the large transaction volumes and the collection value of CryptoKitties. Moreover, the users are also not exactly similar to consumers of ordinary/commodity goods. Lee, Yoo, and Jang (2018) consider CrypoKitties to be a mix of behavior with enjoyable and speculative aspects. Some of the users appreciate the graphic design and fun of the game; some of the users see CryptoKitties as valuable collectibles; yet some acknowledge the obsession with rising cryptocurrency values (Takahashi 2018). To that extent, CryptoKittes has carved its own niche in the market of Ethereum users. Given the profitable economic ramifications and non-negligible social implications of cryptogames, CryptoKitties, compared to other cryptogames, has a long market history. Our research contributes to the understanding of consumers' behavior in the market of crypto collectibles, who are not typical cryptocurrency investors nor are they typical consumers for ordinary goods. The characteristics of the consumers are fairly interesting which lead to several research questions: *Do the customers for digital collectibles in Blockchain platform share any similarity with regular consumers for ordinary goods? How does rarity or the collectible values of the products affect consumers' decision making? What is the implication of the growing value of the collectibles to the overall demand in this platform?*

Several studies address the relationship between transaction fees and the transaction data amount, mainly in Bitcoin's blockchain (Easley et al., 2019; Jiang and Wu, 2019; Kim, 2017; Schmidt and Wagner, 2019). The analysis of transaction fees in Ethereum is very limited. Our research fills the void by focusing on the transaction data of CryptoKitties in the Ethereum platform and exploring the additional research question: *What are the relationships of the transaction cost of Ether and other variables, such as transaction values, exchange rate, rarity of the product?* More specifically, we would like to understand whether the classical Transaction Cost Theory plays the same role under the context of CryptoKitties/Ethereum.

The remainder of the paper is organized as follows. In Section 2, we review the relevant literature. In Section 3, we discuss consumer behavior and transaction cost characteristics in the CryptoKitties platform and develop hypotheses. Then we define data and variables used in our study and the model formulations used to test our hypotheses in Section 4. In section 5, we present the estimation results and a discussion of the findings along with robustness checks of our results. Lastly, we discuss implications of our findings and conclude the paper in Section 6.

II. LITERATURE REVIEW AND THEORETICAL BACKGROUND

2.1. Blockchain and Ethereum

Blockchain is essentially a distributed, consensus-based, and immutable ledger of transaction records (Crosby et al., 2016). A network of blocks is a distributed database that autonomously maintains a public and continuously growing list of transaction records while remaining secure from tampering (Nofer et al., 2017). Thus, the key feature of blockchain transactions is the validation and execution of an encrypted tamper-proof block that contains an immutable, while anonymous, set of transactions (Pilkington, 2016). Recently, blockchain applications have inspired research interests in many areas. Risius and Spohrer (2017) present a research framework to apply blockchain in business information systems. Babich and Hilary (2020) propose research themes in information, automation, and tokenization that may have profound research potential in service and manufacturing operations management.

Proposed in 2014, the vision of Ethereum is an ecosystem for smart contracts rather than just creating another cryptocurrency (Wood, 2020). The Ethereum blockchain operates as a decentralized network where users can execute and verify application code, through a chain of blocks containing transaction data. A smart contract automatically performs a transaction when predetermined conditions are met and/or at the triggering of an identified event (Antonopoulos and Wood, 2018). Statistical analysis of Ethereum transaction data also indicates that Ethereum platform supports secure cryptocurrency transfers as well as various decentralized applications (or Dapps) backed by Ethereum smart contracts (Guo et al., 2019).

On the Ethereum blockchain, executed transactions are grouped into new blocks; each of the new blocks linked to the previous blocks form a chain. Hence, a blockchain grows by adding new blocks to the existing chain. New blocks on the Ethereum network are created by Miners (Gupta S. and Sadoghi M., 2018), who must provide a mathematical proof, known as a “ proof of work”, to validate a block. Since September 2022, the Ethereum network has moved to a new “proof of stake” mechanism where a miner is chosen at random based on the amount of ethereum staked. Every time a Miner proves a block, new Ether tokens are generated and awarded. In Ethereum transactions, gas is used to pay for computational and storage costs incurred during the creation, execution and approval of the transactions. Buyers specify the gas price to pay for the costs of mining a new block and the Miner can agree (or not) to work at that gas price (Wood, 2020). The gas price is a scalar value which is equal to the number of Wei to be paid per unit of gas for all computation costs incurred. The total gas used in transactions in this block is defined as the gasUsed (Wood, 2020). However, please note that in our paper, we distinguish "gasUsed" from the gas used for a single transaction by referring to it with a different term: "receipt gas used."

The aforementioned supply-and-demand dynamic allows users to prioritize time or cost in getting their transactions validated on the blockchain. When processing transactions in blockchain, Miners have a tendency to prefer to pick transactions with a smaller number of blocks involved for better computational efficiency to enhance transaction fee revenue (Jiang and Wu, 2019). In contrast, impatient users may be willing to pay higher transaction fees. As a result, a higher transaction fee may correlate with shorter holding time (Möser and Böhme, 2015). Schmidt and Wagner (2019) observe that blockchain may limit opportunistic behavior and reduce transaction costs, as it allows for transparent and valid transactions in the supply chain.

2.2. Non-Fungible Tokens and Digital Collectibles

Digital collectibles have become an important part of our lives; it can be any form of a virtual item, such as a video clip, digital art, or a crypto-collectible. Some digital collectibles are easily copied and distributed which raises issues of privacy and intellectual property protection. (Denegri-Knott et al., 2013). However, a non-fungible token (NFT) is a unique digital asset that uses blockchain technology to verify the ownership (Kräussl and Tugnetti, 2024). As a unique type of NFT or a crypto-collectible, CryptoKitties provide us a channel to understand how consumers perceive and evaluate the NFT product. We are particularly interested in analyzing the CryptoKitties value determinants and reveal the interplay between buyer valuations and market dynamics.

Whereas all tokens are identical in the case of cryptocurrencies, crypto-collectibles are cryptographically unique non-fungible tokens and represent the ownership of digital property (Sghaier Omar and Basir, 2020). Blockchain researchers have investigated the improvement of the transaction and validation process of digital collectibles that allows creators to receive credit for their digital art properties (Risius and Spohrer, 2017). The most significant crypto-collectible is the launch of CryptoKitties in Nov. 2017 (Evans, 2019). Within 6 months, until April 2018, the total turnover in CryptoKitties reached 43,067.04 ETH, which is about 200 million dollars (Min and Cai, 2019). CryptoKitties demonstrates the concept of non-fungible tokens (NFTs), which might impact more than the world of cryptocurrencies. The legacy of CryptoKitties raised awareness and inspired development talent to new applications for ERC-721 token standard (Serada et al., 2020). Inspired by CryptoKitties, Ethereum NFT has been applied to many digital collectables or asset development games. Among those, DECENTRALAND users are immersed in a shared virtual reality world that they can create and interactively contribute to digital properties (Gaggioli, 2018).

While this paper is interested in the trade of NFT in blockchain, most of the blockchain and smart contract-based applications are in the financial sector (Gomber et al., 2018). In trade finance, a model of decentralized consensus and information using smart contracts has modernized the hundreds of years old Letter of Credit practice (Cong and He, 2019). Years ago, people tended to think digital collectibles lack a number of traditional collectibles' enjoyments (Watkin et al., 2015). However in 2021, NFT investment volume was $656 million (Statistia, 2023). High market volatility, less complex barriers to entry, and investors' search for speculative assets drove the transaction numbers and the prices of NFTs (Baker et al., 2022). Nadini et al. (2021) analyze characteristics of a few leading NFT market places. They find that traders have close relationships with traders merchandising the same type of NFTs. In addition, they find that the collections of NFTs are closely related in their visual characteristics. According to Nadini et al. (2021), visual appearances ensure the differentiation between NFTs. In addition, natural rarity (i.e., scarcity) of collectibles can result in a positive attitude and increase purchase intention (Wu et al, 2012). Therefore, we include the rarity into our research model.
The technical implementation of NFT collectibles opens a gap in the literature on digital collectibles. From the perspective of the supply-and-demand dynamic, we analyze the value fluctuations of the most popular NFTs on the Ethereum platform — CryptoKitties, with a focus on how cryptocurrency trends and market participants influence market outcomes. By studying the factors shaping consumer purchase intentions toward CryptoKitties, our research contributes to a deeper understanding of consumer behavior within this emerging product category.

III. MODEL DEVELOPMENT AND HYPOTHESES

In this section, we discuss the mechanisms that underlie the CryptoKitties transactions. Specifically, we analyze two markets - the market for CryptoKitty collectables and the market for gas to enact the CryptoKitty transactions on the platform of Ethereum. Hypotheses 1-3 concern the first market and hypotheses 4-8 concern the second. Each market can be explained by a supply and demand curve. See Ilk et al. (2020) for a similar approach.

3.1. Market for CryptoKitty Collectibles

The principle of consumers' willingness to pay (WTP) is "the maximum amount of money a consumer is willing to spend for a product or service to measure the value" (Breidert et al., 2006). Nam (2018) analyzes consumer WTP for insurance smart contracts and in their survey, they estimated that 65% of the same respondents were willing to pay additional premium for blockchain and smart contracts. In our research, we use *Transaction Value* to estimate the consumers' WTP towards the CryptoKitty collectibles. This section intends to explore the factors that interact with transaction value of CryptoKitty collectibles.

The classic transaction cost economics (TCE), which studies the impact of transaction cost on consumers' valuation on the product, sheds light on the similar analysis in the context of blockchain. The transaction cost arises because of the asymmetric information in the market in classical economic theory. The basic principle of TCE is the preference to minimize transaction costs while conducting transactions (Rindfleisch and Heide, 1997). Liang and Huang (1998) define transaction costs as costs for "searching information, comparing attributes, examining products, negotiating terms, paying for product, delivering products, and post-sales services." As the transaction cost goes up, the consumer is less likely to purchase.

Tyagi (2004) reveals the same negative relationship between consumers' WTP and transaction cost. They model the demand structures such that a line representing the marginal consumers slopes upward. This indicates that if a consumer with high transaction cost purchases a product, it is because the consumer values the product quality highly.

Another factor of interest affecting transaction value, is the rarity of a CryptoKitty collectible. Evans (2019) considers digital kitties as non-fungible digital collectables with intrinsic scarcity, by giving an example that Genesis, Founders, and Fancy kitties led the "scarcity breed value" charge, with one CryptoKitty selling for over $114,000. Serada et al. (2020) define the monetary value of each digital kitty to be based on its uniqueness and value of the attributes. Their understanding is consistent with the artificial scarcity of digital goods, which helps to form the basis of various online economies. Gregory Lastowka and Hunter (2004) state that the virtual goods gain value as people are willing to pay money or time for them. For that reason, those virtual goods become "market-wise" and "real" for their owners, just as other real-world goods and services. Liang and Huang (1998) prove that the product value is also affected by the specificity of the product and that higher asset specificity would increase likelihood of purchasing decision. The rarity of the digital CrypoKitties collectables can be considered as the specificity of a product. The above results provide us evidence for the second hypothesis H2.

While both transaction cost and product rarity can be direct factors which impact the transaction value of the CryptoKitty collectibles, like the economic theory, the transaction volume which we denoted as transaction count, is a major factor that would interact with the transaction value. Gale (1955) proposes the "law of demand" in microeconomics. That is, the quantity of a good or the demand decreases when its price increases (Borjas, 2003). Burnetas and Ritchken (2005) study the option contracts in a supply chain and observe the same downward-sloping demand curves over the option prices. We then would like to argue that CyptoKitty collectables, as digital collectables, retain a similar property of "law of demand". Castronova (2008) performed an experimental study on demand and pricing in a virtual fantasy world game. They present the evidence that the law of demand holds in fantasy environments, which indicates that the gamers may well be "economically normal". The scale of this experiment is two virtual worlds with 43 players in each and each player played for a month. In our study, we further investigate to verify that law of demand applies to digital collectables in blockchain platforms with over 250,000 transactions over a longer horizon of data collection period (i.e., 12 months).

We then summarize the above discussion and relevant factors into a supply/demand model.

In the market for CryptoKitties, the demand (i.e., transaction count) is positively related to the rarity of the CryptoKitty and negatively related to the transaction value (i.e. price). In other words, the demand for CryptoKitties is a function of rarity and transaction value, Note the rarity would indirectly affect demand through its impact on transaction value. From the sellers' perspective, the cost of selling a CryptoKitty is the transaction cost that must be paid on the Ethereum platform. Sellers weigh the cost of selling with the transaction value they receive from selling the CryptoKitty. Thus the supply of CryptoKitties is a function of transaction cost and transaction value. Note the transaction cost would indirectly affect supply through its impact on transaction value. We then can graph out the market for CryptoKitty collectibles in Figure 1 with the demand curve in blue , which depends positively on the rarity of the CryptoKitty and negatively on the transaction value, and the supply curve in red, which depends negatively on the transaction cost and positively on the transaction value. The market equilibrium is *Value** such that demand equals supply.

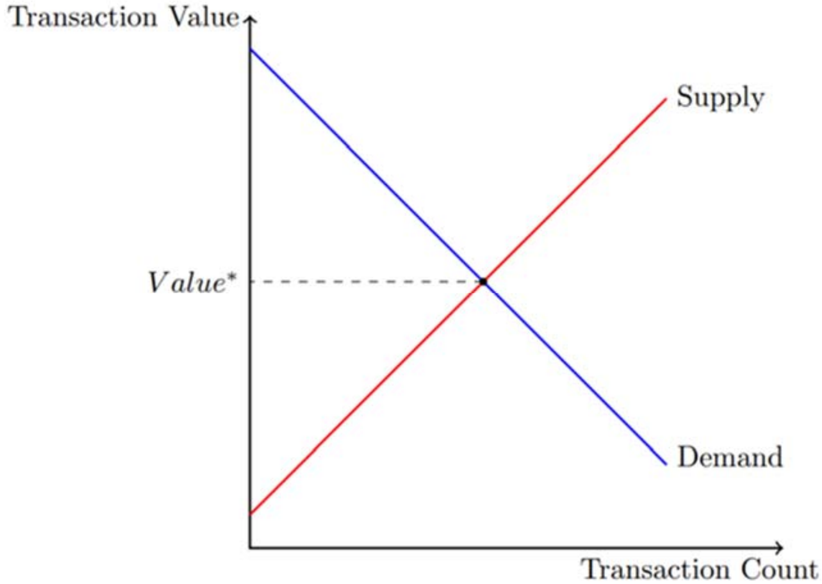

FIGURE 1. SUPPLY/DEMAND MODEL FOR CRYPTOKITTY MARKET

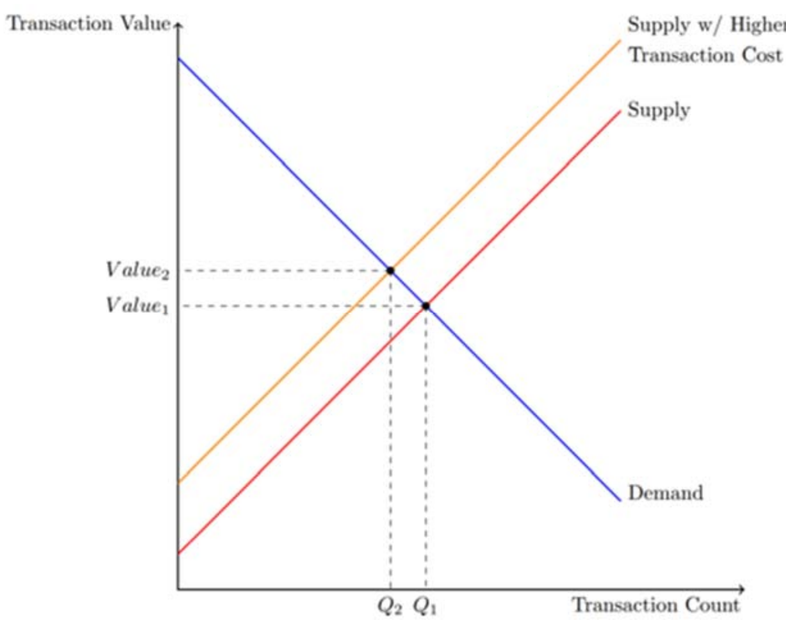

FIGURE 2. ILLUSTRATION OF HYPOTHESIS 1 AND HYPOTHESIS 3

Combining the above arguments, we postulate the impact of transaction cost and product rarity in CryptoKitties on the transaction value (i.e., the estimate of consumers' WTP) in H1 and H2.

Hypothesis 1 (H1): Holding other factors constant, the transaction costs and transaction values are positively associated such that higher transaction costs tend to *correspond to higher transaction values, with no assumption of causality implied.*

An increase in the transaction cost decreases the supply of CryptoKitties (or decreases the demand), as it makes it more costly for the sellers (or the buyers) of CryptoKitties to enter the market. This would shift back the supply curve as shown in Figure 2. The marginal transaction is going to have a higher transaction value ($Value_2$) than its original one ($Value_1$). Intuitively, at a higher transaction cost, only the consumers with a high WTP are going to still enter the market for CryptoKitties.

Hypothesis 2 (H2): Holding other factors constant, CryptoKitty collectables' rarity causes positive changes in the transaction values.

Consumers would have a higher WTP for a rarer CryptoKitty, which would further increase the demand for CryptoKitties. See the shift-up of the demand curve in Figure 3. This means that the marginal transaction is going to have a higher transaction value ($Value_2$). Intuitively, rarer CryptoKitties are more valuable, and so the transaction value for them increases.

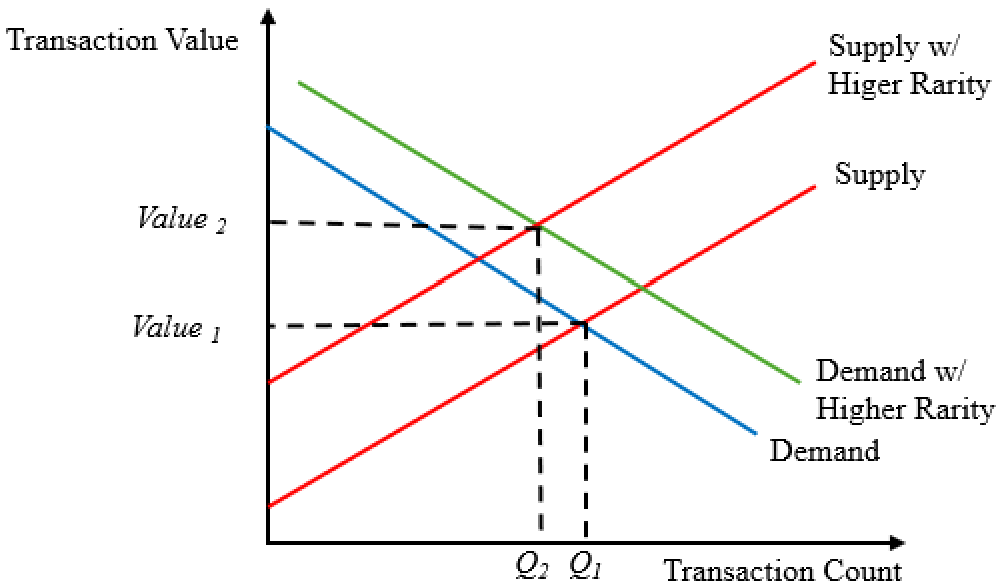

FIGURE 3. ILLUSTRATION OF HYPOTHESIS 2

We then look at the interaction between transaction count and transaction value. From a supply-demand perspective, the transaction value and transaction volume are inversely related. As we can see from Figure 2, if there is an increase in transaction value due to an increase in the transaction cost (i.e. a shift back in the supply curve), then this is going to also cause the transaction volume to decrease. If instead, the increase in transaction value was due to an increase in rarity, this as well could result in a lower quantity since the supply of rare collectibles, by definition is limited. This simultaneous shift in supply (lower supply of rarer CryptoKitties) and demand (higher demand for rare CryptoKitties) is shown in Figure 3. In Figure 2 and Figure 3, Q_1 is the transaction volume associated with transaction value $Value_1$ and Q_2 is the transaction volume associated with transaction value $Value_2$. Thus, we hypothesize the following:

Hypothesis 3 (H3): As transaction values increase, there is a decrease in transaction volume.

3.2. Market for Gas to Enact the CryptoKitty Transactions

Next we turn our attention to the transaction cost in *gas* in CryptoKitties. Gas is used to pay for computational and storage costs incurred during the creation, execution and approval of the transactions. Wood (2020) introduces “gasUsed” as a scalar value equal to the total gas used in transactions in one block. However, in our paper, the receipt gas used refers to the gas used for one transaction. Hence, for each transaction, the actual transaction cost in GWei is calculated as the multiplication of the gas price and the gas used. In the period considered in this paper (from Jan 1st, 2018 to Dec 30th, 2018), the gas price ranged from 0 Gwei to 49 Gwei and the gas used ranged from 41, 307 to 71, 344. Figure 4 shows the histograms of gas price and gas used during the analysis period.

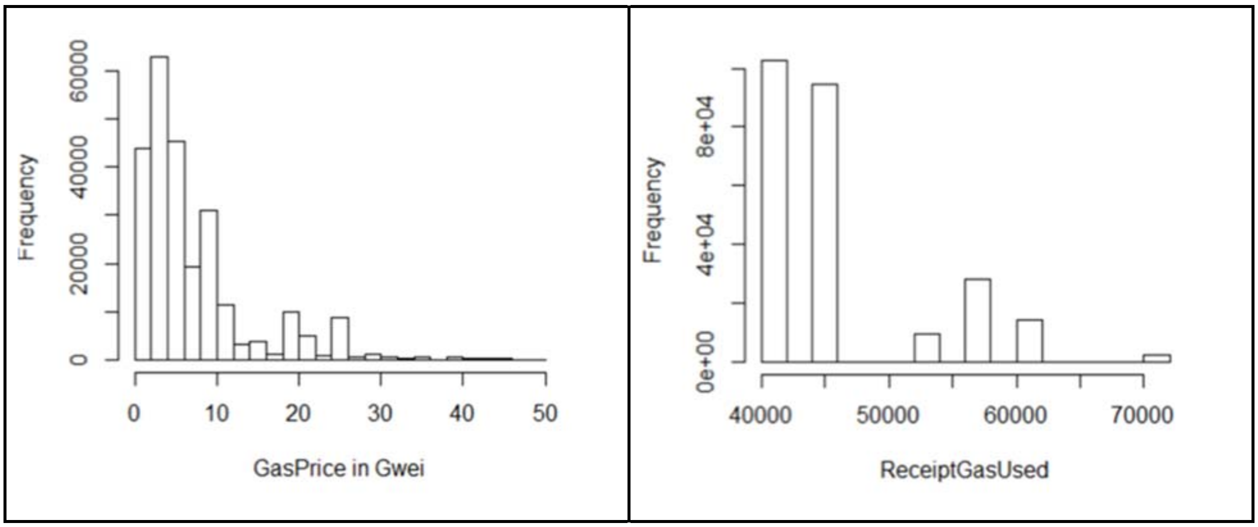

FIGURE 4. HISTOGRAM OF GAS PRICE AND GAS USED

The transaction process in CryptoKitties platform is the same as in the underlying Ethereum platform. In details, firstly the user sends a transaction to the Ethereum network; then a Miner picks up the transaction and puts it in his/her block; the Miner then tries to find the nonce value, which indicates a correct solution. Whichever Miner finds a solution for its block first, would then broadcast the solution to all the interconnected nodes in the Ethereum network. Once the solution is verified to be correct, the block is then added to the blockchain (Pierro and Rocha, 2019a).

The above procedure provides the incentive that when there are multiple transactions waiting, the Miner would prefer one providing the highest reward. Jiang and Wu (2019) verify such speculation by a game-theoretic approach to analyze how the block size in Bitcoin transactions determines a Miner’s payoff. The transaction fees, which aim to accelerate the transaction processes, is heavily affected by the corresponding transaction size. They find that a block with larger size tends to contain transactions with higher transaction cost (higher gas price and higher gas used) and hence more rewards.

Schmidt and Wagner (2019) propose that blockchain and transaction cost theory demonstrate significant conceptual overlap. The reason for the overlap of the two is that transaction cost theory is concerned with any problem that can be posed directly or indirectly as a contracting problem (Williamson, 1987) and blockchain provides a new approach to digital contracting in the form of smart contracts (Christidis and Devetsikiotis, 2016). In addition, Schmidt and Wagner (2019) argue that the blockchain limits opportunistic behavior due to public transparency. Those serve as strong evidence that the traditional transaction cost and transaction value (or product price) relation can be adopted here. In Tyagi (2004), a consumer with high transaction cost would find it optimal to buy the product when the product value is high. There exists a similar relationship between transaction cost and transaction fees in other areas. Vayanos (1998) has noted that the asset prices can be increased by the presence of transaction costs. Buss and Dumas (2019) find that the price of securities increases slightly when there is transaction fee. Accordingly, we hypothesize the following:

Hypothesis 4 (H4): Holding other factors constant, the buyer tends to pay a higher gas price when the transaction value is higher.

Lastly, we discuss the effect of the exchange rate of Ethereum and USD on the transaction cost. Li and Wang (2017) study the factors affecting Bitcoin exchange rate and find that in matured markets in later years, the price dynamics were more in line with changes in the economic fundamentals. Baur et al. (2018) consider the prevalent use of Bitcoin as a trading asset, and state that the exchange rate might be correlated with the transaction fees. As when the exchange rate is high, more users might be attracted to the network and would want to conduct transactions, which would create congestion and increase the transaction fees offered to Miners. The same logic applies to the platform of Ethereum - higher exchange rate would likely induce higher transaction cost. This is also verified by Pierro and Rocha (2019b) as they find Granger causality between number of unconfirmed transactions and oracle gas price. They define oracle gas price as “gas paid to have the transaction confirmed within 1 to 2 blocks time”. It is reasonable to expect that a high exchange rate would attract more transactions and hence more choices are available for the miners to accept the contract requests. To maximize the reward, the Miners tend to choose transactions with higher receipt gas used at a high exchange rate, if holding the gas price constant.

Given above arguments, we hypothesize the following:

Hypothesis 5 (H5): Holding other factors constant, the exchange rate of Ethereum causes positive change in the receipt gas price in transactions.

IV. RESEARCH METHOD

4.1. Data and Variables

We use the Ethereum BigQuery dataset (Day and Medvedev, 2018), a comprehensive database of Ethereum transactions updated daily, to analyze the CryptoKitties related transactions. Specifically, we retrieved CryptoKitties sales transactions conducted in the year 2018 based on the timestamp in each block of the Ethereum blockchain. For each sale transaction, we retrieved the ID of the CryptoKitties digital collectible along with the sale price indicated by the value of ether exchanged in the transaction (ValueGwei), the gas price (GasPrice) paid for the transaction by the buyer, and the complexity of the transaction as indicated by the receipt gas used (ReceiptGasUsed) for the transaction. The total transaction cost (TranCostGwei) is calculated by multiplying the gas price with the receipt gas used. We also retrieved the closing price of the Ethereum cryptocurrency from Yahoo Finance dataset. The US dollar equivalents of transaction costs and the value of the CryptoKitties were estimated based on the closing exchange rate of the Ethereum crypto currency on the day of the transaction. The raw dataset consisted of 256,404 transactions. We cleaned the dataset to remove missing values and outliers using the Interquartile Range method. Our final dataset consisted of 251,273 records.

The rarity of the collectibles was calculated using the inverse frequency of

CryptoKitties attributes, a measure similar to inverse document frequency (Jones, 1972) used in information retrieval. Each CryptoKitties collectible has 12 attributes characterized by a set of 48 genes, whereas each attribute is defined by 4 genes. Each gene can take several character values denoted by either a numeric digit (0-9) or a letter from the English alphabet (a-z). In order to quantify the rarity of a collectible, we first calculated the distribution of specific gene values across each of the 48 genes. We then calculated the inverse gene frequency (IGF) for each value of a gene as log(CK/n_i) where CK represents the total number of CryptoKitties on the blockchain network and n_i represents the number of collectibles that share the i^{th} value of a gene. The rarity of a CryptoKitties was then calculated by summing the IGF scores across all the 48 genes for the CryptoKitties collectible.

$$IGF_i = log\frac{CK}{n_i}, i = (1, 2, \ldots 48) \quad (1)$$

$$SIGF = \sum_{i=1}^{48} IGF_i \quad (2)$$

TABLE 1. VARIABLE DESCRIPTIONS

Variable Name	Description
ValueGwei	The price paid for the CryptoKitties collectible by the buyer in Gwei. Each Gwei is 1/100000000th of an Ethereum Crypto Currency Unit.
GasPrice	The price paid per computational unit in Gwei.
ReceiptGasUsed	The total computations units used for confirming the transaction, measured in 1000’s
TranCostGwei	The total transaction cost for confirming the transaction, measured in Gwei.
SIGF	The sum of inverse gene frequency (IGF) of each of the 48 genetic attributes of a CryptoKitties collectible. This is an index showing the rarity of the CryptoKitties collectible – the higher SIGF means the CryptoKitties collectible is rarer.
Generation	An attribute of CryptoKitties. The initial CryptoKitties have a generation value of 0. Subsequent CryptoKitties created through smart contracts have higher Generation values. Lower generation CryptoKitties are more prized than higher generation CryptoKitties.
TranCount	The total number of CryptoKitties sales transactions occurring on a day
AvgValueGwei	The average value of CryptoKitties collectibles traded on a particular day.
AvgSIGF	The average SIGF value of CryptoKitties collectibles traded on a particular day.
XRETH	The daily closed exchange rate of 1 Ethereum in USD dollars.
GasLimit	The maximum amount of Gas (computational units) that can be expended by the miner for processing the transaction request.

TABLE 2. SUMMARY STATISTICS

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
ValueGwei	251,273	58,030,932	142,675,373	100,000	4,000,000	47,650,017	2,189,044,264
GasPrice	251,273	7.608	7.223	0	3	10	49
ReceiptGasUsed	251,273	46,640.740	6,236.442	41,307	41,872	45,508	71,344
TranCostGwei	251,273	359,530.700	357,097.200	18,340	125,712	446,460.2	3,074,926
TranCostUSD	251,273	0.232	0.369	0.005	0.040	0.227	3.900
SIGF	251,273	13.432	2.015	9.729	11.961	14.486	25.389
Generation	251,273	5.164	6.514	0	1	8	303

4.2. Empirical Models

In order to test the various relationships between the value of digital collectibles (ValueGwei), Rarity of the Collectibles (SIGF), exchange rate of the ETH Crypto Currency (XRETH), and Transaction Costs (TranCostGwei) and its components (GasPrice and ReceiptGasUsed) we develop four different regression models as described below. Model 1 describes the relationship between Value of the collectible (ValueGwei), its transaction cost (TranCostGwei) and rarity of the Collectible (SIGF). To model the relationship between transaction cost and transaction value we use an instrumental variables approach. We are interested in the effect the transaction cost a buyer must pay on their willingness to pay for a CryptoKitty or value for the transaction, but value is also likely to affect cost since buyers may be willing to pay a higher transaction cost for higher value transactions. To deal with this interdependence, we instrument the transaction cost with the US Dollar costs of Ethereum Cryptocurrency (XRETH). Given that transaction costs are used to pay for computational costs, which are often paid in fiat currency by the Miners, the XRETH price of Ethereum is likely to only impact the value of the digital collectible through its effect on transaction costs, making it a good instrument for transaction costs. This regression model is described in equations (3) - (4).

<u>Model 1 for H1, H2</u>

$$\text{ValueGwei} = \beta_0 + \beta_1 \text{ TranCostGwei} + \beta_2 \text{ SIGF} + \varepsilon_1 \quad (3)$$

$$\text{TranCostGwei} = \gamma_0 + \gamma_1 \text{ XRETH} + \mu_1 \quad (4)$$

In order to model the relationship between transaction count and average transaction value, we aggregate transactions by day and regress daily transaction count on average daily transaction value. In this case, the average transaction value of CryptoKitties may be endogenous as it is correlated with other determinants of CryptoKitties value, which affect the transaction count and are considered part of the error term in the regression model in equation (5). For that reason, we instrument for average transaction value using average transaction cost and exchange rate XRETH. These cost variables will impact transaction value (through the channels outlined in Model 1) but are not related to the unobservable determinants of a collectible's value that also may impact transaction count. Please note that we do not incorporate the rarity into the regression. The reason is that the rarity of a CryptoKitty collectible directly tells the transaction frequency of that CryptoKitty collectible. By definition, the rarer a CryptoKitty collectible, the less frequently it is traded. This regression model is described in equations (5) and (6).

Model 2 for H3

$$TranCount = \beta_0 + \beta_1 \, AvgValueGwei + \varepsilon_2 \quad (5)$$

$$AvgValueGwei = \gamma_0 + \gamma_1 \, AvgTranCostGwei + \gamma_2 \, XRETH + \mu_2 \quad (6)$$

We are next interested in the determinants of the transaction cost, particularly its two key components, GasPrice and Receipt Gas Used. In Model 1 we looked at how the transaction cost affects the CryptoKitties buyer's willingness to pay, but here we are interested in what determines that cost. As noted earlier, there is an interdependence between transaction cost and transaction value so that while cost affects value (as modeled earlier), the transaction value can also affect the transaction cost. Particularly, buyers are willing to pay a higher gas price when the value of the collectible is higher. We model that by regressing gas price on collectible value. We also control for the exchange rate XRETH and gas used ReceiptGasUsed since those might directly affect the gas price. Due to simultaneous causality between ValueGwei and GasPrice, we instrument for ValueGwei with the collectible's rarity, SIGF. Rarity works as an instrument since it only affects the final gas price through its impact on the collectible's value. This is described by equations (7) and (8).

Model 3 for H4 H5

$$GasPrice = \beta_0 + \beta_1 \, ValueGwei + \beta_2 \, XRETH + \beta_3 \, ReceiptGasUsed + \varepsilon_3 \quad (7)$$

$$ValueGwei = \gamma_0 + \gamma_1 \, SIGF + \mu_3 \quad (8)$$

We use the two-stage least squares approach (2SLS) to estimate the parameters of the equations above. In the first stage, we regress the endogenous variables on the instrument variables as illustrated in equations (4), (6), and (8). The predicted values of the endogenous variables in the first stage are then used in the second stage of the regression where the models listed in equations (3), (5), and (7) are estimated.

V. RESULTS AND DISCUSSION

We used an instrumental variable regression using the two-stage least squares 2SLS approach (Kleiber and Zeileis, 2008) to estimate Models 1 through 3. We log transformed ValueGwei and TranCostGwei variables to account for their skewed distributions. For each of the models, we performed tests for exogeneity to test whether endogeneity is present and therefore an instrumental variable regression is an appropriate choice. Specifically, we performed the Wu-Hausmann test to test the null hypothesis that residuals are irrelevant and were able to reject the null hypothesis at a significance level of p-value < 0.01, therefore confirming the presence of endogeneity. We also performed an instrument relevance test to verify if the instrument variables are sufficiently correlated with the endogenous variable. The results for each of the models are presented below in Tables 3 through 5. We present results from both 2SLS and ordinary least squares (OLS) for comparison.

5.1. Relationships Influencing the Consumers' Willingness-to-pay for CryptoKitties

The estimates for Model 1 are presented in Table 3. We find strong support for a positive relationship between the rarity of the CryptoKitties and their traded value. We also find strong support for a positive relationship between transaction costs paid by the buyer and the traded value of the CryptoKitty, likely because only buyers with a high willingness to pay will purchase at higher transaction costs. These results support both H1 and H2. The significant positive relationship between rarity of the CryptoKitty and its value are reinforced subsequently in the first stage regression results of Model 3. This finding confirms that valuation of digital collectibles in the Ethereum blockchain is similar to patterns in traditional marketplaces where the valuation of a collectible is positively associated with its rarity. This is verified by (Liang and Huang, 1998) that consumers value the product higher when asset specificity (similar to rarity in our paper) is higher, and therefore become more willing to pay higher transaction cost to get the product.

TABLE 3. MODEL 1 RESULTS

	Dependent variable: log(ValueGwei + 1)	
	Instrumental Variable	*OLS*
log(TranCostGwei + 1)	0.349^{***} (0.017)	0.266^{***} (0.003)
SIGF	0.094^{***} (0.002)	0.091^{***} (0.002)
Constant	10.868^{***} (0.213)	11.924^{***} (0.049)
Observations	251,273	251,273
Diagnostic Tests		
Weak Instruments	11527.42***	
Wu-Hausman	26.11***	
Note:	*p<0.1; **p<0.05; ***p<0.01	

TABLE 4. MODEL 2 RESULTS

	Dependent variable: TranCount	
	Instrumental Variable	*OLS*
log(AvgTranValue + 1)	-472.199^{***} (127.409)	-122.39** (55.68)
Constant	$9{,}121.805^{***}$ (2,271.366)	2,886.11** (992.99)
Observations	364	364
Diagnostic Tests		
Weak Instruments	48.512***	
Wu-Hausman	10.897***	
Sargan	1.508 (p-value = 0.219)	
Note:	*p<0.1; **p<0.05; ***p<0.01	

5.2. Relationships Influencing Transaction Volume

The estimates for Model 2, where we test the relationship between transaction volume and value are presented in Table 4. In estimating Model 2, the Wu-Hausman and Weak Instruments test indicate the presence of endogeneity and the presence of at least one strong instrument. The Sargan test (Sargan, 1958) for instrument validity does not reject the null hypothesis of instrument exogeneity, implying that the instruments are valid and uncorrelated with the error term. We find a negative and significant relationship between Average Transaction Value and Transaction Counts, indicating demand is downward sloping and there is a lower demand for higher value

CryptoKitties and supporting H3. The results for both H2 and H3 thus indicate that trading patterns for digital collectibles on the Ethereum blockchain marketplace are similar to traditional markets. Thus, further analysis of transaction costs on the Ethereum marketplace will allow us to derive blockchain specific insights regarding the relationships between transaction values, transaction complexity, Ethereum exchange rates and consumer willingness to pay transaction costs.

5.3. Characteristics of Equilibrium Transaction Cost

We test various relationships between different components of the transaction cost in an Ethereum transaction, the transaction values and the exchange rate of Ethereum cryptocurrency in Model 3. The estimates for Model 3 are presented in Table 5. The Wu-Hausman test and the Weak Instrument tests indicate the presence of endogeneity and SIGF as a strong instrument variable, thus reinforcing our findings for H2. The results for Model 3 indicate a strong and positive association between Value of the CryptoKitty and the GasPrice component of the transaction costs, indicating consumers are willing to pay a higher GasPrice for high value collectibles (H4).

TABLE 5. MODEL 3 RESULTS

	Dependent variable: GasPrice	
	Instrumental variable	*OLS*
log(ValueGwei + 1)	1.622*** (0.081)	0.327*** (0.009)
XRETH	0.008*** (0.00005)	0.008*** (0.00004)
ReceiptGasUsed	-0.037*** (0.006)	0.060*** (0.002)
Constant	-21.654*** (1.057)	-4.735*** (0.153)
Observations	251,273	251,273
Diagnostic Tests		
Weak Instruments	3256.8***	
Wu-Hausman	285.3***	
Note:	*p<0.1; **p<0.05; ***p<0.01	

The results for H3 that indicate a negative relationship between transaction value and transaction volume, along with those for H4 can help explain the effect of higher gas prices on transaction volume on the blockchain. As gas prices tend higher, only consumers trading higher value objects, and thus willing to pay the higher gas price would trade on the blockchain, leading to a lower transaction volume.

In investigating the effect of Ethereum exchange rate (XRETH) on transaction costs (gas price and/or gas used), we find that the exchange rate has a positive effect on both gas used and gas price components of the transaction costs. As the price of the Ethereum cryptocurrency increases, it impacts both the value of the digital collectibles as well as the number of traders on the platform thus increasing congestion. The high congestion in turn leads to increased gas price. Overall, as a result of the increasing exchange rate and the resulting speculative environment, consumers are willing to pay a higher transaction cost to get their transactions confirmed on the network. Therefore, although we expect transaction costs in Gwei terms to fall with increases in exchange rate, we find a counter-intuitive result that an increase in the exchange rate further increases the transaction costs due to speculative behavior of users thus supporting H5. This phenomena is similar to the asset price bubbles in other markets where speculative purchasing of assets increases their prices (DeLong et al., 1990; Scherbina and Schlusche, 2014).

5.4. Robustness Checks

To further verify the model robustness, we estimated multiple variations of Models 1& 3 by adding additional control variables and evaluating sign stability and significance rate across the model variations (Young and Holsteen, 2017). Specifically, we used different combinations of GasLimit and Generation as control variables and also estimated model variations that measure Value, GasPrice, and Transaction Costs in USD instead of Gwei. The results of our robustness checks are presented in Tables 6 & 7 below.

TABLE 6. MODEL 1 ROBUSTNESS CHECKS

	Dependent Variable: log(ValueGwei +1)				log(ValueUSD + 1)
	(1)	(2)	(3)	(4)	(5)
log(TranCostGwei + 1)	0.349^{***} (0.017)	0.442^{***} (0.016)	0.349^{***} (0.017)	0.441^{***} (0.016)	
log(TranCostUSD + 1)					3.479^{***} (0.021)
SIGF	0.094^{***} (0.002)	0.115^{***} (0.002)	0.093^{***} (0.002)	0.115^{***} (0.002)	0.048^{***} (0.002)
Additional Controls	None	Generation	GasLimit	Generation, GasLimit	None
Note	*p<0.1; **p<0.05; ***p<0.01				

TABLE 7. MODEL 3 ROBUSTNESS CHECKS

	Dependent variable: GasPrice				GasPriceUSD
	(1)	(2)	(3)	(4)	(5)
log(ValueGwei + 1)	1.622^{***} (0.081)	1.337^{***} (0.065)	1.624^{***} (0.081)	1.338^{***} (0.065)	
log(ValueUSD + 1)					0.00001^{***} (0.00000)
XRETH	0.008^{***} (0.00005)	0.008^{***} (0.00004)	0.008^{***} (0.00005)	0.008^{***} (0.00004)	
ReceiptGasUsed	-0.037^{***} (0.006)	0.002 (0.005)	-0.037^{***} (0.006)	0.003 (0.005)	-0.0000^{***} (0.00000)
Control Variables	None	Generation	GasLimit	Generation, GasLimit	None
Note:	*p<0.1; **p<0.05; ***p<0.01				

Regarding the various hypothesized relationships between Value, Rarity, Transaction Costs, GasPrice and Exchange Rates, we find that the significance rate and sign stability are consistent across all the variations of Model 1 & 3 indicating the robustness of our results. We also find similar coefficient signs and significance rates irrespective of whether the units of measurement are in terms of Gwei or USD. However, in the case of Model 3, we observe that the coefficient on ReceiptGasUsed changes sign and significance when controlling for Generation of CryptoKitties. The Generation of CryptoKitty is another indicator of rarity as older generation CryptoKitties are rarer and more valuable. The results here provide further evidence for our interpretation of the Model 3 results that transactions that are of high value not due to rarity are associated with lower gas prices and higher receipt gas used.

To test the robustness of our Model 2 results, we performed Sagan's Over-Identification test for instrument validity. Over-Identification tests work reliably when the number of instruments is more than the number of the endogenous variables. We tested Model 2 using the Sagan test and were unable to reject the null hypothesis, therefore indicating that the instruments are valid.

VI. CONCLUSIONS

In this paper, we use CryptoKitties as an example to study phenomena related to the trading of smart contracts and digital collectibles on blockchain networks. Over the past decade, blockchain networks continue to gain popularity and increased adoption. Some blockchain networks, such as Ethereum, have developed into marketplaces for advanced software enabled contracts and digital goods. To help fully realize the potential for blockchain based marketplaces for smart contracts, we need to study the factors that affect marketplace transactions in blockchain smart contract markets.

From the perspective of the supply-and-demand dynamic, we analyze the value fluctuations of the most popular NFTs on the Ethereum platform — CryptoKitties, with a focus on how cryptocurrency trends and market participants influence market outcomes. Specifically, our research objectives were to understand the inter-relationships between transaction costs, transaction value and transaction volume. We present a theoretical model from a supply and demand perspective and identify factors that influence transaction values and the influence of transaction values on consumer willingness to pay the transaction costs.

The context of our study is the CryptoKitty digital collectibles smart contract on the Ethereum blockchain. We analyzed data from 2018 pertaining to the sales of CryptoKitty smart contracts. For each transaction, we collected information on various components of the transaction cost including per computational unit cost (GasPrice), computational complexity of the contract (ReceiptGasUsed), value exchanged in crypto currency units (ValueGwei), and the closing price of the Ethereum US Dollar exchange rate (XRETH) among other variables.

The results of our analysis show that the valuation of digital collectibles is influenced by the rarity of the collectible. We also find that both transaction costs and Cryptokitties valuations have a positive effect on each other. The valuation of a collectible reflects consumers' willingness-to-pay. Similarly, when highly valued CryptoKitty is being traded, consumers are willing to pay a higher transaction cost to get the transaction recorded on the blockchain. In investigating factors affecting transaction volume, we find that the volume decreases as higher valued CryptoKitty collectables are traded confirming a downward sloping demand as value increases. With regard to the specific components of transaction costs, we find that users tend to pay a higher gas price to get high value transactions recorded on the blockchain. In addition, the USD exchange rate of Ethereum crypto currency is also found to be positively associated with Ethereum gas price and ReceiptGasUsed.

The contributions of our study are mainly in the following aspects.

First, the NFTs have created unprecedented market opportunities and captivated millions of investors. As one of the most successful NFTs, CryptoKitties demonstrate great potential with high demand (Serada et al., 2020). From that perspective, by studying the factors shaping consumer purchase intention in the CryptoKitties market, our research contributes to a deeper understanding of consumer behavior within this emerging marketplace. Results in our study indicate the presence of both rational and speculative processes involved in the trading of CryptoKitty digital collectibles. Our findings that the valuation of digital collectibles is based on rarity and that consumer willingness to pay higher transaction costs is based on higher valuations confirms with traditional market phenomena. The positive effect of Ethereum transaction costs on valuation of the crypto collectibles and the positive effect of exchange rate of Ether on transaction costs are counter intuitive and potentially due to speculative processes. Increases in transaction costs are often due to increased congestion as a result of higher demand. Thus, higher transaction costs and values seem to affect each other.

Second, our study contributes to understanding the trading phenomena on Ethereum blockchain and identifying issues that can help in the further development of the platform. There are two major implications for the Ethereum platform of crypto collectibles. The USD exchange rate of Ethereum has significant implications on trading volume and produces counter intuitive behavior where prices increase with increase in transaction costs, likely due to speculative behavior. However, this limits the market to the trade of high value collectibles and eventually lower trade volumes. We see evidence of traditional market patterns as well, such as rarity's influence on valuation, indicating the potential use of blockchain platforms for smart contracts and valid financial instruments. Therefore, exchange rate stability and low transaction costs are a key factor in widespread adoption of blockchain platforms.

There are some limitations to the generalizability of our findings. First, our analysis is limited to one type of smart contract, the CryptoKitty collectibles and is based on 1-year data. The analysis does not include other digital collectibles or smart contracts in the same domain or in different domains, since they are sparsely traded or are in very early stages of development. Blockchain platforms continue to evolve and change over the years. In 2022, the Ethereum blockchain shifted in the mining mechanism to Proof of Stake (Amure, T.O., 2023). While this is expected to reduce some aspects of the mining computational difficulty, the gas price and gas used mechanisms for transaction pricing are expected to remain the same. Our research is also limited to smart contracts involving the sale and purchase of digital collectibles. Future research can further extend this work to explore the relationship between various types of smart contracts, transaction costs, and exchange rates.

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