# Inclusion and Democratization Through Web3 and DeFi? Initial Evidence from the Ethereum Ecosystem*

*By* LIN WILLIAM CONG, KE TANG, YANXIN WANG, AND XI ZHAO

*Web3 and DeFi are widely advocated as innovations for greater financial inclusion and democratization. We assemble (and share) the most comprehensive data from Ethereum, the largest Web3 ecosystem, to conduct an initial investigation using large-scale computing. We describe its network structure, time trends, and distributions of transactions, mining, and ownership. Mining and ownership of Ether are concentrated in exchanges and a few individual nodes. Network activities evolve from peer-to-peer to user-DApps/DeFi interactions, with significantly more transactions by large players. Moreover, high percentage transaction fee, congestion-induced fluctuation of gas prices, suboptimal reserve setting, and large return volatility of tokens present particular challenges for small, poor, unsophisticated, and new nodes in the network, not to mention that the high failure rates hurt all nodes. We also present evidence that base-fee burning mechanisms (e.g., EIP-1559) and airdrop programs (e.g., OmiseGo Airdrop) facilitate inclusion through token monetary redistribution.*

*JEL: E42, G12, H23*
*Keywords: Airdrop, Big Data, Blockchain, DeFi, EIP-1559, Inclusion, Inequality, Large-Scale Computation, Transaction Fees*

* We thank Jan Bena (discussant), Agostino Capponi (discussant), Hanna Halaburda, Cam Harvey, Po-Hsuan (Paul) Hsu, Fuwei Jiang (discussant), Kose John, Leonid Kogan (discussant), Luca Liebi, Donghwa Shin, David Yermack, Luyao Zhang (discussant), and seminar and conference participants at Asia Innovation and Entrepreneurship Association (AIEA) Seminar Series, Crypto and Blockchain Economic Research (CBER) Forum Symposium, UWA Blockchain and Cryptocurrency (BC) Conference, the Department of the Treasury Office of Financial Research, 2022 Hong Kong Conference for Fintech, AI, and Big Data in Business, Luohan Academy Webinar, MIT GCFP 9th Annaul Conference on "Building and Regulating the New Financial Infrastructure," 3rd NY Fed FinTech Conference, 19th China Finance Association Annual Meeting, National University of Singapore (Department of Accounting), and Southeast University for helpful comments. The authors also thank the Fintech Dauphine Chair in partnership with Mazars and Crédit Agricole CIB as well as Xiaowei Cui and Inddigo platform (http://inddigo.io) for providing financial and technical support. Cong is at Cornell University SC Johnson College of Business and NBER, `will.cong@cornell.edu`. Tang is at Institute of Economics, School of Social Science, Tsinghua University, `ketang@tsinghua.edu.cn`. Wang and Zhao are at the School of Management, Xi'an Jiaotong University, `wyx980107@stu.xjtu.edu.cn` and `zhaoxi1@mail.xjtu.edu.cn`. Please send inquiries to Zhao (the corresponding author) or Cong.

## I. Introduction

How financial technology impacts financial inclusion and democratic access to financial services is central for policy discussions and applied research (World Bank Group, 2016; Philippon, 2019). Meanwhile, blockchain, the foundation for Web3 and deemed to be the next major breakthrough in general purpose technology after the Internet, has spurred many innovations in digital payment and decentralized finance (DeFi, which includes lending, stablecoins, decentralized exchanges, etc.) around the globe. One oft-cited advantage of blockchains over traditional financial systems entails reduced centralization and intermediation costs, because open consensus protocols and smart contracts ensure distributed recordkeeping and executions of transactions (Cong and He, 2019; John, Kogan and Saleh, 2022). Moreover, open access, transparency, and increasing interoperability conceptually enable DeFi to provide financial services to under-served groups and billions of unbanked people around the globe (Harvey, Ramachandran and Santoro, 2020).[1] Yet it is far from clear empirically whether Web3 and DeFi's facilitating financial inclusion and democratization is an economic reality, despite the given the ethos of crypto enthusiasts.[2] In particular, while digitization and decentralization encourage competition and innovation, they do not necessarily benefit consumers if the costs and failure rates of financial services are high.

We use data from the Ethereum ecosystem to systematically examine this first-order question on whether Web3 and DeFi promotes financial inclusion and democratization. Ethereum is by far the most dominant smart contracting and Web3 platform (Schär, 2021) with the second largest cryptocurrency by market capitalization and hosting 93% of all DeFi projects by number and over 60% in the total value locked (TVL) as of 2021 (Browne, 2021; DeFi Prime, 2021).[3] Therefore, we assemble, analyze, and make available to our knowledge the most comprehensive datasets to date on the Ethereum blockchain and its associated DeFi applications.[4] We complement on-chain data with several other online sources and apply large-scale computer clusters for our analyses. We (i) document trends and statistical patterns of network structure, ownership, mining, and transaction on Ethereum, including high mining and ownership concentration, (ii)

[1]In fact, many would argue that the dramatic failure of the FTX exchange is due to centralization and the lack of transparency, for which DeFi offers the remedies.

[2]The lack of scalability (Abadi and Brunnermeier, 2018; Chen, Cong and Xiao, 2019), high transaction fees (Haig, 2021), frauds and manipulation (Cong et al., 2021; Li, Shin and Wang, 2021), and token price volatility (Cong and Xiao, 2021) all present significant obstacles.

[3]Ethereum's on-chain daily volume and total market cap in our sample period easily exceeds 5 billion USD and 200 billion USD respectively. According to the statistics of DeFi Prime (2021), there are 235 listed DeFi projects and 219 are proposed on Ethereum in 2021.

[4]Data used in our analyses are available at http://drzhaoxi.org/DefiPaper.

show how the marginalization of small players through fees, high failure rates, and high token return volatility hinder financial inclusion and democratization in the ecosystem, and (iii) demonstrate how the recently implemented EIP-1559 mechanism and airdropping mitigate these issues through monetary redistribution. Our work adds to a better understanding of arguably the most dominant ecosystem for DeFi and Web3, and provides a comprehensive source of information and useful benchmark for evaluating future changes including the switch of Ethereum to Proof-of-Stake (PoS) and informs the decision-making of both the policymakers and practitioners in general.[5]

We start by providing a description of various network structures in the ecosystem, which reveals information concerning the importance of and competition among the DApps and DeFi protocols. In particular, DeFi applications and exchanges play a central role in the network and DApps mainly interact with users via ERC-20 tokens. We then document that similar to the Bitcoin case, the top 5% mining pools (about 3 to 5 mining pools) received about 60% of block rewards, and the top 0.5% of individual miners receive 30-50% of the rewards. The rewards are distributed to individual miners and subsequently sent by miners primarily through centralized exchanges. Ether ownership has grown in concentration over time, with the top 10% of the nodes owning more than 90% in the second half of our sample. It is also heavily concentrated at a few nodes of institutions and individual users, with over 90% in contract accounts and exchange addresses. Note that the levels of income and ownership concentration are significantly higher on average than that of the income and wealth shares in the United States (Saez and Zucman, 2020). Moreover, ERC-20 tokens other than ETH gradually dominate transaction volume, and overall, transactions have shifted from peer-to-peer to those between users and DApps. For example, DApps accounted for less than 10% of transaction volume in 2017 but accounted for about 90% in 2020. Importantly, transactions are concentrated at nodes with higher on-chain wealth and where larger transactions dominate.

Transactions within the ecosystem and network utilization do provide direct litmus on how inclusive and democratic a platform is. We therefore analyze them further. Note that any activity on Ethereum requires a transaction fee, known as gas fee, which depends on its computing resources consumed as well as users' willingness to pay (Zarir et al., 2021). Gas fees also incentivize the miners for proper record-keeping and smart contract execution, and are crucial for the stability and sustainability of any DeFi system (Ilk et al., 2021). We then take advantage of on-chain information related to the gas mechanism

[5]President Biden's Executive Order specifically calls for a thorough understanding of blockchain and DeFi infrastructure and applications to foster responsible development of digital assets. See, e.g., https://www.whitehouse.gov/briefing-room/statements-releases/2022/03/09/fact-sheet-president-biden-to-sign-executive-order-on-ensuring-responsible-innovation-in-digital-assets/.

to analyze how transactions fee mechanisms affect inclusion and democratization. For a financial platform to be inclusive and democratic, it has to be functional, efficient, fair, and affordable to small, under-served groups (Corrado and Corrado, 2017). A large literature has demonstrated that both direct and indirect transaction costs can hinder financial inclusion (e.g., Dupas and Robinson, 2013; Jack and Suri, 2014; Bachas et al., 2018). We add by demonstrating that digitization and DeFi are no panacea and if not well-designed, can even further the digital divide.

Specifically, we identify multiple transaction-related issues that hinder financial inclusion on Ethereum. First, the percentage transaction fee—transaction fee as a fraction of the transaction amount—varies across the type of financial transactions and is disproportionally high for small players in the ecosystem due to the gas mechanism which features fixed costs for smart contract computation and execution. While it is attractive for cross-border transactions by large institutions, underserved groups likely find DeFi too costly as an inclusive finance instrument. Consistent with Easley, O'Hara and Basu (2019), we also find that the congestion of the network creates significant fluctuations of gas prices, not to mention the Ether returns feature high volatility itself. Coupled with users' limited knowledge and lack of experience (and consequently suboptimal gas parameter setting), they cause a large fraction of transactions to fail, incurring significant losses for users.

Despite aforementioned challenges, recent innovations intentionally or unintentionally improve financial inclusion through redistributing on-chain wealth across network nodes. In particular, EIP-1559 alleviates congestion through an adjustable block gas limit, and dynamically adjusts and burns base fee based on supply and demand. It still causes high transaction fees for small players because it is a matter of scale rather than mechanism design (Roughgarden, 2020*a*). Nonetheless, the burning of base fees collected from large players benefits all players, including small and new agents, by reducing the token supply (a "deflationary" action). Using a difference-in-difference framework, we find that after the introduction of EIP-1559 and thus the redistribution, miners with larger shares of mining income or belonging to smaller mining pools experience greater reductions in mining income, where as smaller and less wealthy users conduct more transactions in the network. Using the case of OmiseGo airdrop program on Ethereum, we also demonstrate how airdrops as redistributive policies can also improve financial inclusion. In particular, airdrops disproportionally encouraged less active and poorer users to utilize the network. Promoting OMG as an alternative and seemingly competing ERC-20 token within the Ethereum ecosystem also boosted the value of Ethers.

Our study adds to the literature on transaction fees in blockchain-based systems, of which Chung and Shi (2021) provides a timely survey. Easley, O'Hara and Basu (2019) and Huberman, Leshno and Moallemi (2021) are the earliest to analyze transaction fees and relate congestion to transaction fee and system stability. Ilk et al. (2021) discusses self-regulation of fees in Bitcoin, while Basu et al. (2019) and Lavi, Sattath and Zohar (2019) study the design of fees within an auction-based framework. We add a more nuanced picture by documenting that the impact of congestion on transaction fees varies according to transaction type. Several recent studies analyze fee mechanisms on DEXs: Hasbrouck, Rivera and Saleh (2022) argue that increases in fees can increase DEX trading volume; using data from Ethereum, Capponi, Jia and Yu (2022) show that traders bid high fees on DEXs primarily to reduce the execution risk of their orders. We are the first to analyze the entire Ethereum ecosystem, which supports a richer ecosystem for DeFi and Web3 than Bitcoin or specific DeFi protocols the extant literature focuses on.

In terms of transaction fee design, several studies evaluate EIP-1559 as one of the first deviations from the widely adopted first-price auction paradigm. For example, Roughgarden (2020*b*) assesses the game-theoretic strengths and weaknesses of the EIP-1559 proposal and explores alternative designs. Reijsbergen et al. (2021) discuss unintended increases in inter-block variability in mining rewards. Most closely related to our study is Liu et al. (2022) which documents that that EIP-1559 makes fee estimation easier for users, mitigates intra-block difference in gas price paid, and reduces users' waiting times. We complement these studies by showing that EIP-1559 helps with financial inclusion and democratization through redistribution.

More broadly, our study contributes to the emerging literature on DeFi and Web3.[6] John, Kogan and Saleh (2022) describe the implementation, benefits, and limitations of smart contracts on the Ethereum blockchain. Other extant studies are either theoretical (Chen and Bellavitis, 2020; Harvey, Ramachandran and Santoro, 2020; Schär, 2021) or focus on specific DeFi applications such as Decentralized Exchanges and automated market-making (Lehar and Parlour, 2021; Capponi and Jia, 2021; Park, 2021; Augustin, Chen-Zhang and Shin, 2022) or lending (e.g., Lehar and Parlour, 2022). Related to our emphasis on ecosystem states, several studies investigate mining concentration and wealth distribution (e.g., Cong, He and Li, 2018; Capponi, Olafsson and Alsabah, 2021; Roşu and Saleh, 2021). Capponi, Jia and Wang (2022) and Auer et al. (2022) examine miner/maximal Extractable values.

Our study adds to recent efforts to assemble large datasets and utilize high-power com-

[6] A related literature examines token valuation and users' and miners' behaviors under game-theoretical settings (e.g., **?**Cong, Li and Wang, 2021; Han and Makarov, 2021; CHOI and JARROW, 2022). A number of studies also point to the limitations of blockchains. Hinzen, John and Saleh (2020) discuss the limited adoption problem of PoW (proof-of-work) mechanism. Sokolov (2021) report congestion and ransomware activities on Bitcoin. Furthermore, the concern about energy consumption and majority attacks (e.g., Chen, Cong and Xiao, 2019; Gonzalez-barahona, 2021) have been widely recognized.

putation to analyze blockchain networks. For example, Makarov and Schoar (2022) use novel datasets and algorithms to combine rich on-chain and off-chain information to provide a detailed analysis of the Bitcoin network, including geographic clustering of miners. Studies such as Foley, Karlsen and Putniņš (2019); Cong et al. (2021, 2022*b*,*a*) apply forensic finance to big data concerning cryptocurrencies to detect and analyze market manipulation, tax evasion, and crypto-enabled crimes. We complement by going beyond payments and examining the largest DeFi and smart contracting platform. Importantly, we provide one of the first documentations of Ethereum network structure, ownership distribution, mining activities, transaction landscape, and activities such as fee mechanism changes and airdrops.

Also closely related is Zhang, Ma and Liu (2022) establishing a taxonomy for analyzing blockchain decentralization and highlighting the lack of research on the transaction aspects — exactly the gap that our study bridges. Ao, Horvath and Zhang (2022) document a significant core-periphery structure in the AAVE network and higher returns and lower volatility of the associated DeFi tokens predicted by more decentralization. We focus on the larger Ethereum ecosystem and differ by emphasizing transactions and fee mechanisms with their implications for financial inclusion and democratization. We are also the first to study the redistributive effects of fee mechanisms and airdrops, adding to recent studies on the monetary policy of crypto-tokens (e.g., Cong, Li and Wang, 2020), airdrops (Froewis et al., 2021; Liebi, 2021), and redistribution through staking (John, Rivera and Saleh, 2021; Cong, He and Tang, 2020).

Finally, our study contributes to the discussion of digitization and financial inclusion. While the literature has mostly focused on the differential impact, direct or indirect, of FinTech and digital technologies on the digital and non-digital populations (e.g., Philippon, 2016; Zhongming et al., 2021; Jiang, Yu and Zhang, 2022), or informational frictions that lead to, e.g., discrimination (Bartlett et al., 2022), an increasing number of studies recognize the important role of transaction costs. For example, Bachas et al. (2018) and Jack and Suri (2014) show how high transaction costs reduce inclusion and risk sharing, using data from Kenya and Mexico. We use the Web3 setting to demonstrate that even within the group of the digital savvy, high fixed transaction fees precludes financial democratization and inclusion.

The remainder of the paper is organized as follows. Section II provides the institutional background of smart contracting and gas mechanisms before introducing our data sets. Section III describes the general network structure and distributions of token ownership, mining, and transactions. Section IV highlights the impact of transaction fees on financial democratization and inclusion. Sections V and VI documents the redistributive effect of the transaction fee reform and airdrops. Section VII concludes.

## II. Institutional Background and Data

### A. *Smart Contracting and Ethereum Gas Mechanism*

**DeFi with smart contracts.** A smart contract is a set of codes based on decentralized consensus, which can be executed automatically (Lauslahti, Mattila and Seppala, 2018; Cong and He, 2019) on-chain. Most decentralized applications (DApps) and DeFi projects rely on smart contracts instead of third-party institutions or infrastructure in traditional centralized systems to ensure trusted transactions among (anonymous) entities. DeFi is widely advocated as inclusive and representing the future of finance because it is believed to solve problems of centralized control, limited access, inefficiency, lack of interoperability and opacity in the traditional financial system (Harvey, Ramachandran and Santoro, 2020).

**Gas limit, price, and usage.** Transaction fees on Ethereum follow its gas mechanism (Zarir et al., 2021). Gas measures the consumption of computing resources, and gas usage is the amount of gas consumed for the transaction's execution. Three key parameters, gas limit, gas price, and gas usage, characterize the mechanism.

Gas limit is the maximum amount of gas consumption by a transaction set by the initiator of the transaction, partially to protect users from malicious attacks on the network. Gas price, usually measured in $gwei/gas$ (1 $gwei$ = $10^{-9}$ ETH), is another parameter set by the user, which is the price the user is willing to pay for each unit of gas. A typical transaction with one user requires 21,000 gas units, with variations dependent on the bytecode operations of the activities (Wood, Savers and Community, 2018).

The gas fee for a transaction is simply the gas used multiplied by the unit price, with the caveat that a user needs to reserve a gas fee limit in the wallet when initiating a transaction. As in the Bitcoin blockchain, transaction fees are paid to miners as rewards for maintaining the ledger and smart contracts. Since the block size is limited, profit-maximizing miners rationally prioritize transactions with the highest gas prices (Basu et al., 2019; Ilk et al., 2021).

Ethereum gas mechanism and the Bitcoin fee mechanism differ in two salient ways: (i) When a user initiates a transaction, the transaction fee on Bitcoin is fixed, while the transaction fee on Ethereum can only be known when the transaction is completed. Therefore, Ethereum users reserve more Ethers than actually used on average. (ii) If the gas limit is set to be less than the actual gas usage, the transaction fails even when the user can afford the gas fee. In contrast, transactions of Bitcoins get delayed (potentially indefinitely) when the transaction fee is not set high enough, but they never truly fail.

### *B. Data and Computation*

We assemble a comprehensive database from multiple sources. First, our baseline dataset covers billions of on-chain observations in the Ethereum ecosystem from October 2017 to February 2022, including 14 million blocks, 1.7 billion external transactions, 4.6 billion internal transactions, 1.8 billion logs of smart contract usage, 1 billion token transfers and 4.4 million smart contract information packets (containing bytecode, function, etc.). Specifically:

- Ethereum accounts entail two categories, external owned account (EOA) and smart contract (SC). An EOA is an address controlled by a private key, which can initiate transactions directly. A smart contract, in contrast, cannot directly initiate a transaction.

- Transactions between EOAs only have external transaction records, similar to transfers on the Bitcoin blockchain. Transactions between EOAs and smart contracts contain an external transaction record, several internal transaction records, several token transfer records, and several logs of smart contract usage.

- External transactions include information on the total amount of Ether transferred, the time the transaction is bundled into the block, gas used, gas price and gas limit set by the initiator, and the final status of transaction (success or failure).

- After a contract is called, it may also call other SCs or EOAs, forming a chain reaction, whose intermediate steps are referred as internal transactions. Each internal transaction contains a pair of call relationships in the chain reaction, including the amount of Ether transferred, call type, status, error type, reward type, etc.

- Token transfers involve ERC20 and ERC721 tokens. The records contain the name and number of tokens transferred, the addresses of both parties, etc. Logs record the specific called functions, parameters, etc.

We build up our data pipeline with 14 servers with dual Xeon E5 CPUs, 128G memory, and 48TB hard disks. The first server runs an Ethereum node dedicatedly to synchronize all raw Ethereum data. Another server runs several web scrapers to collect other relevant data. The NIFI tool is adapted and run on these two servers to send multiple sources of data into the HIVE-based data warehouse supported by 12 big data servers. These big data servers also have Hadoop, Hbase, Spark, Yarn tools on it.

Based on the above nodes, we decode the raw Ethereum data using ETL tools into 8 types of semi-structured HIVE tables. We further compute the amount of Ether held by each address and align the amount with Etherscan.io periodically to ensure the correctness. Moreover, we obtain block information, including the address of the block verifier (i.e., address of the mining pool), block number, timestamp of block verification, block reward, and gas limit and usage of the block.

To associate addresses on the Ethereum blockchain with DApps, we scrape public addresses and classification labels of DApps from DApp Radar (https://dappradar.com), Dapponline (https://dapponline.io), and Ethercan (https://etherscan.io/). We adopt the 9 categories of DApps by DApp Radar: exchanges, DeFi, gambling, games, collectibles, marketplaces, social, high-risk and others. Our sample recognizes a total of 433 DeFi applications and 5,047 DApps on Ethereum. Figure 2 depicts the DApp growth.

Because on-chain data does not contain information on the actual initiation time of the transaction, we also collect “recommended gas prices” at 10-minute intervals from ETH Gas Station (https://www.ethgasstation.info) covering February 2, 2021 to March 2, 2021. The recommended gas prices are the prices corresponding to various expected delays estimated based on a Poisson regression model using the previous 100 blocks. In addition, we obtain historical market information of tokens related to the Ethereum blockchain from CoinMarketCap (https://coinmarketcap.com/), which covers the exchange rate, trading volume and market cap of thousands of cryptocurrencies. Finally, to measure the popularity of the Ethereum blockchain, we obtain a weekly search index of the keyword “Ethereum” from Google Trends (https://trends.google.com/).

To overcome the challenges of handling such gigantic data, we use the large-scale computation tools on the aforementioned big data servers, such as Hive and MapReduce for processing transaction-level data distributedly, Gephi for mapping the various networks, and Spark’s machine learning library for performing linear and logistic regressions. Finally, we make available the data used in the analyses at http://drzhaoxi.org/DefiPaper for other researchers, practitioners, and policymakers.

### *C. Key Variables*

We take external transactions as a unit observation, and use information on internal transactions, token transfers, logs, and other records too for the construction of variables.
**Transaction Fee and Extra Gas Reserved.** The transaction fees in units of Ether and

USD are calculated, respectively, as:

$$GasFee(Ether) = GasPrice \times GasUsed, \tag{1}$$

$$GasFee(Dollar) = GasPrice \times GasUsed \times EtherPrice, \tag{2}$$

where $GasPrice$ is the per-unit transaction fee that users are willing to pay, $GasUsed$ is the amount of gas used to complete the transaction, and $EtherPrice_t$ is the average daily ether to US dollar exchange rate on day t. Table 1a lists gas-related variables. The median gas price is 30.81 $gwei/gas$ with a very large standard deviation of about 27063.14, and the median gas fee (in US dollar) is 0.434 with a standard deviation of 135.55. The median gas used is 21,000, which equals to the amount of gas needed for transactions among users, about more than half of the transactions in our sample. The median gas limit is 51,000 with a standard deviation of 257,359.

Because users are required to reserve more Ethers than the gas limit in order to execute the transaction, we calculate the $ExtraGasReserved$ as the gap between gas limit and the actual gasused :

$$ExtraGasReserved = GasLimit - GasUsed, \tag{3}$$

and $ExtraGasFee$ as the gap between the reserved gas fee and the actual gas fee:

$$ExtraGasFee = GasPrice * (GasLimit - GasUsed) \times EtherPrice. \tag{4}$$

**Value.** We define the value of a DeFi transaction as the total number of ERC20 tokens (or Ether) transferred times the daily exchange rates of the tokens. In the case of transactions with token swap (such as the swap between USDC and WETH), we regard the total amount of tokens sent out by the initiator as the total amount of ERC20 involved in this transaction (instead of the sum of all ERC20 tokens).

**Token Returns and Volatility.** The return of Ether (EthReturnt) and the return of Ethereum-related tokens (TokenReturnit) are also calculated, respectively, as:

$$EthReturn_t = \frac{EtherPrice_t - EtherPrice_{t-1}}{EtherPrice_{t-1}}, \tag{5}$$

TokenReturn$_{it} = \frac{Price_{it} - Price_{it-1}}{Price_{it-1}}$(6)
where $Price_{it}$ represents the exchange rate between token $i$ and the U.S. dollar on day $t$.

Furthermore, we calculate the return volatility and exchange rate volatility of Ether and related tokens: The annualized return volatility of the token is:

$$(7)\qquad ReturnVolatility_{iy} = \sqrt{\frac{\sum_{d=1}^{365}\left(TokenReturn_{iyd} - TokenReturn_{iy}\right)^2}{365-1}} \times \sqrt{365},$$

and the daily exchange rate volatility of Ether is:

$$(8)\qquad EtherVolatility_{t} = \sqrt{\frac{\sum_{j=1}^{n}\left(EtherPrice_{tj} - EtherPrice_{t}\right)^2}{n-1}} \times \sqrt{n},$$

where $TokenReturn_{iy}$ represents the average return of token $i$ in year $y$, $TokenReturn_{iyd}$ the return of token $i$ on day $d$ in year $y$, $EtherPrice_t$ the average exchange rate of Ether on day $t$, and $EtherPrice_{tj}$ the $j^th$ exchange rate of Ether on day $t$.[7]

**Failure Rate.** The overall failure rate of transactions at day $t$ (including both zero-value transactions and non-zero-value transactions) is the number of failed transactions divided by the total number of transactions initiated:

$$(9)\qquad FailureRate_t = \frac{\#Failure_t}{\#Transactions_t} \times 100\%.$$

Panel C shows that the average daily failure rate is 2.03% with a standard deviation of 1.85%; the number of failed transactions in a day is on average 16,392 with a standard deviation of 11,435.

**Miners' Rewards and Users' Transactions.** Miners earn block rewards by verifying blocks with transactions. We use $LnReward_{mt}$ to represent the log of weekly mining rewards received by miners (in ether). In addition, we use $LnVolume_{it}$ and $LnDApps_{it}$ to denote the log of total transaction volume in Ether made and number of DApps used by user $i$ on week $t$.

**Control Variables.** First, we use $NetworkUtilization_t$ to denote network utilization which also measures the congestion rate of the network at certain day $t$:

$$(10)\qquad NetworkUtilization_t = \frac{TotalGasUsed_t}{TotalBlockGasLimit_t} \times 100\%.$$

[7]We pull the exchange rate data every five minutes.

where $TotalGasUsed_t$ is the total amount of gas used in all transactions of Ethereum at day $t$, $TotalBlockGasLimit_t$ is the maximum possible amount of gas limit used for all transactions in a certain block, which is determined by both the network and the miners.[8] This mechanism of the total block gas limit ensures that blocks are not infinitely large. As illustrated in Table 1b, the average congestion (network utilization) during the study period is 87%, with a standard deviation of about 11% (Figure 1). In particular, the second half of 2020 saw the congestion rate persistently above 90%. That said,the launch of EIP-1559 (August 5,2021) with the 'gas targets,' brought the network utilization down to about 50%. Another variable that can measure the degree of congestion is the number of transactions on Ethereum ($Transaction_t$). The average daily number of transactions is 839,602, with a standard deviation of 279,352. The second key control variable is $BlockRewards_t$, which represents the average amount of ether a miner gets for each block mined on day $t$. During our study periods, the average block reward is 2.57 with a standard deviation of 0.64. Finally, $EthPopularity_t$ measures the popularity of Ethereum on day $t$. For Ethereum popularity, we use Google trends score corresponding to the keyword "Ethereum." A google trends score ranging from 0 to 100, with 100 points for the most searched terms. The average popularity of Ethereum is 14 with a standard deviation of 17.936.

## III. The Ethereum Ecosystem

We start by describing basic patterns and trends in the Ethereum ecosystem, focusing on the distribution of miners, ETH owners, and transactions, as well as the network structure derived from on-chain data.

### *A. Network Structure and Activities*

Ethereum represents a complex network and our first task is to map out network activities. Figure 3 reveals that Ether flows among DApps and exchanges are dominated by exchanges and DeFi applications (one of the nine categories of DApps). $i$ indexes all labeled addresses belonging to Dapp or exchange $i$, and an edge between $i$ to $j$ corresponds to Ether flows. The edge size is proportional to the total transaction flow between the two entities, and the node size is proportional to the total Ether received over the period 2015-2022.

The eigenvector centrality of each node reflects its importance. For DApp i, it is the largest solution ($\lambda$) to the equation $Ax = \lambda x$, where matrix elements $A_{ij}$ are the total

[8]Note that any miner of the block can alter it by a maximum of 0.1% from the gas limit of its previous block. The current gas limit per block is 30,000,000 (around December 2022).

Ether flows from DApp i to j over 2015-2022 (Makarov and Schoar, 2022). Figure 4 depicts the top 25 DApps and exchanges with the highest network centrality and their total received Ethers. Again, exchanges and DeFi applications dominate. However, the DApps occupying the center of the DApps network do not necessarily receive the most Ethers, suggesting that some (such as Uniswap) receive Ethers mainly from the users.

Next, we describe how various categories of DApps compete or complement. Figure 5 plots the shared user network among DApps on Ethereum. Different colors represent different categories of DApps. Shorter distance between nodes indicates more common users. In other words, the DApps with the same color close to each other are competitive, and the DApps with different colors close to each other are cooperative. Uniswap, the largest decentralized exchanges (DEX) on Ethereum, is taken as an example to show the above relationship. There is strong competition between Uniswap and Sushiswap, and strong complementarity between Uniswap and Mintbase marketplace.[9]

Finally, we can display any network of Ethereum-related activity centered on DAPP. The cluster of the sphere in Figure 6 represents a DApp and its users, with the center of the cluster as the DApp, and surrounding points as users. The color of the sphere represents its category. Lines in different coloers represent different Ethereum-related activities. The blue line represents trading activities using Layer-1 token, i.e., Ether. The yellow line represents the holdings of ERC-20 token. And the green line represents the interaction between users and DApps.

### *B. Distribution of Miners and Rewards*

Miners (now stakers) are responsible for verifying and recording transactions and executing smart contracts on Ethereum. They compete via Proof-of-Work throughout our sample period. Miners are rewarded with newly minted Ethers (block reward) and transaction fees (also in ETH).

It is important that mining is decentralized. If a miner or some colluding miners possess excessive mining power, the ledger is prone to single point of failure and attacks such as the 51% attacks. In such an attack, these miners can change previously verified records, which jeopardizes the integrity and functionality of the network.

As shown in Figure 7, most of the block rewards go to a few mining pools. Specifically, the top 5% mining pools (3-5 pools) received about 60% of block rewards, and the top 50% of mining pools received almost 100% of block rewards. The pattern in Figure 7a is similar to Bitcoin. For example, Makarov and Schoar (2022) report that the top 6 mining

[9]Sushiswap is a DApp that completely plagiarizes Uniswap contract codes and grabs uniswap's users through some targeted marketing strategies.

pools resulted in the 60% of block rewards in the Bitcoin network. Figure 7b reveals a slightly downward trend in Gini coefficients for mining pools, but the level is quite high throughout our sample, and higher than the average Gini coefficients for Bitcoin (around 0.5). Figure 7c uses Shannon Entropy to quantify the randomness and lack of order in the block reward distribution among network nodes. Ethereum mining is also slightly more centralized than Bitcoin mining based on Shannon Entropy (around 4 for Bitcoin). These findings are consistent with Lin et al. (2021).

However, Cong, He and Li (2018) point out that risk diversification and markups in pool fees ensure that no single mining pool would persistently dominate. Mining pools also distribute the rewards to individual miners, and thus a mining pool concentration does not necessarily imply mining concentration at the individual miner level. Following Makarov and Schoar (2022), we use on-chain transactions to trace mining rewards from mining pools to the individual miners participating in the pools. Figure 8 illustrates this tracing process using Ethermine pool. The top layer in the figure represents the nodes of the mining pool (gold-colored dots). The lower three layers are miners, miners' primary trading network, and secondary trading network. The dark blue points represent EOA accounts, and the light blue points represent exchanges. Lines in the figure represent flows of ether. The light blue line is the ether flow with EOA accounts, and the dark blue line is the ether flow with exchanges. Though the block rewards of Ethermine mining pool rarely flow directly to exchanges, its miners and miners' "friends" mainly transfer Ether to exchanges, indicating that centralized nodes are still quite important.

The percent of received mining rewards for different percentiles of miners (excluding exchanges) is given in Figure 7d. At the individual node level, mining is still concentrated: the top 0.5% individual miners receive around 50% of the rewards (the fraction is 60% in Bitcoin). Note that the top 1% income earners in the United States has less than 30% income shares (Saez and Zucman, 2020). In that sense, the income inequality in DeFi and Web3 seems even more severe than the traditional econonmy, based on evidence from the Ethereum ecosystem.

### *C. Distribution of Token Ownership*

If Ethers are owned by a selected few, it is hard to imagine it enables inclusive DeFi for the masses. Figure 9 shows the ownership distribution. As shown in Panel 9a, the vast majority (about 80%) of Ethers in circulation are still held by EOAs, but the percentage has been decreasing over time. Figure 9b depicts the top 50 users who hold Ether from 2015 to 2022, which shows the evolution of ownership of Ether and how the top 50 user addresses occupy a considerable wealth in Ethereum ecosystem. Furthermore, as shown in Figure 9c and Figure 9d, the top 0.1% of accounts, both for all addresses and EOAs, own more than 50% of mined Ethers and top 10% own more than 90%. This trend has also increased over time. Note that despite the dramatic rise of wealth inequality globally, the wealthiest 10% of the population in the United States 65-85% of the wealth Saez and Zucman (2016, 2020). The new financial paradigm in blockchains and DeFi ironically features more wealth concentration, at least as of now.

One caveat is that we do not observe users' identities or their entire income and investment portfolios (including off-chain and offline ones). We therefore can only draw limited inference from the distributions of token ownership and mining incomes. But to the extent that wealthier agents or agents with higher income tend to own multiple wallets, not connecting wallets using off-chain identities only biases against our findings. We are also agnostic on the mechanisms leading to the concentration of on-chain wealth. Blockchain conglomerates' capturing the governance of a PoW-based ecosystem is one possible reason Ferreira, Li and Nikolowa (2022), but the Merge to switch to Proof-of-Stake may alter the situation, which constitutes interesting future research.

### *D. Distribution of Transactions*

We compute and show in Figure 10 the daily transaction volume (includes both Ethers and other tokens on Ethereum) between October 16, 2017 and October 3, 2022.[10] Figure 10a-10b display the distributions of transaction volume (in dollars) among Ether and tokens on Ethereum, and Figure 10c-10d display the distributions of transaction volume (in dollars) among stakeholders on Ethereum ecosystem.

Transaction volume in Ethereum peaked in late 2017 to early 2018 and in the second half of 2020 to 2022. In the early years, transaction volume mainly entails the native cryptocurrency Ether. But in recent years, ERC-20 tokens become dominant in transaction volume percentage. Moreover, transactions have gradually shifted from peer-to-peer to be between users and DApps. In particular, about 90% of transaction volume in 2022 was contributed by DApps, of which DeFi applications and exchanges accounted for about 30%, whereas DApps accounted for less than 10% of transaction volume in 2017.

[10]While Makarov and Schoar (2022) illustrate the presence of large "spurious transactions" in the Bitcoin network, this is not a severe problem in the Ethereum network because Ethereum accounts are based on EOA and smart contract addresses instead of the UTXO model.

## IV. Transaction Fees: Hindrance to Financial Democratization and Inclusion?

As Corrado and Corrado (2017) describe, the three main characteristics of inclusive finance are universal access, affordable costs, and diversity of financial services, which are crucial to providing stable financial services to the poor or marginalized groups. DeFi has been introducing a variety of financial products, such as insurance and loans etc., which can be accessed globally and promptly wherever the internet is accessible. However, transaction costs and unreliable services constitute material challenges preventing DeFi from being inclusive or democratic.

Fees constitute a major challenge in the adoption of Web3 and DeFi is worth emphasizing also because it differs from the conventional financial industry. None of the high relative fees for small users, high failure rate, or high uncertainty due to the high volatility of ETH that we document next is due to market power or economic rents to those who run the platform. It is fundamentally about the technology and suboptimal design of the fee mechanisms.

### Percentage Transaction Fee

To better understand transaction costs, we define a percentage transaction fee as the transaction fee divided by the value transferred:

$$PercentageTransactionFee = \frac{GasPrice \times GasUsed}{Value} \times 100\%. \tag{11}$$

Table 2 provides the fee rate of two types of received addresses (externally owned accounts (EOA) and contract accounts), two types of cryptocurrencies (Ether and ERC20 tokens on Ethereum) and DeFi applications and others. Panel A shows the percentage transaction fee for transactions with EOA and contract accounts, Panel B shows the percentage transaction fee for Ether-related transactions and token-related transactions, and Panel C shows the percentage transaction fee for transactions with DeFi applications and others. Figure 11 further illustrates the median percentage transaction fee for the aforementioned types of transactions.

We first discuss the distribution of transaction values of different types of transactions (Figure 12). From the perspective of accounts, transactions with EOAs are typically under \$100, while transactions with contract accounts are typically over \$1000. From the perspective of trading cryptocurrencies, transactions using Ether are typically under \$100, while transactions using tokens on Ethereum are typically over \$100, or even \$1,000. From the perspective of interacting DApps, most transactions with DApps are over \$1000, while other transactions are usually under \$100.

Then, we can see that the median percentage transaction fee for different groups varies from 0.25% to 0.37%, it is overall cheaper than the transaction of major banks in the SWIFT (Table A2 in the Appendix) system.[11] However, the transaction fee of small-value transactions is very high for the marginal area and compared with current inclusive financial services. When the transaction value is less than one dollar, a median amount of 23%, 102%, 23%, 201%, and 60.88% of the transferred value ought to be paid as the fee, respectively, for transactions with EOA, transactions with contract account, transactions using Ether, transaction using tokens on Ethereum and transactions with DApps. Using DeFi for daily trades is expensive for people in poor countries living under $1.25/day (Bartley Johns et al., 2015; Ventura, 2021). In addition, existing institutions that commit to providing financial inclusive services, such as PayPal, typically charge no fees for domestic transactions and a 5% transaction fee for international transactions.[12] In contrast, the percentage transaction fee for small amount transactions using DeFi is too high and volatile for inclusive finance.[13] Meanwhile, there is no upper bound for transaction fee and percentage transaction fee when using DeFi, which is opposite to existing payment systems that normally have a cap on the transaction fee. For example, PayPal set a cap of $4.99 of transaction fee for international personal transactions.

### Network Congestion and Gas Price

As Figure 13 shows, transaction delay times are negatively correlated with gas prices, consistent with previous studies on Bitcoin (Easley, O'Hara and Basu, 2019; Ilk et al., 2021). Users are willing to pay higher gas prices for quicker transactions in response to network congestion. We next investigate the influences of congestion on gas prices by analyzing the relationships between gas prices and delay times and between gas prices and network utilization.

Because the delay time we obtained is fixed class data and ordered, we adopt an ordinal logistic model to study the relationship between gas price and delay time:

$$y_i^* = \beta_1 GasPrice_i + \mu_i. \tag{12}$$

[11] Note that there are some extreme values in the sample, this can be seen from the extremely large average percentage transaction fees. For example, a user paid five high transaction fees (210 ether, 420 ether, 420 ether, 840 ether, and 2100 Ether) on February 19, 2019 for five transactions with values of no more than 0.1 ether. We, therefore, do not use average, but instead use the median in our analysis.

[12] https://www.paypal.com/us/webapps/mpp/paypal-feesSendAndReceiveMoney

[13] Note that the percentage transaction fees for large-value transactions (more than one dollar) are relatively low: A median of 0.16%, 0.33%, 0.18%, 0.29%, 0.30% percentage transaction fee are, respectively, for transactions with EOA, transactions with contract account, transactions using Ether, transaction using tokens on Ethereum and transactions with DApps, respectively.

$y_i^*$ is the latent variable, and $mu_i$ is the disturbance term, which follows a logistic distribution.

$$DelayTime_i = \begin{cases} 0.5 & y_i^* \leq \alpha_1 \\ 2 & \alpha_1 < y_i^* \leq \alpha_2 \\ 5 & \alpha_2 < y_i^* \leq \alpha_3 \\ 30 & \alpha_3 < y_i^* \end{cases} \tag{13}$$

Table 3a shows that there is a significant negative relationship between gas price and delay time, which is consistent with the perception that users pay high gas prices for fast transactions. The three cutoff points $\alpha_1$,$\alpha_2$,$\alpha_3$ are $-2.40$, $-1.20$, $-0.02$ respectively in Equation (13). Table 3b shows that for each unit increase in the gas price paid by users, the probabilities of completing a transaction at the fastest rate ($DelayTime = 0.5$) and fast rate ($DelayTime = 2$) are increased by 1.48% and 0.52%, respectively, while the probability of completing a transaction at a low rate ($DelayTime = 5$) and the lowest rate ($DelayTime = 30$) decreased by 0.46% and 1.50%, respectively. Overall, increasing gas price tends to speed up the transaction. We also check robustness using ordered Probit and OLS models. The regression results in Table 3 are consistent with the logistic-regression results.

Next, we run both the transaction-level and day-level regressions:

$$\ln(GasPrice_{it}) = \beta_0 + \beta_1 \ln(NetworkUtilization_{t-1}) + \gamma C_{it-1} + \varepsilon_{it} \tag{14}$$

where the subscription $i$ and $t$ denote the $i^{th}$ trade in day $t$. The control vector, $C_{it-1}$, includes the daily block rewards, Ethereum popularity and the return of Ether exchange rate in day $t-1$.

Table 4 reports the transaction-level regression results for different types of activities using Ethereum. The first column shows that the utilization of the Ethereum network has a significantly positive impact on the gas price; particularly, a 1% increase in network utilization results in an additional 3.43% gas price for all transactions. This is consistent with our conjecture and evidence from the Bitcoin blockchain (Easley, O'Hara and Basu, 2019; Ilk et al., 2021). For control variables, the return of Ether exchange rate has a significant positive impact on gas price; a 1% increase in the return of Ether results in users being willing to pay an additional 0.52% gas price. Moreover, block rewards and Ethereum popularity have negative and positive impacts on gas price, respectively.

The results of token-related activities, transactions with users and transactions with contracts are reported in the second, third, and fourth columns, respectively. The degree of network utilization has a significant impact on gas prices for all the three categories. Chow test shows that the impact for the token-related group is larger than transactions with users ($p < 0.001$), which is likely to be caused by a large price fluctuation of the tokens, i.e., users want to make the transaction go through quickly instead of taking the risk of price fluctuation. Therefore, token-related activities are likely to crowd out others in a congested network. That is, users willing to pay a higher gas price for token-related transactions will be accelerated, while other types of transactions queue up for execution.

### Transaction Fee and Extra Gas Fee Reserved

We first discuss the distribution of transaction fees among stakeholders on Ethereum. As illustrated in Figure 14, similar to the distribution of transaction volume among Ethereum's stakeholders, transaction fees have gradually shifted from peer-to-peer transactions to transactions between users and DApps. Specifically, about 80% of transaction fees in 2020 and early 2021 was contributed by user-DApps interactions, of which DeFi applications and exchanges accounted for about 40%, whereas, DApps accounted for less than 20% of transaction fees in 2017. However, this trend has weakened in 2022. Next, Table 5a reports the statistics of *ExtraGasFee* and the real gas fee used as a comparison. Surprisingly, the *ExtraGasFee* is quite large with a magnitude around 5.46 dollars on average, which is larger than the gas fee actually used. Therefore, the gas-limit policy is not inclusive because people need to reserve a significant amount of extra money for their payments. In the following, we examine the drivers for the extra gas reserved and report the findings in Table 5b.

$$\begin{aligned} ExtraGasReserved_{it} = \beta_0 + \beta_1 \ln\left(NetworkUtilization_{t-1}\right) + \beta_2 \left(EthReturn_{it-1}\right) \\ + \gamma C_{it-1} + \varepsilon_{it}. \end{aligned} \tag{15}$$

The network utilization and median gas price have a significantly positive impact on the *ExtraGasReserved*. When the network is congested, users want to complete the transaction once, but not repeatedly, so they tend to reserve more gas in this case. However, the return of Ether, block rewards and the popularity of Ehtereum are negatively correlated with *ExtraGasReserved*. As Ether rose in value, users are more likely to trade rather than "block" ether in their wallets in the form of transaction fees.

Recall that gas prices increase in network congestion and the high return of Ether, this section shows that on top of gas price increases, Ether return and network congestion tend to increase extra gas reserved in the wallet, lowering the efficiency of the usage of money.

If a transaction cannot be fulfilled due to some reason, the transaction "fails" and yet the gas fee is non-refundable because the computational power is used during the process. The main reasons for transaction failures include: (i) "Out of Gas"—the gas limit set by the user is lower than the amount needed. (ii) "Reverted"—backoff mechanisms written in the smart contract are triggered to stop the transaction. (iii) "Bad Instruction" entailing problems in the operation logic of transaction execution. For example, in crowdfunding, the transaction for the excess amount raised fails when the amount raised has reached the funding target. (iv) "Bad Jump Destination" caused by errors in smart contract codes.

The average daily failure rate, as Table 1c and Figure 15 show, is 2.03%. As shown in Table 6, during the sample period there are 8,135,712 transactions with contracts unrelated to tokens failed (2.71% of such type of transactions), with a total gas fee of 57,171,289 dollars. And 14,633,202 token-related transactions (a total gas fee of 31,367,076 dollars) have failed (5.56% of such types of transactions).

In addition, Table 6b reports the statistics of the number of non-zero-value transaction failures due to different non-mutually-exclusive reasons. The most common cause of failure is reverted, resulting in a total of 65,355,497 dollars in gas fee loss, accounting for 76.72% of all failures. The second reason for transaction failure is out of gas, resulting in a total of 18,660,388 dollars gas fee loss, accounting for 21.47% of fall failures. The remaining two causes of failure (i.e., bad instruction and bad jump destination) account for about 10% of the total number of failures.[14]

As mentioned above, an insufficient gas limit and gas price may lead to transaction failures or longer delays that indirectly cause failures. We formally test these by first running the following linear-probability regression at the transaction level (regression 12):

$$Failure_{it} = \beta_0 + \beta_1 GasExtra_{it} + \beta_2 \ln\left(GasPrice_{it}\right) + \gamma C_{t-1} + \mu_{it}, \tag{16}$$

where the subscription $i$ and $t$ denote the $i^{th}$ trade in day $t$. $GasExtra_{it}$ is a dummy variable that is set to 1 when transaction $i$ reserves additional gas, and 0 otherwise. $C$ is the vector of control variables including daily median gas price, ETH return, network utilization, block rewards and Ethereum popularity.

Table 7 shows that in general if the user reserves extra gas when initiating a transaction,

[14]Note that the sum of the percentage of failures of four failure causes is larger than 1. This is because some complicate transactions (including internal transactions) may fail due to more than one reason.

the probability of a failing transaction drops by 0.67%.[15] If the gas price set by the user increased by 1%, the probability of the failed transaction drops by 0.25%.

Turning to control variables, block rewards and the popularity of Ethereum have positive impacts on the failure of transactions. The increasing popularity of Ethereum accompanies the increasing number of new users. These users who are new to the fee mechanism are more likely to fail due to the improperly setting of parameters. In addition, median gas price, Ether return and network utilization show negative impacts on the failure of transactions.

### TOKEN EXCHANGE RATE RISK

As shown in Table A1 and Figure 16, high price volatilities of Ether (about 163% for 3 years) and ERC-20 tokens create high risks on DeFi users, excluding users with low risk tolerance and causing other frictions for adoption (Harvey, Ramachandran and Santoro, 2020). Second, the high volatility of ETH leads to high uncertainty of transaction fees in DeFi applications, which harms the sustainability of financial services provided by DeFi. Liu et al. (2022) find that when Ether's price is more volatile, the waiting time is significantly higher.

We further explore the determinants that contribute to the high volatility of Ether exchange rate. The regression results are shown in Table 8. Average daily ether exchange rate, number of transactions, block rewards and Ethereum popularity have a significant positive impact on ether volatility, while daily failure rate has a significant negative impact on ether volatility.

In addition, we also study the impact of ether returns on relative returns of Ethereum-related tokens in this section. It is easy to understand that as tokens built on Ethereum, their values should highly depend on the price of Ether. Thus, the tokens on Ethereum should have a positive return correlation with Ethereum. However, since the transaction cost of these tokens is Ether, the high Ether price tends to increase the transaction cost of these tokens, and hence decrease their prices. Therefore, the correlation between tokens and Ether tends to be jeopardized when the Ether price is high. To formally test these hypotheses, we perform the following regression:

$$\text{TokenReturn}_{it} = \beta_0 + \beta_1 \text{ EthReturn}_t + \beta_2 \text{ EthReturn}_t^2 + \varepsilon_{it} \tag{17}$$

We include the square of *EthReturn* to the model to study the influence of ether returns

[15] On Ethereum, if a token-related transaction fails, the transaction value is not recorded (i.e., the transaction value is 0). Therefore, we include these transactions in our sample when analyzing the factors influencing failure. In addition, transactions with users will not fail, so transactions with users are excluded from our sample.

on the correlation between Tokens on Ethereum and the Ether prices. Token fixed effects are employed in the above panel regression. The regression results are reported in Table 9. Ether returns have a significantly negative impact ($\beta_2$) on the Ether-token correlations. This is consistent with the conjecture mentioned above.

## V. Redistributive Effect of the EIP-1559 Fee Mechanism

### *A. Background: EIP-1559*

On August 5, 2021, Ethereum adopted the new EIP-1559 policy, a major technical upgrade also dubbed as "London Hardfork on Ethereum." It is a major overhaul of the original transaction fee mechanism to address the problems of high fee volatility, network congestion, and overpayments due to fee unpredictability. Roughgarden (2020) models transaction fees under EIP-1559 and indicates two potential benefits of EIP-1559: EIP-1559 can reduce the transaction fee variance and improve user experience by providing simpler fee estimations. Figure 17 illustrates the primary adjustments of the EIP-1559 fee mechanism. One of the critical changes is the new "base fee" scheme. It is the minimum gas price that a transaction needs to pay to enter the block, which is regulated by the protocol. Intuitively, if the gas used in the parent block exceeds its gas target, the base fee of the next block will increase, and vice versa. The gas target is constant at 15 million. The base fee follows a pre-specified formula:

$$\text{BaseFee}_{\,h+1} = \text{BaseFee}_{\,h} \times \left(1 + \frac{1}{8} \times \frac{GasUsed_h - GasTarget}{GasTarget}\right). \tag{18}$$

As part of transaction fee, the base fee is no longer awarded to miners but is removed from the circulation forever. The second adjustment is the way users bid. Users can bid on two fee-related parameters named "max priority fee per gas" and "max fee per gas" under the EIP-1559 policy. Max priority fee per gas is the tip that users are willing to pay the miners. Whereas the max fee per gas is the maximum gas price users are willing to bear. The final gas price paid by the user is as follows:

$$GasPrice = \min\{BaseFee + MaxPriorityFee, MaxFee\}. \tag{19}$$

Finally, the block gas limit is adjusted from around 15 million to around 30 million under the EIP-1559. The gas target is set at 15 million.

Figure 18 describes the adoption rate, daily average base fee, priority fee per gas, max fee per gas and gas price after the launch of EIP-1559. Figure 18a shows that nearly half of all transactions on Ethereum have adopted EIP-1559, while the rest follows the previous mechanism conditional on those transactions having reached the base fee requirement. Note that EIP-1559 will be retained after Ethereum's switch to PoS.

### *B. Empirical Strategy*

We investigate the impact of the EIP-1559 fee mechanism on the distribution of mining rewards among individual miners and transaction volume among individual users. We first estimate the overall effects of EIP-1559 on all individual miners and users using a sharp regression discontinuity (RD) design with August 5 as the threshold. Then, we extend the specification to consider the heterogeneity of miners and users using a difference-in-difference method.

Our dataset includes all active miners' and users' on-chain transaction behavior six months before and after the launch of the EIP-1559 fee mechanism, i.e., from Feb 5, 2021 to Feb 5, 2022. We first identify active miners and users using labeled mining pools information of each block and the flow of mining rewards, as was done for Bitcoin in Makarov and Schoar (2022). Data on Ethereum only records the addresses of mining pools where blocks are mined, and there is no information about individual miners. Therefore, we use transaction data on Ethereum to relate miners to different pools.

First, we consider the addresses of mining pools having had transactions with exchanges, contract addresses, and individual miners. A total of 2,763,430 separate individual miner addresses have received block rewards since the release of Ethereum. Second, we specialize to miners who have received mining rewards before February 05, 2021, and have at least received a mining reward after February 05, 2021. Third, we exclude miners who belong to multiple mining pools. These filters leave us 135,414 miner addresses associated with 102 separate mining pools. Table 10a provides summary statistics on these miners' received rewards and transaction activities before and after the launch of EIP-1559.

We define active users as those who made transactions before February 05, 2021, and have at least one transaction after February 05, 2021. A total of 12,614,467 distinct addresses have been identified. Since the existing econometric analysis software cannot process the entire data, we adopt two methods of constructing user samples. The first sample is constructed with 252,290 randomly selected user addresses (about 2% of the total addresses). The second sample is constructed based on Sokolov (2021)'s methods of grouping users on Bitcoin. In particular, we divide users into three groups based on their transactions between February to August 05, 2021. Group 1 consists of 239,294 addresses representing highly active users, defined as those who have transactions on Ethereum for at least 20 days over a six-month period. Group 2 represents active users, defined as those who have transactions on Ethereum for at least two days but less than 19 days over a six-month period. For computational efficiency, we merge the transactions from these addresses and average weekly transactions for every 10 addresses (sorted by the number of transactions), i.e., we consider addresses with ranks 239,295-239,304 as one address, and so on. After processing, Group 2 consists of 258,897 addresses. Group 3 represents inactive users, defined as those who have transactions on Ethereum for at most one day over six months. Similar to Group 2, we merge the transactions from addresses in Group 3 and average weekly transactions for every 50 addresses. Group 3 consists of 195,725 addresses. Table 10b provides the summary statistics on users' transaction activities before and after the launch of EIP-1559.[16]

To estimate the overall effects of EIP-1559 on miners' mining rewards and users' transaction activities, we estimate the following regression:

$$y_{it} = \alpha + \beta \text{ Burning } g_{it} + \gamma f(\text{ date }_{it}) + \delta X_{it} + \varepsilon_{it}. \tag{20}$$

For miners, $y_{it}$ refers to the mining rewards received by miner $i$ on week t; for users, $y_{it}$ refers to the transaction volume and number of DApps used by user $i$ on week $t$. $Burning_{it}$ is a binary variable taking a value of 1 when EIP-1559 is in effect and 0 otherwise, and $date_{it}$ is the day number centered on August 5, 2021. The RD is a sharp RD in that $date_{it}$ completely determines $Burning_{it}$. Function $f(date_{it})$ captures the potential endogenous relationship between $\varepsilon_{it}$ and the date. $X_{it}$ denotes a set of additional control variables described in Table A3.

The impact of EIP-1559 on different players in the Ethereum network ought to be different. Burning base fees "deflate" the ecosystem and effectively and redistribute wealth from the most active players to the rest. We use the following difference-in-difference specifications to test these heterogeneous effects formally:

$$\begin{aligned}
(21)\quad y_{mt} &= \beta \ln(\text{ PercentBlock }_m) \times \text{ Burning }_t + \omega X_{mt} + \lambda_m + \gamma_t + \varepsilon_{mt}, \\
(22)\quad y_{mt} &= \beta \ln(\text{ BeforeRewards }_m) \times \text{ Burning }_t + \omega X_{mt} + \lambda_m + \gamma_t + \varepsilon_{mt}, \\
(23)\quad y_{it} &= \beta \ln(\text{ BeforeTransactions }_i) \times \text{ Burning }_t + \omega X_{it} + \lambda_i + \gamma_t + \varepsilon_{it}, \\
(24)\quad y_{it} &= \beta \ln(\text{ BeforeBalance }_i) \times \text{ Burning }_t + \omega X_{it} + \lambda_i + \gamma_t + \varepsilon_{it}.
\end{aligned}$$

Equations (21) and (22) test the impacts of pool size and miners' computing power on the redistribution effect for miners. $PercentBlock_m$ is the percentage of blocks mined by the mining pool to which the miner m belongs between February 5, 2021, and August

[16] Table A5 and A6 in the appendix contain the analyses using the second user sample for robustness check.

5, 2021. $BeforeRewards_m$ is the total mining rewards received by miners m between February 5, 2021, and August 5, 2021.

Equations (23) and (24) test the impacts of transaction frequency and wealth on the redistribution effect for users. $BeforeTransactions_i$ is the total number of user transactions between February 5, 2021, and August 5, 2021. $BeforeBalance_i$ is the average daily number of Ether held by users between February 5, 2021, and August 5, 2021.

For specification 20, the major endogenous problem stems from the well-known "Ashenfelter's Dip" problem, i.e., miners and users may anticipate the launch date of EIP-1559 fee mechanism and react in advance. For example, one may worry about technical glitches of the new mechanism and thus decrease his or her transactions in August. To solve this problem, we estimate the effects with symmetrically excluding a number of periods around the launch of EIP-1559 (Proserpio and Zervas, 2017; Li, Gan and Hu, 2011).

### *C. Empirical Results*

We start by presenting our findings concerning the miners. Figure 19a plots the average log of weekly mining rewards received by miners for a 20-week window containing the introduction of EIP-1559. The log of weekly mining rewards average around 0.05 in the 10 weeks ahead the launch drop discontinuously to 0.04 after the launch. Table 11 shows an overall negative effect of the EIP-1559 fee mechanism on miners' mining rewards. This finding suggests that the new fee policy "burned" part of the transaction fee that was originally awarded to miners. The individual weekly mining rewards drop approximately 0.7%.

Table 13 reports the results of the heterogeneous effect of EIP-1559 on miners. Columns 1 and 3 in Table 13 indicate that miners belonging to larger mining pools experienced a slight decrease of weekly mining rewards following the launch of EIP-1559. Moreover, Columns 2 and 4 in Table 13 indicate that miners with higher computation power experienced a larger decrease in weekly mining rewards following the launch of EIP-1559. These findings reveal that EIP-1559 potentially reduces the income of individuals with higher incomes.

Regarding the results on the user-side, Table 12 shows an overall positive effect of the EIP-1559 fee mechanism on users' transaction volume and the number of used DApps. Figure 19b and 19c plot the average log of users' transaction volume and the number of used DApps per week for a 20-week window containing the introduction of EIP-1559 seperately. The log of weekly transaction volume and the number of used DApps increase discontinuously after the launch of EIP-1559, and then followed by a decrease.

The results of heterogeneous effects of EIP-1559 on users are reported in Tables 14a and 14b. In particular, the significant negative coefficients of the interaction terms indicate that users with a lower frequency of transactions or Ether balance benefit more from EIP-1559.

Our results demonstrate that the EIP-1559 fee mechanism reform significantly impacts both mining and transactions on Ethereum. This policy effectively encourages participation of small and inactive users in the network.

## VI. Inclusion and Democracy Through Airdropping

Airdrops are often considered marketing strategies for expanding the user network (Froewis et al., 2021; Li et al., 2021). However, airdrops can also have some adverse effects. First, airdropping governance tokens may inadvertently distribute governance rights to speculators seeking only short-term profits (Froewis et al., 2021). Second, airdropping high-quality tokens can be value-destroying for native cryptocurrency due to substitution of usage (Liebi, 2021). In addition, if some tokens are distributed to inactive users, they become illiquid or permanently lost.

The extant literature mainly focuses on the impacts of airdropping for the distributors or platform founders. However, as a common strategy for distributing tokens in blockchain, it is important to explore its impact on the whole network, especially on the distribution of transactions. To this end, we use the large-scale airdrop of OmiseGo as an external shock to study the impact of airdropping on financial inclusion.[17]

### *A. Background: OmiseGo Airdropping*

OmiseGo aims to launch a wallet and payment network that allows people send and transfer money to other accounts without a bank, doing so peer-to-peer. It sponsored the first airdrop on Ethereum, and dispensed OmiseGo tokens (known as OMG) at a ratio of 0.075 to addresses with an Ether balance over 0.1 ETH at block height 3,988,888. [18] That is, an address with the account balance of 1 ETH would receive 0.075 OMG.

The announcement date of OmiseGo airdrop is August 17, 2017, while the snapshot date is July 7, 2017. This snapshot date, which is later than the announcement date, makes it impossible for users to intentionally change their account balance in advance in order to obtain the airdropped tokens, making this airdrop a completely exogenous shock. OmiseGo airdrop lasted for 11 days from September 13, 2017 to September 23,

[17]Since airdrops typically target EOA accounts and are not related to mining, we focus on their impacts on transactions and the valuation of native tokens, i.e., Ether.

[18]The block height 3,988,888 corresponds to July 7, 2017.

2017. During this period, the daily exchange rate of OMG was around 10 dollars.

### B. *Empirical Strategy*

We first adopt the identification strategy of difference-in-difference with RD sample to examine the effect of airdropping on users' financial activities on Ethereum (Jo et al., 2020). Addresses that received OMG airdrop with a balance over 0.1 ether are considered the treatment group, while addresses that do not receive OMG airdrop with a balance under 0.1 ether are considered the control group. The specific formula for regression is as follows:

$$y_{it} = \beta\left(\text{ After }_{it} \times \text{ Airdrop }_{i}\right) + \omega X_{it} + \lambda_i + \gamma_t + \varepsilon_{it}; \tag{25}$$

$$\text{weighted } = 1 - \left|\frac{balance_c}{bandwidth}\right|, \tag{26}$$

where $Airdrop_i$ represents whether the user belongs to the treatment group or control group, $After_{it}$ represents whether period $i$ is before or after the airdrop. $X_{it}$ represents a set of control variables (Table A4), $\lambda_i$ represents user fixed effect, and $\gamma_t$ represents time fixed effect.

In addition, we use the synthetic control method (SCM, see, e.g., Abadie, Diamond and Hainmueller, 2010; Abadie and Gardeazabal, 2003) to verify the impact of airdropping on the return of relevant native cryptocurrencies . Since a perfect control blockchain of Ethereum cannot be found, we constructed a "synthetic Ethereum" by linearly combining 14 blockchains with native cryptocurrency exchange rates over 1 dollar in the same period. None of these 14 potential blockchains in the control group had a hard fork or airdrop during our analysis period from September 6, 2017 to September 26, 2017 (Liebi, 2021). This "synthetic Ethereum" reflects the value of the predictors of Ether price before the OmiseGo airdrop. We estimate the impact of the airdropping on the exchange rate of the parent cryptocurrency by calculating the difference between the native cryptocurrency exchange rate of Ethereum (Ether) and its synthetic version within 14 days after the airdrop. We further confirm this effect with some placebo tests.

The predictors used to construct the "synthetic Ethereum" include the log of transaction volume of native cryptocurrency in dollars (LnVolume), market capitalization (LnMarketCap), daily exchange rate volatility (LnVolatility), whether the blockchain uses proof-of-work consensus or others, and the returns of native cryptocurrencies on September 6 (return8), September 9 (return11), and September 12 (return14), respectively.

### *C. Empirical Results*

**Impact of Airdropping on Users' Transaction Volume.** Figure 20 provides a visual image showing the parallel trends and post-treatment dynamics, and Table 15 presents the regression results. The airdrop has a significantly positive impact on users' transaction volume. These results illustrate that airdrop improves the transaction volume of those who received airdropped tokens, indicating that airdrop would lead to the concentration of transactions on a certain segment of players in the network.

**Impact of Airdropping on Native Cryptocurrency Exchange Rate.** The weight of each blockchain in the control group is illustrated in Table 16a. Before the launch of OmiseGo airdrop, the trend of Ether return is best represented by the combination of Bitcoin, Ethereum Classic, Litecoin, Peercoin and Waves, in which Bitcoin occupies the highest weight. Table 16b further shows the similar trend of mean values of predictors between Ethereum and synthetic Ethereum.

The estimated effects are shown in Figure 21 and Table 16c. Different from (Liebi, 2021), we do not find an immediate negative impact of the start of OmiseGo airdropping on its native token return using SCM. However, we find that the end of the airdropping has an immediate and significant positive effect on native token return. This is in favor of the concept that by enabling other blockchain projects, Ethereum as an infrastructure also becomes more valuable, over the alternative that OMG and ETH are strong substitutes as payment tokens.

## VII. Conclusion

Web3 and DeFi are widely advocated as innovations for greater financial inclusion and democratization (e.g., Tapscott and Tapscott, 2017). We conduct an initial investigation using data from the Ethereum network. We provide detailed description of the ecosystem including its network structure and distributions of transactions, mining, and ownership. Mining and ownership are concentrated in exchanges and a small set of individuals. For transactions and usage, we observe a shift from peer-to-peer interactions to user interactions with Dapps and DeFi protocols, and significantly more network activities by large players. More importantly, under the current gas fee mechanisms, high transaction-fee rates for small players, significant congestion-induced fluctuation of gas prices, and large return volatility of tokens hinder financial democratization and inclusion. These issues, coupled with users' suboptimal gas parameter setting and opportunity costs of additional gas limit reservations, cause high rates of transaction failures.

Some proposals (Buterin et al., 2019) are introduced to ease the congestion of the

Ethereum network and the problem of high transaction fees. In particular, EIP-1559 alleviates congestion through an adjustable block gas limit, and dynamically adjusts and burns base fee based on supply and demand. While transaction fees are still disproportionally high for small players, the burning of base fees has a perhaps unanticipated benefit of transferring wealth from large players to small and new agents, which facilitates financial inclusion. Using the case of OmiseGo airdrop program, we demonstrate how airdrops as redistributive policies can also improve financial inclusion.

The full potential of DeFi and Web3 can only be realized after a long, iterative process. Our paper can be viewed as an attempt to understand the landscape, mechanisms, and limitations of the current design, so as to inform future iterations. The data platform developed for the study also contributes to the field by allowing other researchers public access to blockchain and DeFi big data. Note that the switch to PoS (the Merge) can alter the Ethereum ecosystem dramatically.[19] Nevertheless, the issues we document remain because the Merge does not reduce transaction fees directly, although it opens the possibility for further reforms including sharding and third-party roll-ups. Overall, our findings can serve as a useful benchmark to evaluate future evolution of the Web3 and DeFi sector.

## REFERENCES

**Abadie, Alberto, Alexis Diamond, and Jens Hainmueller.** 2010. "Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program." *Journal of the American statistical Association*, 105(490): 493–505.

**Abadie, Alberto, and Javier Gardeazabal.** 2003. "The economic costs of conflict: A case study of the Basque Country." *American economic review*, 93(1): 113–132.

**Abadi, Joseph, and Markus Brunnermeier.** 2018. "Blockchain economics." National Bureau of Economic Research.

**Ao, Ziqiao, Gergely Horvath, and Luyao Zhang.** 2022. "Are decentralized finance really decentralized? A social network analysis of the Aave protocol on the Ethereum blockchain." *arXiv preprint arXiv:2206.08401*.

[19]For example, there will be more validators participating (one only needs 32 ETH and loading up three programs), which likely makes validation more decentralized. But block building could still be centralized. Because mining rewards are no longer needed to offset the equipment cost, the amount of ETH paid out will drop significantly, which has a similar effect as EIP-1559 burning of tokens in that both would reduce the increase in Ether supply. Further studies on "maximal extractable value" (MEV) and block builders, given the separation of block proposing and block building, are likely fruitful.

**Auer, Raphael, Jon Frost, Jose María Vidal Pastor, et al.** 2022. "Miners as intermediaries: extractable value and market manipulation in crypto and DeFi." Bank for International Settlements.

**Augustin, Patrick, Roy Chen-Zhang, and Donghwa Shin.** 2022. "Yield Farming." *Available at SSRN 4063228*.

**Bachas, Pierre, Paul Gertler, Sean Higgins, and Enrique Seira.** 2018. "Digital financial services go a long way: Transaction costs and financial inclusion." Vol. 108, 444–48.

**Bartlett, Robert, Adair Morse, Richard Stanton, and Nancy Wallace.** 2022. "Consumer-lending discrimination in the FinTech era." *Journal of Financial Economics*, 143(1): 30–56.

**Bartley Johns, Marcus, Paul Brenton, Massimiliano Cali, Mombert Hoppe, and Roberta Piermartini.** 2015. "The Role of Trade in Ending Poverty." World.

**Basu, Soumya, David Easley, Maureen O'Hara, and Emin Gün Sirer.** 2019. "Towards a functional fee market for cryptocurrencies." *arXiv*, 1–32.

**Browne, Ryan.** 2021. "Ethereum-the world's second-largest cryptocurrency-soars above $4,000 for the first time."

**Buterin, Vitalik, Eric Conner, Rick Dudley, Matthew Slipper, Ian Norden, and Abdelhamid Bakhta.** 2019. "Fee market change for ETH 1.0 chain."

**Capponi, Agostino, and Ruizhe Jia.** 2021. "The Adoption of Blockchain-based Decentralized Exchanges: A Market Microstructure Analysis of the Automated Market Maker." *Available at SSRN 3805095*.

**Capponi, Agostino, Ruizhe Jia, and Shihao Yu.** 2022. "The Information Content of Blockchain Fees."

**Capponi, Agostino, Ruizhe Jia, and Ye Wang.** 2022. "The Evolution of Blockchain: from Lit to Dark." *arXiv preprint arXiv:2202.05779*.

**Capponi, Agostino, Sveinn Olafsson, and Humoud Alsabah.** 2021. "Proof-of-Work Cryptocurrencies: Does Mining Technology Undermine Decentralization?" *arXiv preprint arXiv:2106.09783*.

**Chen, Long, Lin William Cong, and Yizhou Xiao.** 2019. *A Brief Introduction to Blockchain Economics.*

**Chen, Yan, and Cristiano Bellavitis.** 2020. "Blockchain disruption and decentralized finance: The rise of decentralized business models." *Journal of Business Venturing Insights*, 13(April).

**CHOI, SOON HYEOK, and ROBERT A JARROW.** 2022. "APPLYING THE LOCAL MARTINGALE THEORY OF BUBBLES TO CRYPTOCURRENCIES." *International Journal of Theoretical and Applied Finance*, 2250013.

**Chung, Hao, and Elaine Shi.** 2021. "Foundations of transaction fee mechanism design." *arXiv preprint arXiv:2111.03151*.

**Cong, Lin William, and Yizhou Xiao.** 2021. "Categories and functions of crypto-tokens." In *The Palgrave Handbook of FinTech and Blockchain*. 267–284. Springer.

**Cong, Lin William, and Zhiguo He.** 2019. "Blockchain disruption and smart contracts." *The Review of Financial Studies*, 32(5): 1754–1797.

**Cong, Lin William, Campbell R Harvey, Daniel Rabetti, and Zong-Yu Wu.** 2022*a*. "An anatomy of crypto-enabled cybercrimes." *Available at SSRN 4188661*.

**Cong, Lin William, Wayne Landsman, Edward Maydew, and Daniel Rabetti.** 2022*b*. "Tax-loss harvesting with cryptocurrencies." National Bureau of Economic Research.

**Cong, Lin William, Xi Li, Ke Tang, and Yang Yang.** 2021. "Crypto wash trading." *arXiv preprint arXiv:2108.10984*.

**Cong, Lin William, Ye Li, and Neng Wang.** 2020. "Token-based platform finance." National Bureau of Economic Research.

**Cong, Lin William, Ye Li, and Neng Wang.** 2021. "Tokenomics: Dynamic adoption and valuation." *The Review of Financial Studies*, 34(3): 1105–1155.

**Cong, Lin William, Zhiguo He, and Jiasun Li.** 2018. "Decentralized Mining in Centralized Pools." *SSRN Electronic Journal*.

**Cong, Lin William, Zhiheng He, and Ke Tang.** 2020. "Staking, Token Pricing, and Crypto Carry." *Available at SSRN*.

**Corrado, Germana, and Luisa Corrado.** 2017. "Inclusive finance for inclusive growth and development." *Current Opinion in Environmental Sustainability*, 24(September 2015): 19–23.

**DeFi Prime.** 2021. “Ethereum DeFi Ecosystem.”

**Dupas, Pascaline, and Jonathan Robinson.** 2013. “Savings constraints and microenterprise development: Evidence from a field experiment in Kenya.” *American Economic Journal: Applied Economics*, 5(1): 163–92.

**Easley, David, Maureen O’Hara, and Soumya Basu.** 2019. “From mining to markets: The evolution of bitcoin transaction fees.” *Journal of Financial Economics*, 134(1): 91–109.

**Ferreira, Daniel, Jin Li, and Radoslawa Nikolowa.** 2022. “Corporate Capture of Blockchain Governance.” *The Review of Financial Studies*. hhac051.

**Foley, Sean, Jonathan R Karlsen, and Tālis J Putniņš.** 2019. “Sex, drugs, and bitcoin: How much illegal activity is financed through cryptocurrencies?” *The Review of Financial Studies*, 32(5): 1798–1853.

**Froewis, Michael, Kiran Sridhar, Christos Makridis, and Rainer Böhme.** 2021. “The Rise of Decentralized Cryptocurrency Exchanges: Evaluating the Role of Airdrops and Governance Tokens.” *Available at SSRN*.

**Gonzalez-barahona, Jesus M.** 2021. “Factors determining maximum energy consumption of Bitcoin miners.” *SSRN Electronic Journal*, 1–24.

**Haig, Samuel.** 2021. “Ethereum posts new highs as DeFi gas fees go through the roof.”

**Han, Brandon Yueyang, and Igor Makarov.** 2021. “Feedback trading and bubbles.” *Available at SSRN 3796200*.

**Harvey, Campbell R., Ashwin Ramachandran, and Joseph Santoro.** 2020. “DeFi and the Future of Finance.” *SSRN Electronic Journal*.

**Hasbrouck, Joel, Thomas J Rivera, and Fahad Saleh.** 2022. “The need for fees at a dex: How increases in fees can increase dex trading volume.” *Available at SSRN*.

**Hinzen, Franz J., Kose John, and Fahad Saleh.** 2020. “Bitcoin’s Fatal Flaw: The Limited Adoption Problem.” *SSRN Electronic Journal*.

**Huberman, Gur, Jacob D Leshno, and Ciamac Moallemi.** 2021. “Monopoly without a monopolist: An economic analysis of the bitcoin payment system.” *The Review of Economic Studies*, 88(6): 3011–3040.

**Ilk, Noyan, Guangzhi Shang, Shaokun Fan, and J. Leon Zhao.** 2021. "Stability of Transaction Fees in Bitcoin: A Supply and Demand Perspective." *MIS Quarterly*, 45(2): 563–592.

**Jack, William, and Tavneet Suri.** 2014. "Risk sharing and transactions costs: Evidence from Kenya's mobile money revolution." *American Economic Review*, 104(1): 183–223.

**Jiang, Erica Xuewei, Gloria Yang Yu, and Jinyuan Zhang.** 2022. "Bank Competition amid Digital Disruption: Implications for Financial Inclusion." *Available at SSRN 4178420*.

**John, Kose, Leonid Kogan, and Fahad Saleh.** 2022. "Smart Contracts and Decentralized Finance." *Working paper*.

**John, Kose, Thomas J Rivera, and Fahad Saleh.** 2021. "Equilibrium staking levels in a proof-of-stake blockchain." *Available at SSRN 3965599*.

**Jo, Wooyong, Sarang Sunder, Jeonghye Choi, and Minakshi Trivedi.** 2020. "Protecting consumers from themselves: Assessing consequences of usage restriction laws on online game usage and spending." *Marketing Science*, 39(1): 117–133.

**Lauslahti, Kristian, Juri Mattila, and Timo Seppala.** 2018. "Smart Contracts How Will Blockchain Technology Affect Contractual Practices?" *SSRN Electronic Journal*.

**Lavi, Ron, Or Sattath, and Aviv Zohar.** 2019. "Redesigning Bitcoin's fee market." *The Web Conference 2019 - Proceedings of the World Wide Web Conference, WWW 2019*, 2950–2956.

**Lehar, Alfred, and Christine A Parlour.** 2021. "Decentralized exchanges." Working paper.

**Lehar, Alfred, and Christine Parlour.** 2022. "Systemic Fragility in Decentralized Markets."

**Liebi, Luca.** 2021. "Raining Cryptos." *Available at SSRN 3918432*.

**Li, Jian, Xiang Shawn Wan, Hsing Kenneth Cheng, and Xi Zhao.** 2021. "Operation Dumbo Drop: To Airdrop or Not to Airdrop for Initial Coin Offering Success?" *Hsing Kenneth and Zhao, Xi, Operation Dumbo Drop: To Airdrop or Not to Airdrop for Initial Coin Offering Success*.

**Lin, Qinwei, Chao Li, Xifeng Zhao, and Xianhai Chen.** 2021. "Measuring decentralization in bitcoin and ethereum using multiple metrics and granularities." 80–87, IEEE.

**Li, Tao, Donghwa Shin, and Baolian Wang.** 2021. "Cryptocurrency pump-and-dump schemes." *Available at SSRN 3267041*.

**Liu, Yulin, Yuxuan Lu, Kartik Nayak, Fan Zhang, Luyao Zhang, and Yinhong Zhao.** 2022. "Empirical Analysis of EIP-1559: Transaction Fees, Waiting Time, and Consensus Security." *arXiv preprint arXiv:2201.05574*.

**Li, Xia, Christopher Gan, and Baiding Hu.** 2011. "The welfare impact of microcredit on rural households in China." *The Journal of Socio-Economics*, 40(4): 404–411.

**Makarov, Igor, and Antoinette Schoar.** 2022. "Blockchain Analysis of the Bitcoin Market." *SSRN Electronic Journal*.

**Park, Andreas.** 2021. "The conceptual flaws of constant product automated market making." *Available at SSRN 3805750*.

**Philippon, Thomas.** 2016. "The fintech opportunity." National Bureau of Economic Research.

**Philippon, Thomas.** 2019. "On fintech and financial inclusion." National Bureau of Economic Research.

**Proserpio, Davide, and Georgios Zervas.** 2017. "Online reputation management: Estimating the impact of management responses on consumer reviews." *Marketing Science*, 36(5): 645–665.

**Reijsbergen, Daniël, Shyam Sridhar, Barnabé Monnot, Stefanos Leonardos, Stratis Skoulakis, and Georgios Piliouras.** 2021. "Transaction Fees on a Honeymoon: Ethereum's EIP-1559 One Month Later." 196–204, IEEE.

**Roşu, Ioanid, and Fahad Saleh.** 2021. "Evolution of shares in a proof-of-stake cryptocurrency." *Management Science*, 67(2): 661–672.

**Roughgarden, Tim.** 2020*a*. "Transaction Fee Mechanism Design for the Ethereum Blockchain: An Economic Analysis of EIP-1559." *Working paper*, 1–58.

**Roughgarden, Tim.** 2020*b*. "Transaction fee mechanism design for the Ethereum blockchain: An economic analysis of EIP-1559." *arXiv preprint arXiv:2012.00854*.

**Saez, Emmanuel, and Gabriel Zucman.** 2016. “Wealth inequality in the United States since 1913: Evidence from capitalized income tax data.” *The Quarterly Journal of Economics*, 131(2): 519–578.

**Saez, Emmanuel, and Gabriel Zucman.** 2020. “The rise of income and wealth inequality in America: evidence from distributional macroeconomic accounts.” *Journal of Economic Perspectives*, 34(4): 3–26.

**Schär, Fabian.** 2021. “Decentralized Finance: On Blockchain- and Smart Contract-based Financial Markets.” *Federal Reserve Bank of St. Louis REVIEW*, 153–174.

**Sokolov, Konstantin.** 2021. “Ransomware activity and blockchain congestion.” *Journal of Financial Economics*, 141(2): 771–782.

**Tapscott, Alex, and Don Tapscott.** 2017. “How Blockchain is Changing Finance.” *Harvard Business Review*, 1(9): 2–5.

**Ventura, Luca.** 2021. “Poorest Countries in the World 2021.”

**Wood, Gavin, Nick Savers, and Community.** 2018. “Ethereum: A Secure Decentralised Generalised Transaction Ledger-Byzantium Version.”

**World Bank Group.** 2016. *World development report 2016: Digital dividends.* World Bank Publications.

**Zarir, Abdullah A., Gustavo A. Oliva, Zhen M.Jack Jiang, and Ahmed E. Hassan.** 2021. “Developing Cost-Effective Blockchain-Powered Applications: A Case Study of the Gas Usage of Smart Contract Transactions in the Ethereum Blockchain Platform.” *ACM Transactions on Software Engineering and Methodology*, 30(3).

**Zhang, Luyao, Xinshi Ma, and Yulin Liu.** 2022. “SoK: Blockchain Decentralization.” *arXiv preprint arXiv:2205.04256*.

**Zhongming, Zhu, Lu Linong, Yao Xiaona, Zhang Wangqiang, Liu Wei, et al.** 2021. “Don’t let the digital divide become ‘the new face of inequality’: UN deputy chief.”

**Tables and Figures**

Table 1—: Summary Statistics

This table shows summary statistics of the variables used in this paper. Panel A describes gas-related variables (i.e., $GasPrice$, $GasUsed$, $GasLimit$, $ExtraGasReserved$, $GasFee$, and $Value$). The sample period is from October 2017 to August 2021, and includes 748,738,026 unique transactions. Panel B describes network dependent variables (i.e., $NetworkUtilization$, $\#Transaction$, $BlockRewards$, and $EthPopularity$). The sample period is from October 2017 to August 2021, resulting in a total number of 1,389 days. Panel C reports daily failure rate and failure number, which covers 1,389 days from October 2017 to August 2021. Panel D lists the summary statistics of gas price in four levels of delay time. The sample period is from February 2021 to May 2021.

(a) Gas-related Variables

| | mean | median | 25% | 75% | standard deviation |
|---|---|---|---|---|---|
| GasPrice ($Gwei$) | 61.183 | 30.810 | 10.000 | 77.027 | 27063.140 |
| GasUsed | 47853.727 | 21000.000 | 21000.000 | 41000.000 | 95534.784 |
| GasLimit | 114896.217 | 51000.000 | 21000.000 | 116000.000 | 257359.441 |
| ExtraGasReserved | 67042.491 | 29000.000 | 0.000 | 69000.000 | 220877.892 |
| GasFee ($ETH$) | 0.003 | 0.000 | 0.000 | 0.002 | 0.568 |
| GasFee ($dollar$) | 4.075 | 0.434 | 0.068 | 2.703 | 135.545 |
| Value ($dollar$) | $1.05*10^{49}$ | 72 | 9 | 577 | $2.26*10^{53}$ |

*Note:* The average value is very high because the values of some specific token-related transactions are very high, for example, a transaction on SmartMesh token consists more than $10^{56} dollars (transaction hash on Ethereum : 0x1abab4c8db9a30e703114528e31dee129a3a758f7f8abc3b6494aad3d304e43f). Excluding token - related transactions, the average value is 3423.71 dollar.$

(b) Network-dependent Variables

| | mean | median | 25% | 75% | standard deviation | Obs. |
|---|---|---|---|---|---|---|
| NetworkUtilization (%) | 86.742 | 89.680 | 79.070 | 96.680 | 10.802 | 1,389 |
| #Transaction | 839601.885 | 757712.000 | 611188.000 | 1096582.000 | 279352.418 | 1,389 |
| BlockRewards | 2.571 | 2.115 | 2.089 | 3.309 | 0.636 | 1,389 |
| EthPopularity | 14.089 | 6.000 | 4.000 | 14.000 | 17.936 | 1,389 |

(c) Failure-related Variables

| | mean | median | 25% | 75% | standard deviation | Obs |
|---|---|---|---|---|---|---|
| Failure | 0.071 | 0.00 | 0.00 | 0.00 | 0.257 | 319,679,841 |
| FailureRate | 2.034% | 1.674% | 1.368% | 2.091% | 1.846% | 1,389 |
| #Failure | 16392.307 | 13531.000 | 9781.000 | 19308.000 | 11434.661 | 1,389 |

Table 1—: Summary Statistics (continued)

(d) Gas Price and Delay Time

| GasPrice | $DelayTime = 0.5min$ | $DelayTime = 2min$ | $DelayTime = 5min$ | $delay_time = 30min$ |
|---|---|---|---|---|
| mean | 16.85 | 15.71 | 12.28 | 11.27 |
| median | 15.50 | 15.60 | 11.70 | 10.90 |
| 25% | 12.30 | 11.00 | 8.90 | 8.30 |
| 75% | 20.40 | 19.30 | 15.00 | 13.90 |
| standard deviation | 0.073 | 0.068 | 0.051 | 0.050 |
| Obs. | 12,073 | 12,073 | 12,073 | 12,073 |

Table 2—: Percentage Transaction Fee

This table gives a detailed description of the percentage transaction fee variable, which is measured by the gas fee of a transaction divided by the transaction value. Panel A shows the overall statistics of percentage transaction fee for six specific categories, i.e., transactions with EOAs and with contract accounts, transactions using Ether and using tokens on Ethereum, transactions with DApps and others. Panel B (EOAs and contract accounts), panel C (Ether and token on Ethereum) and panel D (DApps and others) list the summary statistics of six categories of percentage transaction fees at different transaction value levels separately. The sample period is from October 2017 to August 2021.

(a) General Description of Percentage Transaction Fee

| | mean (%) | median (%) | 25% (%) | 75% (%) | standard deviation | Obs. |
|---|---|---|---|---|---|---|
| EOA | $1.026*10^{14}$ | 0.247 | 0.035 | 4.200 | $2.239*10^{14}$ | 448,145,174 |
| Contract Account | $4.560*10^{20}$ | 0.367 | 0.050 | 2.562 | $6.245*10^{22}$ | 300,592,852 |
| Ether | $1.056*10^{14}$ | 0.290 | 0.038 | 4.441 | $3.026*10^{14}$ | 500,060,320 |
| Token | $5.513*10^{20}$ | 0.316 | 0.044 | 2.088 | $6.866*10^{22}$ | 248,677,706 |
| DApps | $5.464*10^{20}$ | 0.320 | 0.048 | 2.133 | $7.129*10^{22}$ | 230,497,041 |
| Others | $2.148*10^{19}$ | 0.289 | 0.037 | 4.295 | $1.212*10^{21}$ | 518,240,985 |
| All | $1.831*10^{20}$ | 0.301 | 0.040 | 3.341 | $3.957*10^{22}$ | 748,738,026 |

Table 2—: Percentage Transaction Fee (continued)

(b) EOA and Contract Account

| value | Percentage transaction fee of transactions with EOA | | | | | | Percentage transaction fee of transactions with contract account | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | mean | median | 25% | 75% | standard deviation | count | mean | median | 25% | 75% | standard deviation | count |
| ($) | (%) | (%) | (%) | (%) | | | (%) | (%) | (%) | (%) | | |
| 0-0.01 | $2.750*10^{16}$ | 2132.303 | 146.873 | $1.260*10^{5}$ | $3.655*10^{15}$ | 1,671,974 | $8.885*10^{22}$ | $1.180*10^{5}$ | 6744.588 | $1.867*10^{6}$ | $8.716*10^{23}$ | 1,575,441 |
| 0.01-0.1 | 243.581 | 37.816 | 21.000 | 70.000 | 52.120 | 10,547,122 | $1.084*10^{4}$ | 480.010 | 67.721 | 5136.898 | 571.000 | 2,161,592 |
| 0.1-1 | 44.694 | 18.539 | 8.400 | 35.36 | 6.712 | 33,696,799 | 589.035 | 26.451 | 9.711 | 134.950 | 30.130 | 5,460,002 |
| 0-1 | $1.001*10^{15}$ | 23.333 | 10.500 | 49.320 | $6.993*10^{14}$ | 45,915,895 | $1.496*10^{22}$ | 101.843 | 16.137 | 2478.908 | $3.576*10^{23}$ | 9,197,035 |
| 1-10 | 16.376 | 5.484 | 0.664 | 19.368 | 6.912 | 64,995,372 | 67.945 | 9.693 | 2.512 | 27.925 | 4.293 | 20,345,748 |
| 10-100 | 3.946 | 0.323 | 0.050 | 2.898 | 1.767 | 141,888,797 | 12.324 | 2.357 | 0.45 | 10.493 | 0.395 | 54,058,840 |
| 100-1000 | 0.759 | 0.086 | 0.020 | 0.502 | 1.760 | 121,468,232 | 2.412 | 0.492 | 0.099 | 2.082 | 0.077 | 102,400,888 |
| 1000- | 0.069 | 0.008 | 0.001 | 0.050 | 0.025 | 73,876,878 | 0.339 | 0.056 | 0.009 | 0.277 | 0.011 | 114,590,341 |
| 1- | 4.29 | 0.156 | 0.027 | 1.685 | 3.124 | 402,229,279 | 8.011 | 0.329 | 0.047 | 2.104 | 1.161 | 291,395,817 |
| All | $1.026*10^{14}$ | 0.247 | 0.035 | 4.200 | $2.239*10^{14}$ | 448,145,174 | $4.560*10^{20}$ | 0.367 | 0.050 | 2.562 | $6.245*10^{22}$ | 300,592,852 |

Table 2—: Percentage Transaction Fee (continued)

(c) Ether and Tokens on Ethereum

| | Percentage transaction fee of transactions with Ether | | | | | | Percentage transaction fee of transactions with tokens | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| value ($) | mean (%) | median (%) | 25% (%) | 75% (%) | standard deviation | count | mean (%) | median (%) | 25% (%) | 75% (%) | standard deviation | count |
| 0-0.01 | $2.722*10^{16}$ | 2425.500 | 140.000 | $3.549*10^{5}$ | $4.851*10^{15}$ | 1,940,417 | $1.076*10^{23}$ | $1.502*10^{5}$ | 9689.449 | $1.520*10^{6}$ | $9.591*10^{23}$ | 1,306,998 |
| 0.01-0.1 | 316.956 | 39.622 | 21.320 | 80.125 | 71.722 | 11,080,624 | $1.381*10^{4}$ | 777.803 | 65.826 | 8016.499 | 641.844 | 1,628,090 |
| 0.1-1 | 51.211 | 18.480 | 8.400 | 36.651 | 7.073 | 35,664,898 | 829.264 | 33.497 | 10.487 | 246.113 | 36.440 | 3,491,903 |
| 0-1 | $1.085*10^{15}$ | 23.333 | 10.500 | 50.974 | $9.699*10^{14}$ | 48,685,939 | $2.144*10^{22}$ | 201.352 | 21.926 | 6702.047 | $4.281*10^{23}$ | 6,426,991 |
| 1-10 | 16.810 | 5.612 | 0.795 | 18.564 | 6.490 | 74,134,677 | 107.130 | 14.696 | 3.529 | 53.428 | 5.619 | 11,206,443 |
| 10-100 | 4.506 | 0.409 | 0.062 | 3.438 | 1.665 | 160,382,318 | 14.156 | 3.050 | 0.619 | 11.939 | 0.439 | 35,565,319 |
| 100-1000 | 0.880 | 0.096 | 0.021 | 0.561 | 1.669 | 135,062,684 | 2.482 | 0.542 | 0.110 | 2.227 | 0.075 | 88,806,436 |
| 1000- | 0.088 | 0.010 | 0.002 | 0.058 | 0.024 | 81,794,702 | 0.345 | 0.058 | 0.010 | 0.285 | 0.011 | 106,672,517 |
| 1- | 4.641 | 0.183 | 0.030 | 1.986 | 2.956 | 451,374,381 | 8.096 | 0.289 | 0.042 | 1.778 | 1.241 | 242,250,715 |
| All | $1.056*10^{14}$ | 0.290 | 0.038 | 4.441 | $3.026*10^{14}$ | 500,060,320 | $5.513*10^{20}$ | 0.316 | 0.044 | 2.088 | $6.866*10^{2}2$ | 248,677,706 |

Table 2—: Percentage Transaction Fee (continued)

(d) DApps and Others

| | Percentage transaction fee of transactions with DApps | | | | | | Percentage transaction fee of transactions with others | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| value ($) | mean (%) | median (%) | 25% (%) | 75% (%) | standard deviation | count | mean (%) | median (%) | 25% (%) | 75% (%) | standard deviation | count |
| 0-0.01 | $2.398*10^{23}$ | $2.094*10^{4}$ | 1099.845 | $8.485*10^{5}$ | $1.493*10^{24}$ | 527,711 | $4.139*10^{21}$ | $1.633*10^{4}$ | 527.341 | $1.136*10^{6}$ | $1.683*10^{22}$ | 2,719,704 |
| 0.01-0.1 | 7383.468 | 356.368 | 81.765 | 2697.555 | 815.257 | 656,319 | 1754.389 | 42.000 | 22.857 | 94.500 | 161.757 | 12,052,395 |
| 0.1-1 | 483.048 | 23.116 | 8.998 | 97.104 | 28.961 | 2,418,670 | 96.734 | 18.900 | 8.400 | 38.655 | 11.130 | 36,738,131 |
| 0-1 | $3.498*10^{22}$ | 60.876 | 12.994 | 665.080 | $5.704*10^{23}$ | 3,602,700 | $2.162*10^{20}$ | 24.871 | 10.500 | 55.732 | $3.846*10^{21}$ | 51,510,230 |
| 1-10 | 58.610 | 9.998 | 2.999 | 32.465 | 4.516 | 11,877,579 | 23.830 | 5.929 | 0.771 | 19.931 | 6.642 | 73,463,541 |
| 10-100 | 11.717 | 2.020 | 0.314 | 9.959 | 0.367 | 43,019,921 | 4.721 | 0.426 | 0.060 | 3.610 | 1.707 | 152,927,716 |
| 100-1000 | 2.332 | 0.477 | 0.099 | 2.048 | 0.070 | 84,527,206 | 1.020 | 0.106 | 0.022 | 0.654 | 1.644 | 139,341,914 |
| 1000- | 0.340 | 0.053 | 0.009 | 0.277 | 0.010 | 87,469,635 | 0.141 | 0.015 | 0.002 | 0.090 | 0.023 | 100,997,584 |
| 1- | 6.290 | 0.303 | 0.046 | 1.941 | 1.055 | 226,894,341 | 5.633 | 0.183 | 0.029 | 1.859 | 2.952 | 466,730,755 |
| All | $5.464*10^{20}$ | 0.320 | 0.048 | 2.133 | $7.129*10^{22}$ | 230,497,041 | $2.148*10^{19}$ | 0.289 | 0.037 | 4.295 | $1.212*10^{21}$ | 518,240,985 |

Table 3—: The Effect of Gas Price on Delay Time

This table gives regression results of the delay time on gas price. Panel A lists ordered logistic regression results in Regression 1, ordered probit regression results in Regression 2, and OLS regression results in Regression 3. Panel B shows the marginal effect of gas price on four levels of delay time. The sample period is from February 2021 to May 2020. There are 48,292 observations in each regression.

(a) Main Effect

| DelayTime | Ologit (1) | Oprobit (2) | OLS (3) |
|---|---|---|---|
| GasPrice | -0.0861** | -0.0508** | -0.48** |
| | (-64.17) | (-64.99) | (-74.66) |
| Cut point 1 | -2.40 | -1.43 | |
| Cut point 2 | -1.20 | -0.71 | |
| Cut point 3 | -0.02 | 0.01 | |
| Log likelihood | -64402.247 | -64464.91 | |
| Pseudo R2 | 3.8% | 3.7% | 7.3% (R2) |

(b) The Average Marginal Effect of Gas Price on Delay Time

| | Ologit (1) | Oprobit (2) |
|---|---|---|
| | dy/dx | dy/dx |
| DelayTime | 0.0148 | 0.0150 |
| (=0.5 min) | (69.28) | (70.24) |
| DelayTime | 0.0052 | 0.0041 |
| (=2 min) | (49.89) | (47.17) |
| DelayTime | -0.0046 | -0.0038 |
| (=5 min) | (-51.02) | (-49.16) |
| DelayTime | -0.0150 | -0.0153 |
| (=30 min) | (-65.00) | (-66.96) |

Table 4—: The Effect of Congestion on Gas Price

This table reports OLS (ordinary least squares) regression results of the log of gas price $ln(GasPrice)$ on the log of network utilization with a lag of one day $L.ln(NetworkUtilization)$ at transaction-level. We employ a generalized linear regression model in Spark ml library to estimate the transaction-level regression which involves all 748,738,026 transactions. The sample period is October 2017-August 2021. There are 748,738,026, 248,677,706, 448,145,174 and 51,915,146 observations in Regression 1-4 for all transactions and three types of transactions separately.

| Ln(GasPrice) | All (1) | Token (2) | User (3) | SC (4) |
|---|---|---|---|---|
| L.Ln(NetworkUtilization) | 3.429*** | 4.316*** | 2.809*** | 3.087*** |
| | (0.000) | (0.001) | (0.001) | (0.001) |
| L.EthReturn | 0.523*** | 0.474*** | 0.553*** | 0.377*** |
| | (0.001) | (0.001) | (0.001) | (0.003) |
| L.ln(BlockRewards) | -1.561*** | -1.841*** | -1.145*** | -1.363*** |
| | (0.000) | (0.001) | (0.000) | (0.001) |
| L.ln(EthPopularity) | 0.349*** | 0.234*** | 0.391*** | 0.404*** |
| | (0.000) | (0.000) | (0.000) | (0.00) |
| Obs. | 748,738,026 | 248,677,706 | 448,145,174 | 51,915,146 |
| AIC | $2.614*10^9$ | $7.241*10^8$ | $1.644*10^9$ | $1.716*10^8$ |
| Null Deviance | $1.935*10^9$ | $3.908*10^8$ | $1.290*10^9$ | $1.178*10^8$ |

Table 5—: Extra Gas Fee Reserved

This table reports extra gas reserved due to the gas limit policy. Panel A illustrates how much users need to preserve in their wallets compared with the actual paid gas fee. Panel B gives OLS regression prediction of extra gas reserved using the lag of network utilization, the return of Ether exchange rate, median gas price, block rewards and the popularity of Ethereum as predictors. We employ generalized linear regression model in Spark ml library to estimate transaction-level regression, and set a series parameters including Family, Link, MaxIter.

(a) How Much Users Need to Reserve in the Wallets

| | mean | median | 25% | 75% | standard deviation | Obs. |
|---|---|---|---|---|---|---|
| ExtraGasFee ($) | 5.455 | 0.077 | 0.00 | 1.559 | 37.049 | 748,738,026 |
| GasFee ($) | 4.075 | 0.434 | 0.068 | 2.701 | 135.535 | 748,738,026 |

(b) The Determinants of Extra Gas Reserved

| Ln(ExtraGasReserved) | All |
|---|---|
| L.Ln(NetworkUtilization) | 0.409*** |
| | 0.002 |
| L.EthReturn | -0.695*** |
| | 0.003 |
| L.ln(MedianGasPrice) | 0.048*** |
| | 0.000 |
| L.ln(BlockRewards) | -0.990*** |
| | 0.001 |
| L.ln(EthPopularity) | -0.076*** |
| | 0.000 |
| Obs. | 748,738,026 |
| AIC | $4.622*10^9$ |
| Null Deviance | $2.043*10^{10}$ |

Table 6—: Gas Fee Incurred by Failed Transactions

This table describes the total transaction fee lost by all users due to failed transactions using Ethereum. Panel A summarizes the total gas fee incurred by each type of failed transaction, the number of failed transactions and their proportion to each type of transaction. Panel B summarizes the gas fee incurred due to different failed reasons. The sample period is from October 2017 to August 2021.

(a) Gas Fee Incurred with Different Transaction Type Due to Failure

| Transaction type | Total gas fee ($) | Avg gas fee ($) | Failed transactions | Percentage of failures in each type of transaction |
|---|---|---|---|---|
| Transactions with SC | 57,171,289 | 7.027 | 8,135,712 | 2.707% |
| Token-related transactions | 31,367,076 | 2.144 | 14,633,202 | 5.557% |

(b) Gas Fee Incurred Due to Different Failed Reasons (non-zero-value transactions)

| Failed reason | Total gas fee | nFailed transactions | Percentage of failures |
|---|---|---|---|
| Out of gas | 18,660,388 dollars | 4,746,143 | 21.47% |
| Reverted | 65,355,497 dollars | 16,960,457 | 76.72% |
| Bad instruction | 11,699,221 dollars | 1,630,477 | 7.38% |
| Bad jump destination | 1,725,939 dollars | 537,755 | 2.43% |

Table 7—: Factors Influencing Failure

This table gives transaction-level logistic regression prediction of Failure using whether there is extra gas set for the transaction (*GasExtra*), the log of gas price $ln(GasPrice)$, and the lag of median gas price, the return of Ether exchange rate, network utilization, block rewards and the popularity of Ethereum. We employ generalized linear regression model in Spark ml library to estimate transaction-level regression, and set a series parameters including Family, Link, MaxIter and RegParam as "binomial", "logit", 10, and 0.3 respectively.

| | Transaction-level | |
|---|---|---|
| failure | All (1) | Token (2) |
| GasExtra | -0.670*** | -0.877*** |
| | (0.000) | (0.000) |
| Ln(GasPrice) | -0.247*** | -0.421*** |
| | (0.000) | (0.000) |
| L.ln(MedianGasPrice) | -0.120*** | -0.311*** |
| | (0.000) | (0.000) |
| L.EthReturn | -0.002*** | -0.004*** |
| | (0.000) | (0.001) |
| L.ln(NetworkUtilization) | -0.073*** | -0.103*** |
| | (0.000) | (0.001) |
| L.ln(BlockRewards) | 0.200*** | 0.302*** |
| | (0.000) | (0.001) |
| L.ln(EthPopularity) | 0.087*** | 0.023*** |
| | (0.003) | (0.003) |
| Obs. | 319,679,841 | 267,764,695 |
| AIC | $1.484*10^8$ | $8.842*10^7$ |
| Null Deviance | $1.614*10^8$ | $1.104*10^8$ |

Table 8—: The Determinants of Ether Volatility

This table reports the OLS regression results of the log of daily Ether exchange rate volatility (LnVolatility) on the log of the average Ether exchange rate (LnAvgEtherPirce), the log of failure rate (LnFailureRate), the log of a number of transactions (LnTransaction), the log of daily median gas price (LnGasPrice), the log of block rewards (LnBlockRewards) and the log of Ethereum popularity (LnPopularity). The sample period is January 2018 to September 2020.

| | LnVolatility |
|---|---|
| LnAvgEtherPrice | 0.679*** |
| | (0.046) |
| LnFailureRate | -3.728*** |
| | (0.708) |
| LnTransaction | 0.291*** |
| | (0.102) |
| LnGasPrice | 0.002 |
| | (0.025) |
| LnBlockRewards | 0.563*** |
| | (0.138) |
| LnPopularity | 0.353*** |
| | (0.046) |
| Observations | 1,163 |
| R-squared | 0.618 |

Robust standard errors in parentheses
*** p¡0.001, ** p¡0.01, * p¡0.05

Table 9—: Relative Token Returns

This table reports the coefficient and R square of Ethereum-related token return on ether return and the square of ether return. The results of the fixed individual (regard each token as an individual) effect regression are listed in the first column, and the results of OLS regression with the average token return as the dependent variable are listed in the second column. The sample period is December 2017 to December 2020. There are 157 tokens in the regressions.

| TokenReturn | (1) Fixed Effect | (2) OLS |
|---|---|---|
| EthReturn | 0.777*** | 0.776*** |
| | (0.016) | (0.024) |
| $\text{EthReturn}^2$ | -0.826*** | -0.802*** |
| | (0.052) | (0.278) |
| Observations | 171,758 | 1,094 |
| R-squared | 2.1% | 64.6% |
| Number of tokens | 157 | |

Table 10—: Transaction-level Summary Statistics on EIP-1559 Analyses Sample

This table reports summary statistics of key transaction-level variables used in the analyses of EIP-1559. Panel A describes weekly block rewards, number of transactions, transaction volume and number of used DApps of miners before and after the launch of EIP-1559. Panel B describes the weekly number of transactions, transaction volume and number of used DApps of the three group of users before and after the launch of EIP-1559. The sample period is from February 2021 to February 2022.

(a) Summary Statistics of Miners

| | Before EIP-1559 | | After EIP-1559 | |
|---|---|---|---|---|
| | mean | Standard error | Mean | Standard error |
| Rewards | 0.207 | 21.747 | 0.065 | 8.243 |
| nTrans | 0.502 | 15.706 | 0.225 | 8.451 |
| Volume | 1.340 | 441.432 | 0.456 | 136.134 |
| nDApps | 0.033 | 0.432 | 0.022 | 0.339 |

(b) Summary Statistics for Users

| | Before EIP-1559 | | | After EIP-1559 | | | Original | Merged |
|---|---|---|---|---|---|---|---|---|
| | nTrans | Volume | nDApps | nTrans | Volume | nDApps | | |
| Group1 | 11.776<br>(168.514) | 53.810<br>(2048.037) | 1.645<br>(2.907) | 5.745<br>132.336 | 24.559<br>(1212.136) | 0.993<br>(2.411) | 236,636 | 236,636 |
| Group2 | 1.493<br>(16.865) | 4.016<br>(195.298) | 0.772<br>(1.355) | 1.111<br>(25.213) | 2.706<br>(249.256) | 0.501<br>(1.303) | 2,588,965 | 258,401 |
| Group3 | 0.716<br>(1.154) | 1.323<br>(188.411) | 0.152<br>(0.633) | 0.638<br>(5.846) | 1.374<br>(167.762) | 0.237<br>(0.866) | 9,786,208 | 195,659 |
| All | 4.796<br>(99.304) | 20.313<br>(1209.112) | 0.896<br>(2.013) | 2.565<br>(79.075) | 9.816<br>(731.239) | 0.594<br>(1.713) | 12,614,467 | 693,916 |

Table 11—: The Overall Effects of EIP-1559 on Miners' Mining Rewards

This table reports the estimated effects of the launch of EIP-1559 mechanism on miners' mining behavior. It describes the linear regression results with the log of weekly mining rewards (*LnRewards*) as the dependent variable and indicator of EIP-1559 (*Burning*) as independent variables using different estimated time windows and excluding a number of periods around the launch of EIP-1559. The time function $f(week)$ used in the regression equals to $week + week \times burning$. The first two columns use the whole 10 weeks and 20 weeks before and after the launch of EIP-1559. The third and forth columns systematically exclude one week before and after the launch of EIP-1559. The last two columns systematically exclude two weeks before and after the launch of EIP-1559. All columns include miner fixed effect and a set of controls ((i.e., the log of the total number of mining pools' miners, the log of weekly median gas price, the log of a weekly deviant of gas price, the average return of ether exchange rate, the log of weekly difficulty of mining blocks, the log of the weekly average number of transactions). Standard errors are also reported in parentheses. The sample period is from February 2021 to February 2022 which covers a total of 135,469 miner addresses.

| | Main | | Exclude a week | | Exclude two weeks | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| LnRewards | 10 weeks | 20 weeks | 10 weeks | 20 weeks | 10 weeks | 20 weeks |
| Burning | -0.007*** | -0.008*** | -0.007*** | -0.006*** | -0.008*** | -0.002*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) | (0.000) |
| Observations | 2,709,380 | 5,418,760 | 2,438,442 | 5,147,822 | 2,167,504 | 4,876,884 |
| R-squared | 0.020 | 0.058 | 0.022 | 0.060 | 0.019 | 0.062 |
| Number of miners | 135,469 | 135,469 | 135,469 | 135,469 | 135,469 | 135,469 |
| Controls | YES | YES | YES | YES | YES | YES |
| Miners FE | YES | YES | YES | YES | YES | YES |
| Month FE | NO | NO | NO | NO | NO | NO |

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table 12—: The Overall Effects of EIP-1559 on Users Trading Behavior

This table reports the estimated effect of the launch of EIP-1559 mechanism on users' transaction behavior. Panel A describes the linear regression results with the log of weekly transaction volume (*LnRewards*) as the dependent variable and indicator of EIP-1559 (*Burning*) as independent variables using different estimated time windows and excluding a number of periods around the launch of EIP-1559. The time function $f(week)$ used in the regression equals to $week + week \times burning$. The first two columns use the whole 10 weeks and 20 weeks before and after the launch of EIP-1559. The third and forth columns systematically exclude one week before and after the launch of EIP-1559. The last two columns systematically exclude two weeks before and after the launch of EIP-1559. All columns include user fixed effect and a set of controls ((i.e., the log of weekly median gas price, the log of a weekly deviant of gas price, the average return of ether exchange rate, the log of weekly difficulty of mining blocks, the log of the weekly average number of transactions). Panel B describes the linear regression results with the log of weekly number of used DApps ($LnDApps$) as dependent variable. All columns include user-fixed effects and a set of controls. Standard errors are also reported in parentheses. The sample period is from February 2021 to February 2022 which covers a total of 252,112 user addresses.

(a) Weekly Transaction Volume

| | Main | | Exclude a week | | Exclude two weeks | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| LnVolume | 10 weeks | 20 weeks | 10 weeks | 20 weeks | 10 weeks | 20 weeks |
| Burning | 0.002*** | 0.003*** | 0.003*** | 0.004*** | 0.005*** | 0.006*** |
| | (0.000) | (0.000) | (0.001) | (0.000) | (0.001) | (0.001) |
| Observations | 5,045,800 | 10,091,600 | 4,541,220 | 9,587,020 | 4,036,640 | 9,082,440 |
| R-squared | 0.000 | 0.002 | 0.000 | 0.002 | 0.000 | 0.002 |
| Number of users | 252,112 | 252,112 | 252,112 | 252,112 | 252,112 | 252,112 |
| Controls | YES | YES | YES | YES | YES | YES |
| Miners FE | YES | YES | YES | YES | YES | YES |
| Month FE | NO | NO | NO | NO | NO | NO |

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table 12—: The Overall Effects of EIP-1559 on Users Trading Behavior (continued)

(b) The Number of DApps Used Per Week

| | Main | | Exclude a week | | Exclude two weeks | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| LnDApps | 10 weeks | 20 weeks | 10 weeks | 20 weeks | 10 weeks | 20 weeks |
| Burning | 0.002*** | 0.004*** | 0.004*** | 0.006*** | 0.003*** | 0.006*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) | (0.001) |
| Observations | 5,045,800 | 10,091,600 | 4,541,220 | 9,587,020 | 4,036,640 | 9,082,440 |
| R-squared | 0.000 | 0.002 | 0.000 | 0.002 | 0.000 | 0.002 |
| Number of users | 252,112 | 252,112 | 252,112 | 252,112 | 252,112 | 252,112 |
| Controls | YES | YES | YES | YES | YES | YES |
| Miners FE | YES | YES | YES | YES | YES | YES |
| Month FE | NO | NO | NO | NO | NO | NO |

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table 13—: DID—Heterogenous effect of EIP-1559 on miners' week rewards

This table describes the heterogenous effects of EIP-1559 on miners' weekly mining rewards using a DID approach with different estimated time windows. The dependent variable is the log of weekly mining rewards (*LnRewards*), and the heterogeneous effects are captured by the interaction term of the log of the percentage of blocks mined by the mining pool to which the miner belongs and the indicator of EIP-1559 ($LnPercentBlocks \times Burning$), and the interaction term of the log of rewards received before the launch of EIP-1559 and the indicator of EIP-1559 ($LnBeforeRewards \times Burning$). Miner fixed effects, month fixed effects and a set of controls (i.e., the log of the total number of mining pools' miners, the log of weekly median gas price, the log of a weekly deviant of gas price, the log of the average weekly exchange rate of ether, the log of weekly difficulty of mining blocks, the log of the weekly average number of transactions) are included.The sample period is from February 2021 to February 2022 which covers a total of 135,469 miner addresses.

| VARIABLES | (1)<br>20 weeks | (2)<br>20 weeks | (3)<br>10 weeks | (4)<br>10 weeks |
|---|---|---|---|---|
| LnPercentBlocks*Burning | 0.056*** | | 0.010*** | |
| | (0.004) | | (0.002) | |
| LnBeforeRewards*Burning | | -0.068*** | | -0.029*** |
| | | (0.001) | | (0.001) |
| LnMiners | 0.009*** | 0.008*** | 0.017*** | 0.016*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| LnGasprice | 0.013*** | 0.013*** | 0.008*** | 0.008*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| LnDeviantGasprice | 0.001*** | 0.001*** | 0.000*** | 0.000*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| LnEtherprice | 0.005*** | 0.004*** | -0.009*** | -0.011*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| LnDifficulty | -0.091*** | -0.093*** | -0.028*** | -0.030*** |
| | (0.001) | (0.001) | (0.002) | (0.002) |
| LnCongestion | 0.015*** | 0.017*** | 0.085*** | 0.090*** |
| | (0.002) | (0.002) | (0.004) | (0.004) |
| Observations | 5,418,760 | 5,418,760 | 2,709,380 | 2,709,380 |
| R-squared | 0.080 | 0.185 | 0.030 | 0.065 |
| Number of miners | 135,469 | 135,469 | 135,469 | 135,469 |
| Miners FE | YES | YES | YES | YES |
| Month FE | YES | YES | YES | YES |

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table 14—: DID—Heterogenous Effects of EIP-1559 on users' Transactions

This table describes the heterogenous effects of EIP-1559 on users' weekly trading activities using a DID approach with different estimated time windows. The dependent variable is the log of weekly transaction volume (*LnVolume*) and the log of the number of weekly used DApps, and the heterogenous effects are captured by the interaction term of the log of transaction volume made before the launch of EIP-1559 and the indicator of EIP-1559 ($BeforeTransactions \times Burning$), and the interaction term of the log of balance held before the launch of EIP-1559 and the indicator of EIP-1559 ($BeforeBalance \times Burning$). User fixed effects, month fixed effects and a set of controls (i.e., the log of weekly median gas price, the log of weekly deviant of gas price, the log of average weekly exchange rate of ether, the log of weekly difficulty of mining blocks, the log of weekly average number of transactions) are included.The sample period is from February 2021 to February 2022 which covers a total of 252,112 user addresses. Panel A reports the results of transaction volume, and Panel B reports the results of the number of used DApps.

(a) Heterogenous Effects of EIP-1559 on users' weekly transaction volume

| | (1)<br>20 weeks | (2)<br>20 weeks | (3)<br>10 weeks | (4)<br>10 weeks |
|---|---|---|---|---|
| BeforeTransactions*Burning | -0.042*** | | -0.009*** | |
| | (0.001) | | (0.001) | |
| BeforeBalance*Burning | | -0.031*** | | -0.009*** |
| | | (0.002) | | (0.002) |
| LnGasprice | 0.004*** | 0.004*** | 0.006*** | 0.006*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| LnDeviantGasprice | 0.000** | 0.000** | -0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| LnEtherprice | 0.015*** | 0.015*** | 0.001 | 0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| LnDifficulty | -0.020*** | -0.020*** | -0.004 | -0.004 |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| LnCongestion | -0.009*** | -0.009*** | 0.015*** | 0.015*** |
| | (0.002) | (0.002) | (0.003) | (0.003) |
| Observations | 10,091,600 | 10,091,600 | 5,045,800 | 5,045,800 |
| R-squared | 0.013 | 0.004 | 0.001 | 0.001 |
| Number of users | 252,112 | 252,112 | 252,112 | 252,112 |
| Users FE | YES | YES | YES | YES |
| Month FE | YES | YES | YES | YES |

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table 14—: DID—Heterogenous Effects of EIP-1559 on users' Transactions (continued)

(b) Heterogenous Effect of EIP-1559 on Users' Weekly Use of DApps

| | (1) 20 weeks | (2) 20 weeks | (3) 10 weeks | (4) 10 weeks |
|---|---|---|---|---|
| BeforeTransactions*Burning | -0.037*** | | -0.014*** | |
| | (0.001) | | (0.001) | |
| BeforeBalance*Burning | | -0.004*** | | -0.000 |
| | | (0.001) | | (0.001) |
| LnGasprice | -0.001*** | -0.001*** | -0.001*** | -0.001*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| LnDeviantGasprice | -0.000*** | -0.000*** | -0.000*** | -0.000*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| LnEtherprice | 0.011*** | 0.011*** | 0.006*** | 0.006*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| LnDifficulty | -0.007*** | -0.007*** | 0.005** | 0.005** |
| | (0.001) | (0.001) | (0.002) | (0.002) |
| LnCongestion | -0.010*** | -0.010*** | -0.004 | -0.004 |
| | (0.002) | (0.002) | (0.003) | (0.003) |
| Observations | 10,091,600 | 10,091,600 | 5,045,800 | 5,045,800 |
| R-squared | 0.014 | 0.003 | 0.003 | 0.001 |
| Number of users | 252,112 | 252,112 | 252,112 | 252,112 |
| Users FE | YES | YES | YES | YES |
| Month FE | YES | YES | YES | YES |

Robust standard errors in parentheses
*** $p<0.001$, ** $p<0.01$, * $p<0.05$

Table 15—: The impact of Airdrop on Users' Weekly Transaction Volume

This table reports the linear regression results of the log of transaction volume on the interaction term of indicator of airdrop and indicator of treatment group ($after \times airdrop$) with different bandwidth. The first two columns use a bandwidth of 0.015 to divide the RD sample, the third and fourth columns use the bandwidth of 0.01 to divide the RD sample, and the last two columns use the bandwidth of 0.015 to divide the RD sample. User fixed effects and a set of controls (i.e., the log of weekly median gas price, the log of weekly average exchange rate of ether, the log of weekly average exchange rate of OMG token, the log of weekly average difficulty of mining blocks, the log of weekly average hash rate, the log of weekly average number of transactions, the log of weekly average daily number of blocks mined, etc.) are included. The sample period is from June 2017 to December 2017.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | bandwidth 0.015 | | bandwidth 0.01 | | bandwidth 0.005 | |
| after*airdrop | 0.038*** | 0.035*** | 0.037*** | 0.033*** | 0.038*** | 0.034*** |
| | (0.005) | (0.005) | (0.005) | (0.005) | (0.006) | (0.006) |
| after | -0.101*** | | -0.102*** | | -0.097*** | |
| | (0.002) | | (0.002) | | (0.002) | |
| Observations | 880,771 | 880,771 | 760,608 | 760,608 | 585,100 | 585,100 |
| R-squared | 0.010 | 0.013 | 0.011 | 0.013 | 0.011 | 0.013 |
| Number of users | 36,700 | 36,700 | 31,693 | 31,693 | 24,380 | 24,380 |
| Controls | NO | YES | NO | YES | NO | YES |
| Weighted | YES | YES | YES | YES | YES | YES |
| Users FE | YES | YES | YES | YES | YES | YES |
| Month FE | NO | YES | NO | YES | NO | YES |

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table 16—: The Impact of Airdrop on Native Token Return

This table reports the impacts of airdrop on native token return using SCM. Panel A describes the weights of each blockchain that constitutes ”synthetic Ethereum”. Panel B describes the means of native token return predictors of Ethereum and ”synthetic Ethereum”. Panel C describes the daily return difference between Ethereum and ”synthetic Ethereum” (i.e., the average treatment effect), as well as the placebo test results (in the third column).

(a) Blockchain Weights in the Synthetic Ethereum

| Blockchain | Weight | Blockchain | Weight |
|---|---|---|---|
| Bitcoin | 0.713 | Neo | 0 |
| Bitcoin Cash | 0 | Peercoin | 0.116 |
| Binance Smart Chain | 0 | SpreadCoin | 0 |
| Dash | 0 | Steem | 0 |
| Ethereum Classic | 0.032 | Waves | 0.04 |
| Litecoin | 0.099 | Monero | 0 |
| Zclassic | 0 | Zcash | 0 |

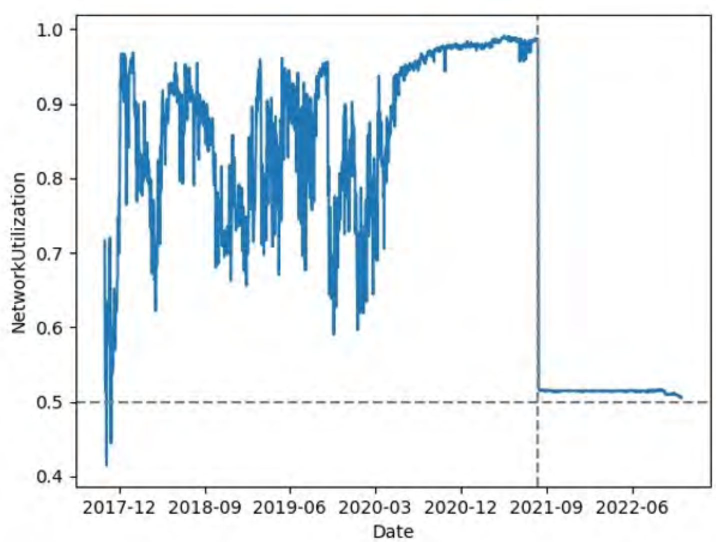
(b) Native Token Returns Predictor Means

| Variables | Real Ethereum | Synthetic Ethereum |
|---|---|---|
| LnVolume | 20.484 | 19.989 |
| LnMarketCap | 24.085 | 23.502 |
| LnVolatility | 1.603 | 2.501 |
| PoW | 1 | 0.96 |
| Return8 | 0.101 | 0.100 |
| Return11 | -0.064 | -0.064 |
| Return14 | 0.021 | 0.020 |

Table 16—: The Impact of Airdrop on Native Token Return (continued)

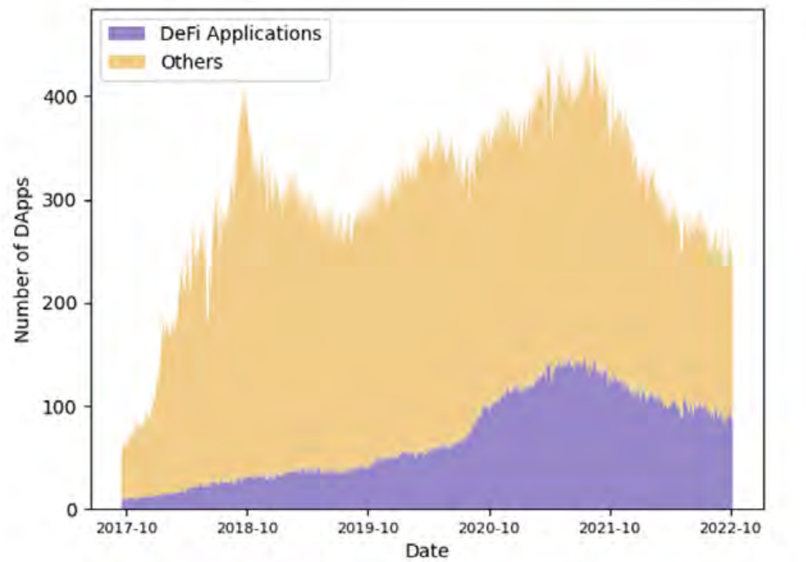
(c) Post-Treatment Effects with Placebo Test

| Variables | Estimates | Pvals-std |
|---|---|---|
| c1 | -0.007 | 0.429 |
| c2 | 0.005 | 0.643 |
| c3 | 0.012 | 0.429 |
| c4 | -0.013 | 0.286 |
| c5 | 0.005 | 0.357 |
| c6 | 0.052 | 0.000 |
| c7 | -0.009 | 0.500 |
| c8 | 0.011 | 0.429 |
| c9 | 0.008 | 0.286 |
| **c10 (end day)** | -0.004 | 0.714 |
| c11 | 0.021 | 0.000 |
| c12 | 0.044 | 0.000 |
| c13 | -0.017 | 0.214 |
| c14 | -0.024 | 0.000 |



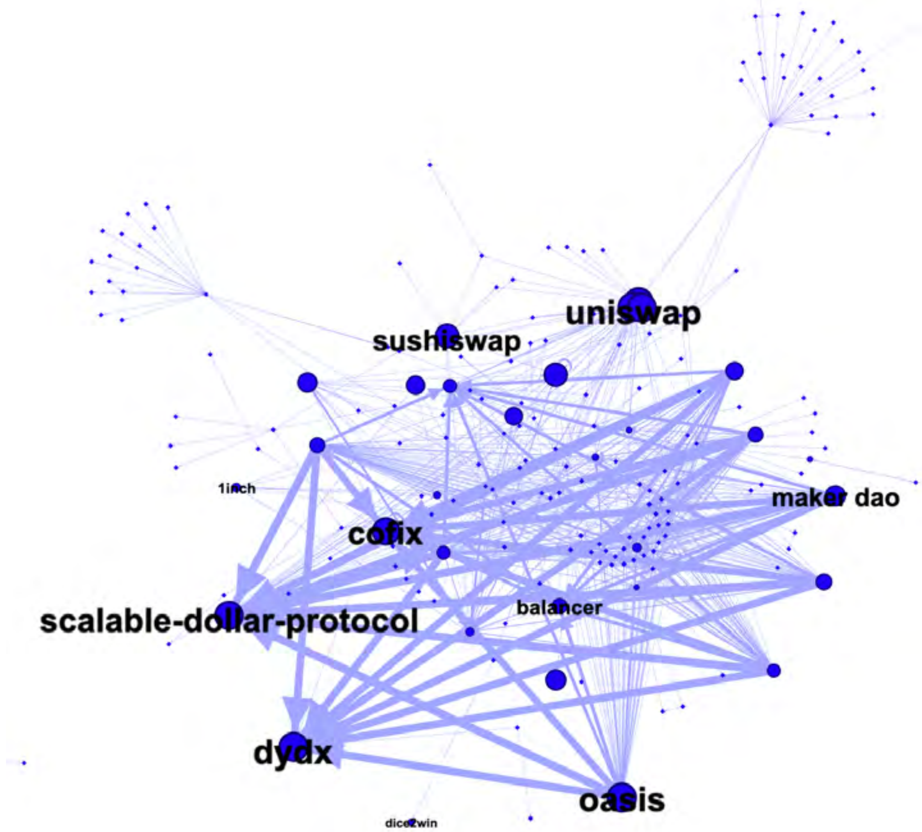

*Note:* This figure depicts the daily network utilization of Ethereum from August 2015 to October 2022. Network utilization is measured as the total gas used divided by the total gas limit of the Ethereum network. The dash line perpendicular to the X-axis represents the launch date of EIP-1559 (August 5, 2022).

Figure 1. : Network Utilization



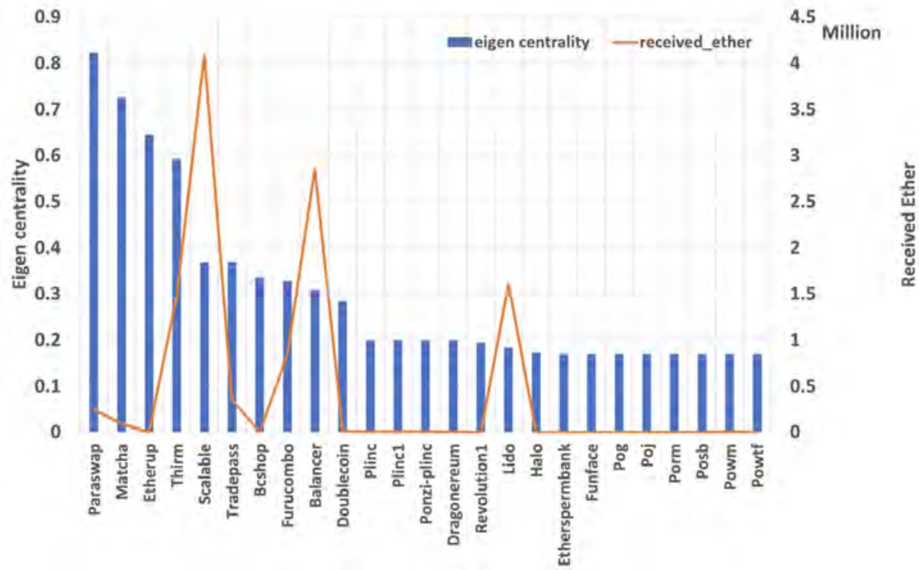

*Note:* This figure depicts the evolvement of daily active DeFi applications and other DApps, with the y-axis representing the number of active DApps.

Figure 2. : Daily Active DeFi Applications



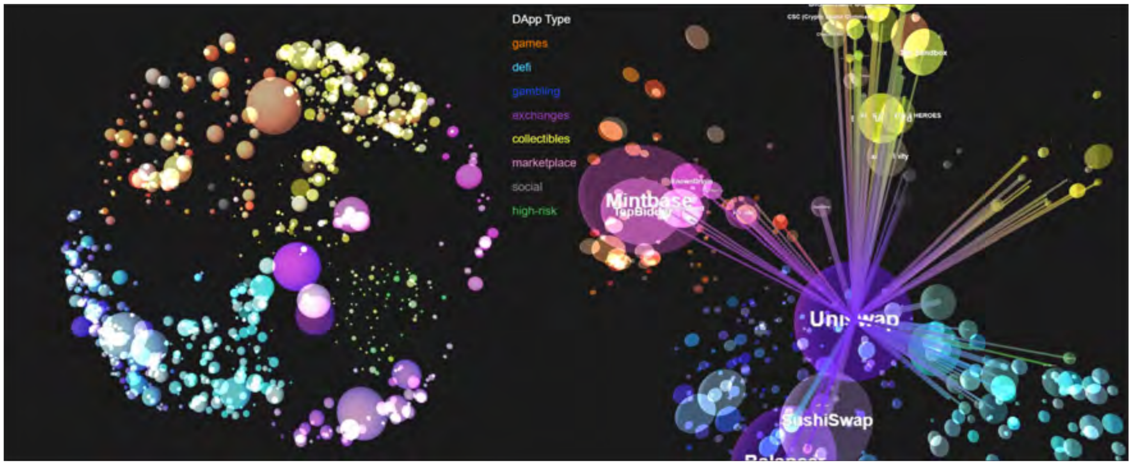

*Note:* This figure shows the flow of ETH among DApps and exchanges on Ethereum from 2015 to 2022. A node i corresponds to all labeled addresses belonging to DApp or exchange i, and an edge between i to j corresponds to the total Ether flows. The edge size is proportional to the total flow between the two entities, and the node size is proportional to the total Ether received.

Figure 3. : Ether Network among Exchanges and DApps



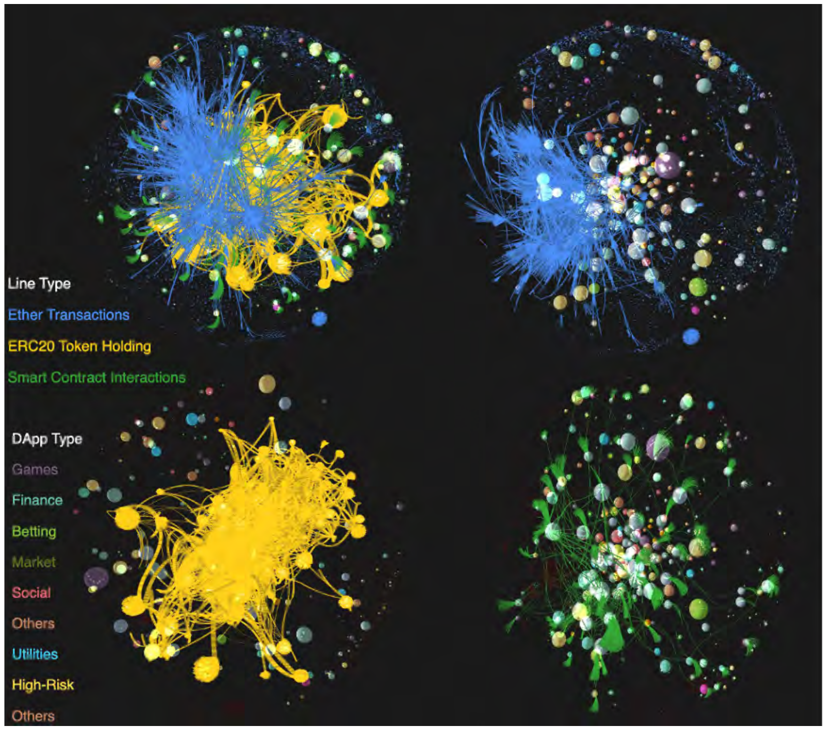

*Note:* This figure reports the the enginevector centrality and total received Ether of each DApps from 2015 to 2022. The centrality for DApp i is the largest solution ($\lambda$) to the equation $Ax = \lambda x$, where matrix elements $A_{ij}$ are the total Ether flows from DApp i to j over 2015-2022. The primary y-axis represents the centrality, the secondary y-axis represents DApps' total received Ether, and the x-axis represents DApps.

Figure 4. : Enginevector Centrality of DApps

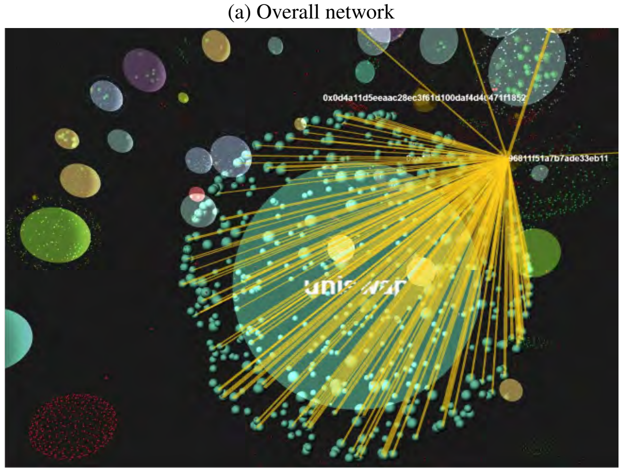



*Note:* This figure shows the competition and partnership among various categories of DApps on July 28,2021.A node i corresponds to all labeled addresses belonging to Dapp i. The same category of DApps is similar in color, and different colors represent different categories of DApps. The distance between nodes depends on the number of common users. The more common users, the closer the distance. Therefore, we can see that the DApps with the same color close to each other are competitive, and the DApps with different colors close to each other are cooperative. On the left side of the figure, uniswap is taken as an example to show the above relationship. This visualization is supported by the Inddigo platform (http://inddigo.io).

Figure 5. : User Network among Exchanges and DApps



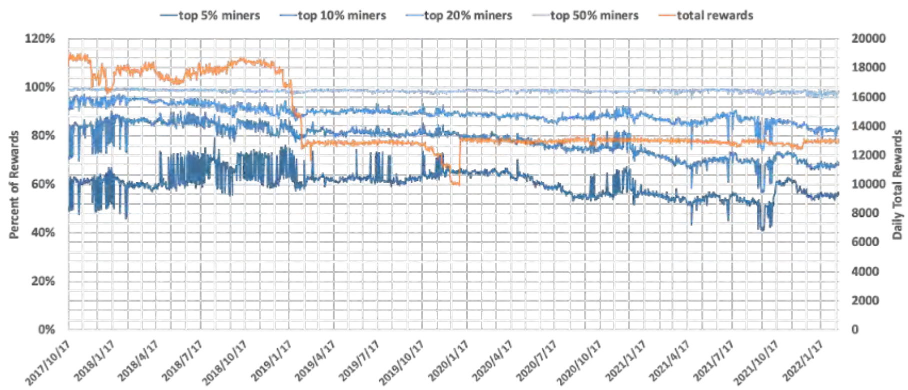

(a) Overall network



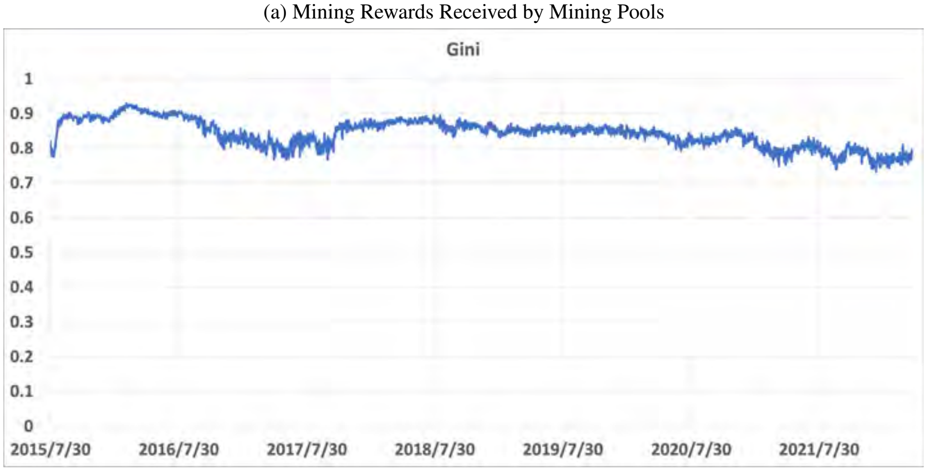

(b) Uniswap as an example

*Note:* This figure shows various types of activities on Ethereum, i.e., Layer-1 token transfer, ERC-20 token holding, and interaction with smart contracts. In panel A, each cluster of the sphere represents a DApp and its users. The center of the cluster is the DApp, and the surrounding points are its users. The color of the sphere represents its category. Lines in different coloers represent different Ethereum-related activities. The blue line represents trading activities using layer1 token, i.e., Ether. The yellow line represents the holdings of ERC-20 tokens. And the green line represents the interaction between users and DApps. Panel B further shows these Ethereum-related activities associated with Uniswap as an example. This visualization is supported by the Inddigo platform (http://inddigo.io).

Figure 6. : Ethereum-related activities network



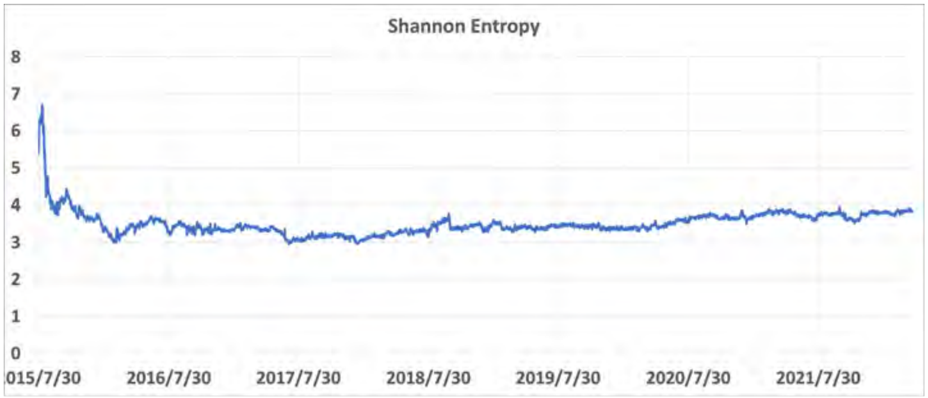

(a) Mining Rewards Received by Mining Pools



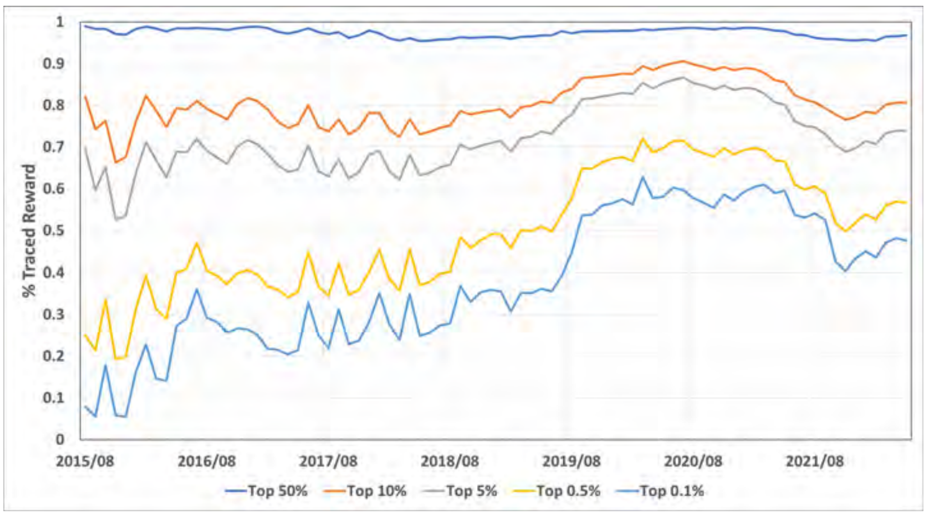

(b) Gini for Mining Pools

*Note:* This figure shows the concentration of mining capacity on Ethereum. Panel A depicts the distribution of block rewards for mining pools and daily total block rewards. The primary y-axis represents the percentage of block rewards, the secondary y-axis represents daily total block rewards. Each blue line represents a different group of miners, and the orange line represents total block rewards. Panel B and Panel C depicts the daily Gini coefficients and Shannon entropy coefficients at the mining pools level respectively. Panel D depicts the traced mining rewards for individual miners. The y-axis represents the percentage of total mining rewards, and the x-axis represents the date. Each line represents a different percentage of miners.

Figure 7. : The Concentration of Mining Capacity

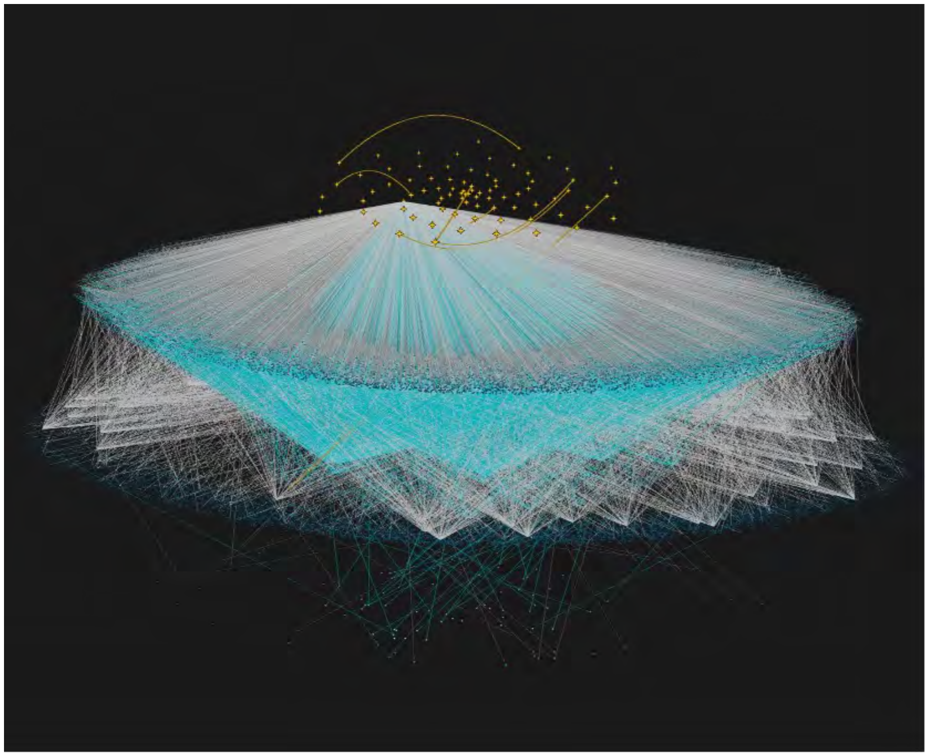



(c) Shannon Entropy for Mining Pools



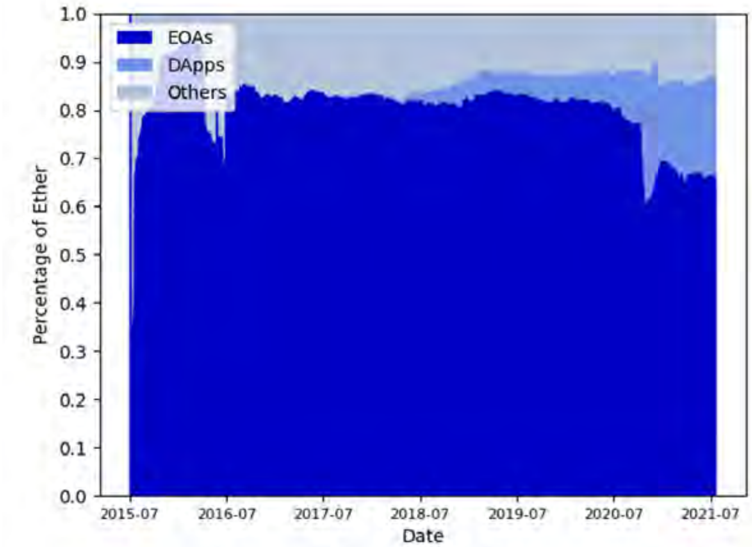

(d) Traced Mining Rewards for Miners

Figure 7. : The Concentration of Mining Capacity (Continued)

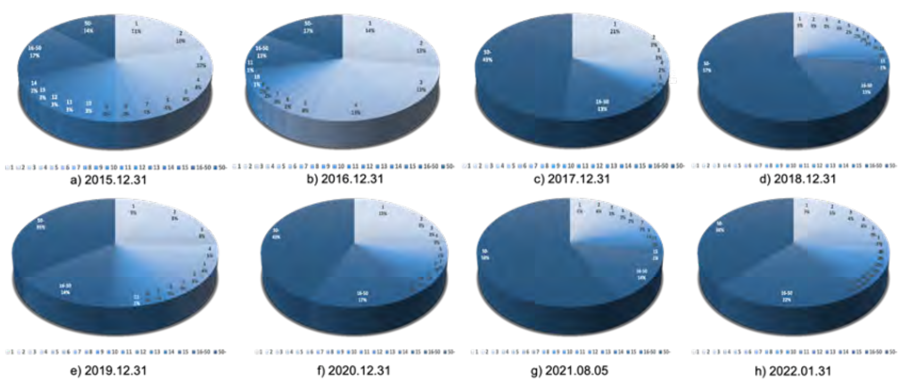


*Note:* This figure visualizes the tracing process of mining rewards and contains a network of four layers. The top layer is the mining pool, and a gold dot represents a mining pool. The lower three layers are miners, miners' primary trading network and secondary trading network. The dark blue points represent EOA accounts, and the light blue points represent exchanges. Lines in the figure represent flows of ether. The light blue line is the ether flow with EOA accounts, and the dark blue line is the ether flow with exchanges. This visualization is supported by the Inddigo platform (http://inddigo.io).

Figure 8. : The Tracing Process of Mining Rewards



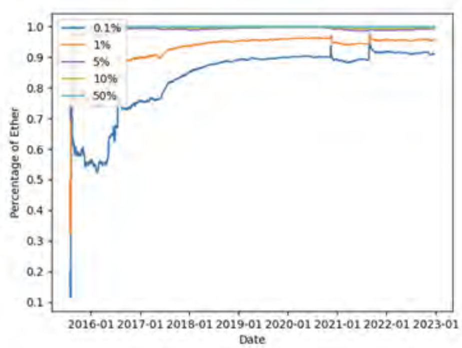

(a) Distribution of Ether between Users and Other Stakeholders



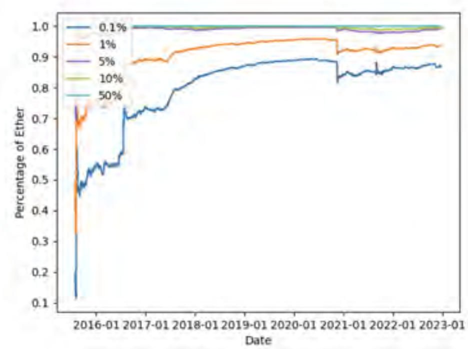

(b) The Evolution of Ownership Concentration of Users

*Note:* This figure depicts the distribution of Ether. Panel A illustrates the ownership of Ether between EOAs, DApps and other smart contract, the y-axis represents percentage of Ether. Panel B illustrates the evolution of Ether ownership of Users from 2015 to 2022, which includes top 50 users and others ranking by balance. Panel C illustrates the distribution of Ether among all addresses. The y-axis represents percentage of Ether, and the x-axis represents date. Each line represents a different group of addresses (i.e., top x% addresses sorted by balance). Panel D illustrates the distribution of Ether among EOAs. Panel E depicts the HHI of the distribution of ether tokens among all addresses and EOAs.

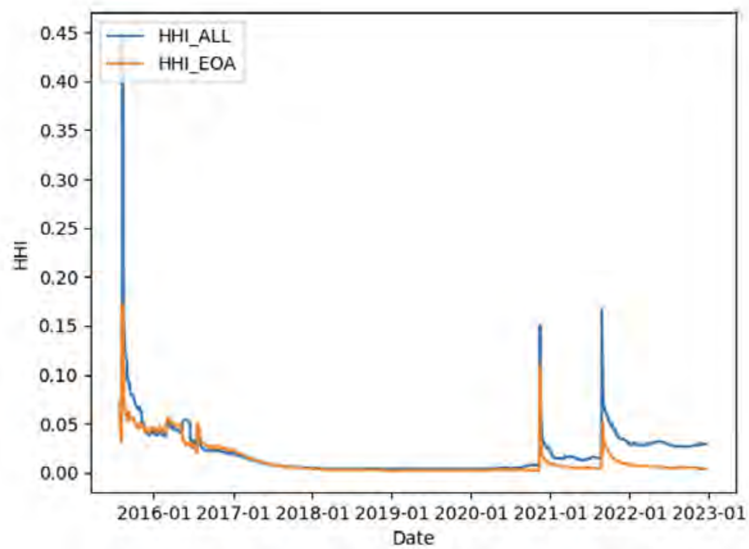
Figure 9. : Ownership of Ether




(c) The Concentration of All Addresses

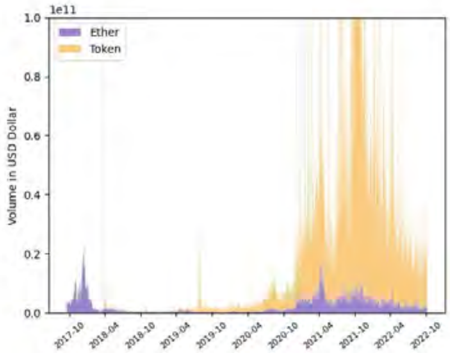



(d) The Concentration of EOAs

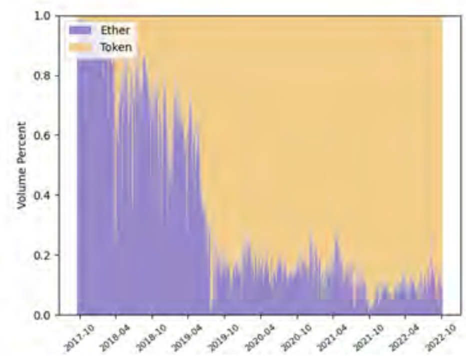



(e) Herfindahl–Hirschman Index

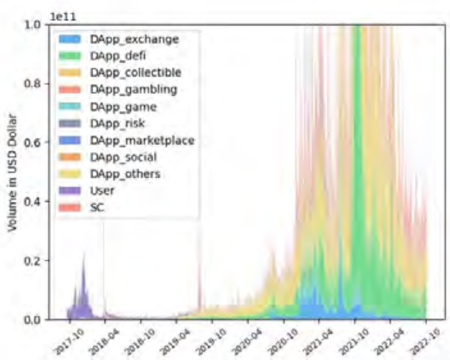
Figure 9. : Trends in Ownership Distribution of Ether (Continued)



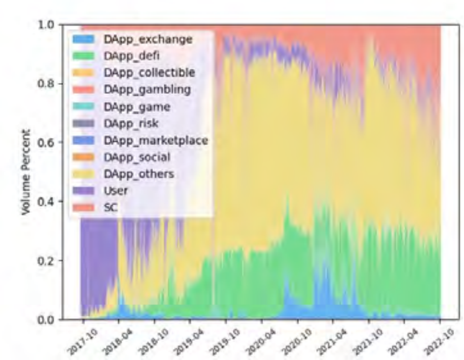

(a) Ether and token




(b) Ether and token



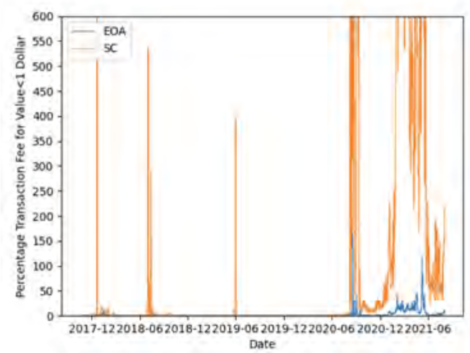

(c) DApps, EOAs and SCs



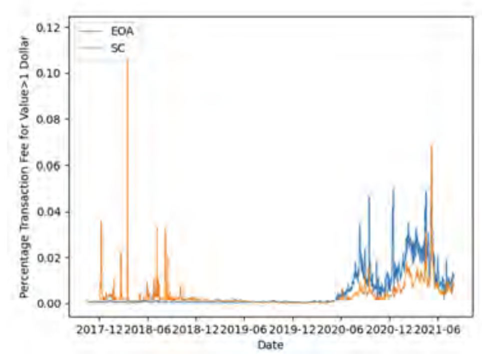

(d) DApps, EOAs and SCs

*Note:* This figure depicts daily transaction volume on Ethereum and its composition. The two pictures at top illustrate the transaction volume using Ether and transaction volume using ERC20 tokens on Ethereum. The two pictures at bottom illustrate the transaction volume of 9 categories of DApps, users and other contracts. Transaction volume is calculated in dollar. For the visibility of figure, we exclude data on 2017.11.03 and 2018.04.24 due to two extremely high transaction value of token-related transactions.

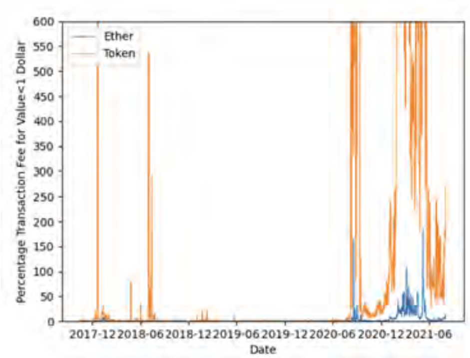
Figure 10. : Decomposition of Transaction Volume



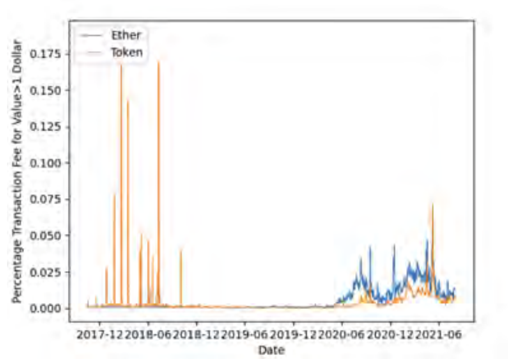

(a) EOA and SC: Value<1



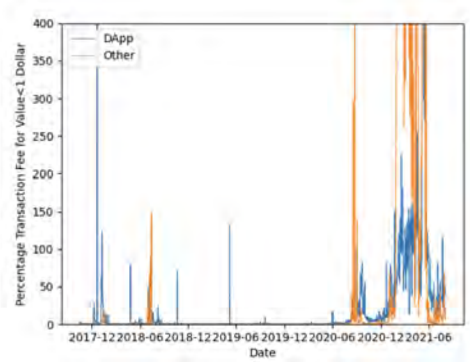

(b) EOA and SC: Value>1



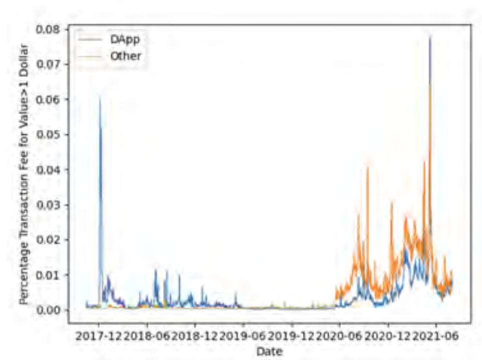

(c) Ether and Token: Value<1




(d) Ether and Token: Value>1



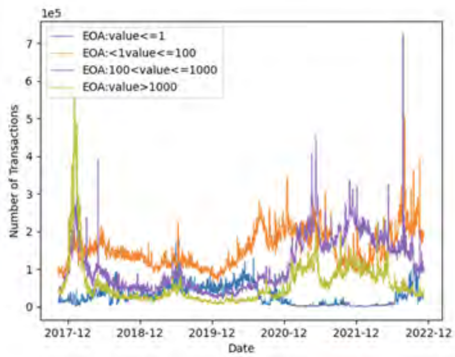

(e) DApp and Others: Value<1



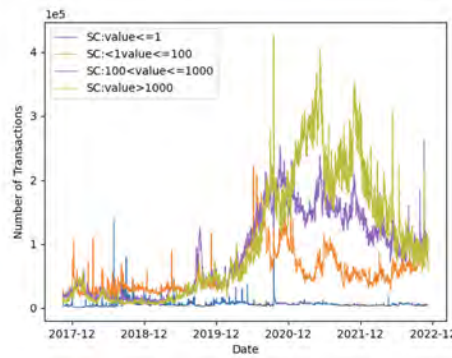

(f) DApp and Others: Value>1

*Note:* This figure depicts the daily median percentage transaction fee of six types of transactions with different transaction value, with the y-axis representing median transaction rate, and the x-axis representing date.

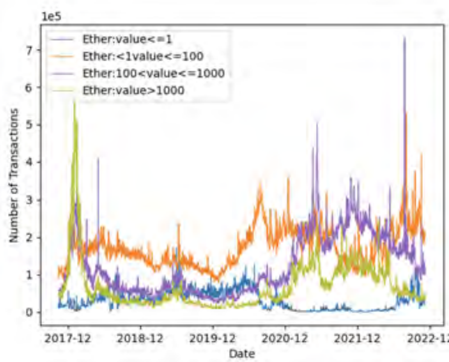
Figure 11. : Median Percentage Transaction Fee



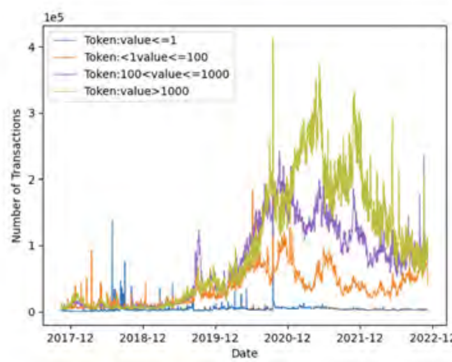

(a) Number of Transactions-EOA



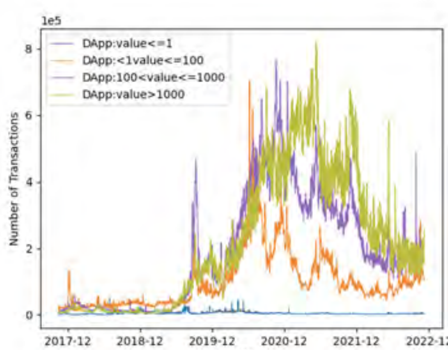

(b) Number of Transactions-SC



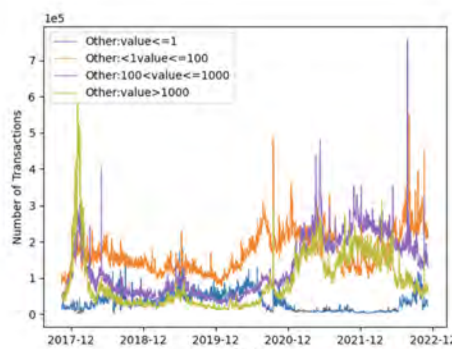

(c) Number of Transactions-Ether




(d) Number of Transactions-Token



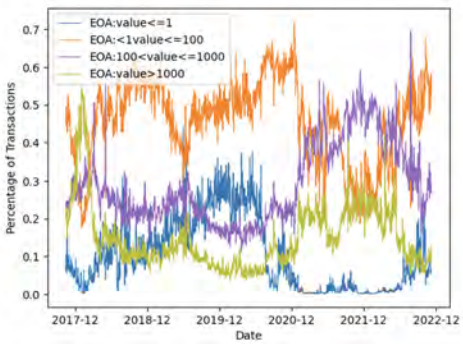

(e) Number of Transactions-DApp



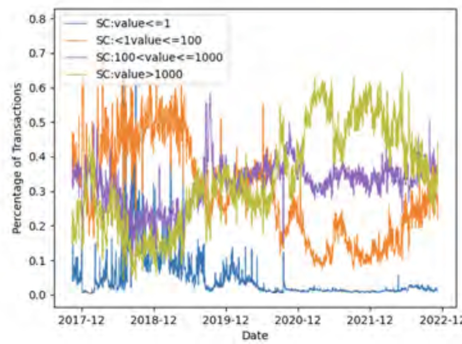

(f) Number of Transactions-Other

*Note:* This figure depicts the distribution of different types of transactions by value. Panel A-F illustrate the daily number of transactions of different types and value, with the y-axis representing the number of transactions, and the x-axis representing date. Likewise, Panel G-L illustrates the daily proportion of transactions of different types and value.

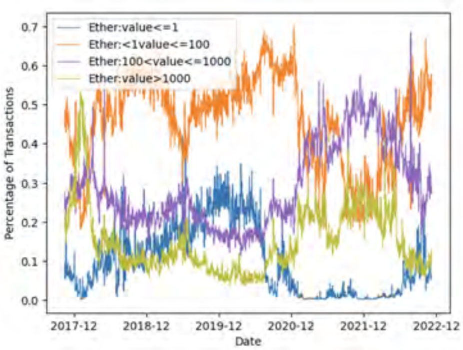
Figure 12. : Distribution of Transactions by Value



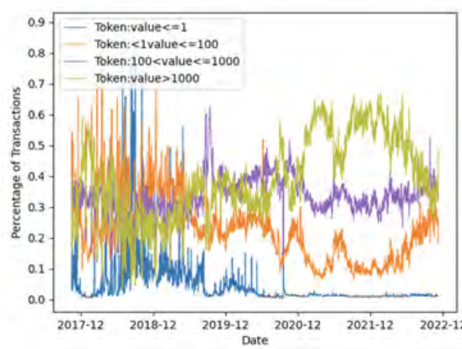

(g) Percentage of Transactions-EOA



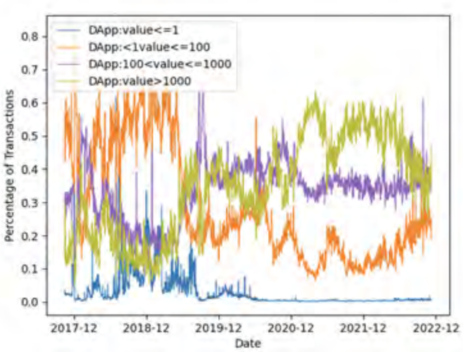

(h) Percentage of Transactions-SC



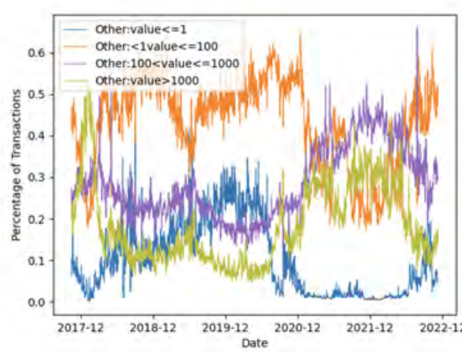

(i) Percentage of Transactions-Ether




(j) Percentage of Transactions-Token

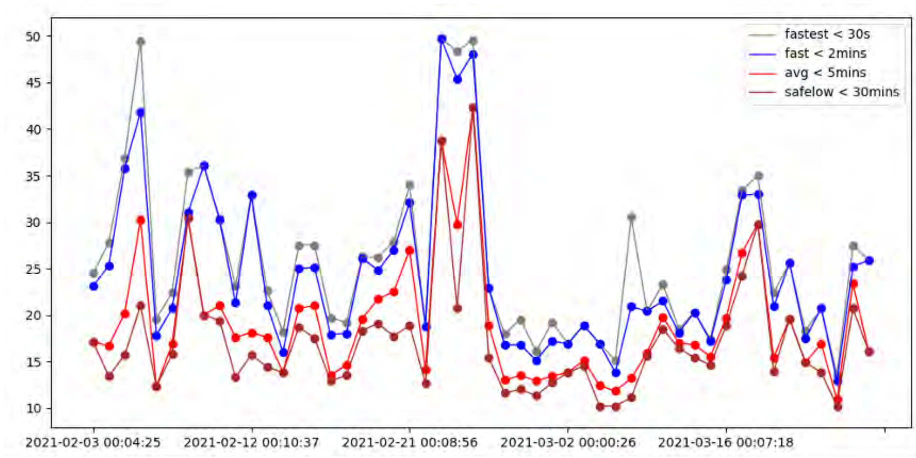



(k) Percentage of Transactions-DApp



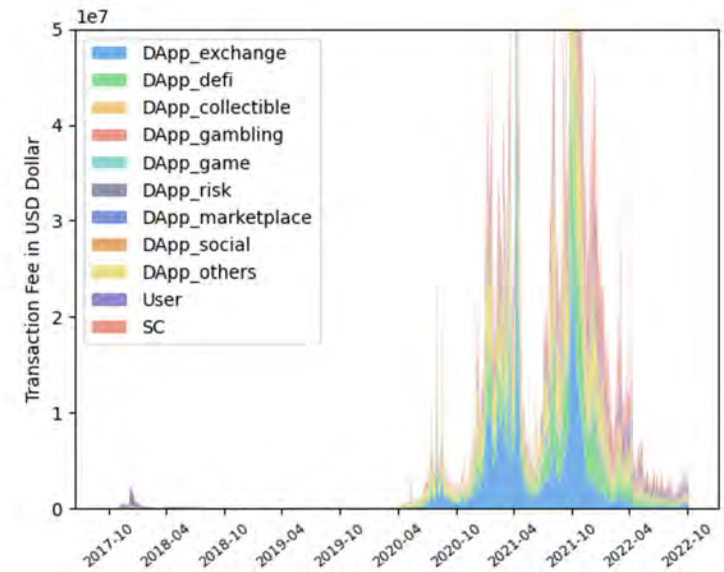

(l) Percentage of Transactions-Other

Figure 12. : Distribution of Transactions by Value (Continued)

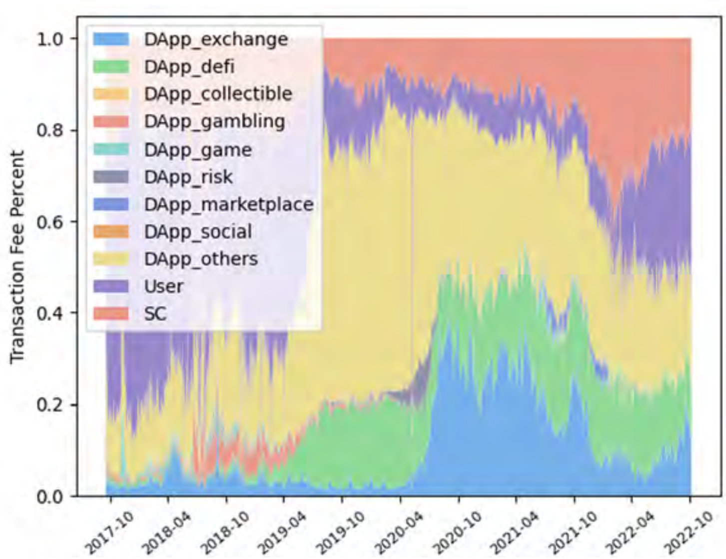



*Note:* This figure shows the relationship between gas price and delay time. The y-axis represents gas price (gwei), and the x-axis represents date. Each line represents the lowest gas price you need to set if you expect to close the deal in X (0.5, 2, 5 and 30) minutes.

Figure 13. : Gas Price and Delay Time



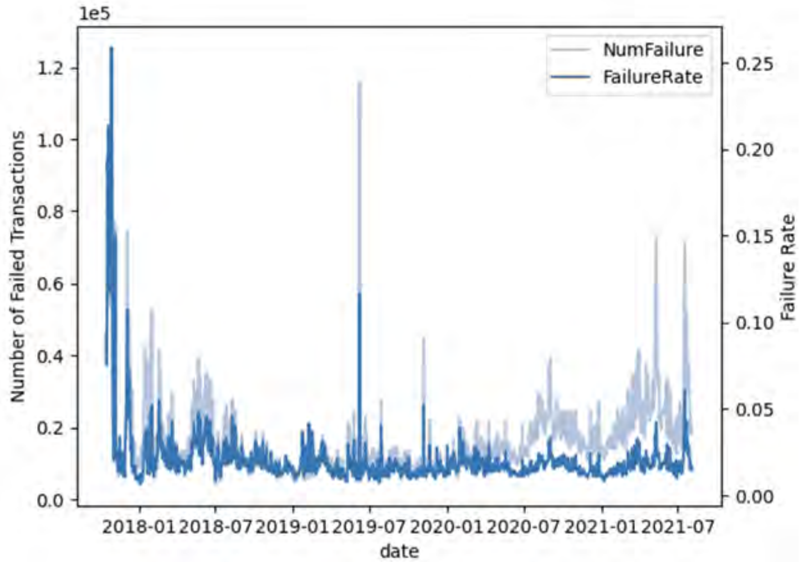

(a) Transaction Fee in USD Dollar



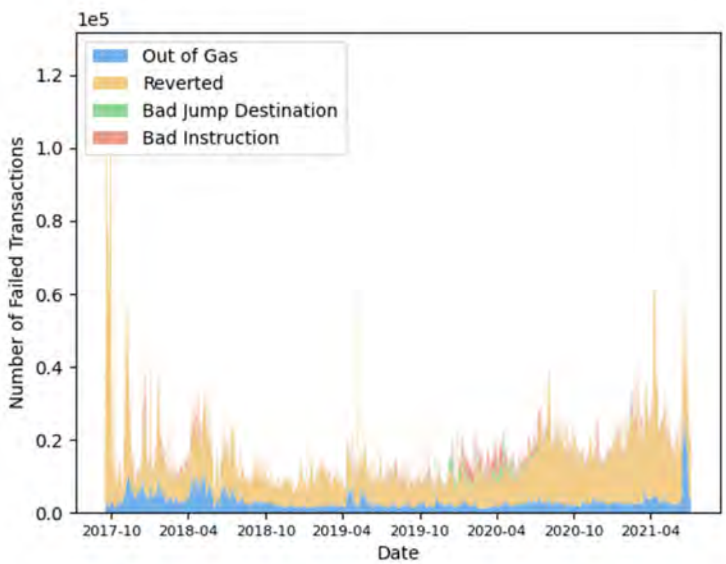

(b) Percentage of Transaction Fee

*Note:* This figure depicts daily transaction fee on Ethereum and its composition. Each color represents one of the nine categories of DApps, or users and contracts. Transaction fee is calculated in dollar.

Figure 14. : Distribution of Transaction Fee



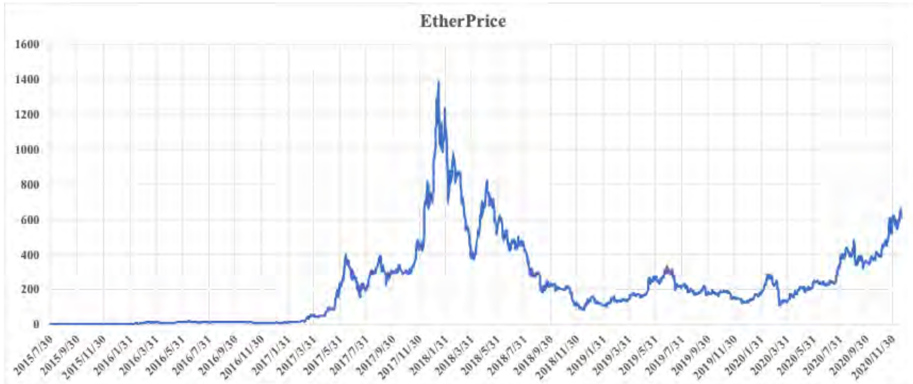

(a) Daily Failure Rate




(b) Ratio of different reasons for transaction failure

*Note:* This figure shows the daily failure rate with its failed reasons. Panel A illustrates daily failed transaction amounts and failure rate from October 2017 to August 2021. The primary y-axis represents daily failed transaction amounts, the secondary y-axis represents daily failure rate, and the x-axis represents date. Panel B illustrates the number of failed transactions per day for different reasons. The y-axis represents the number of transactions, and the x-axis represents date. Different colors represent the different failed reasons, i.e., out of gas, reverted, bad jump destination and bad instruction.

Figure 15. : Daily Failure Rate

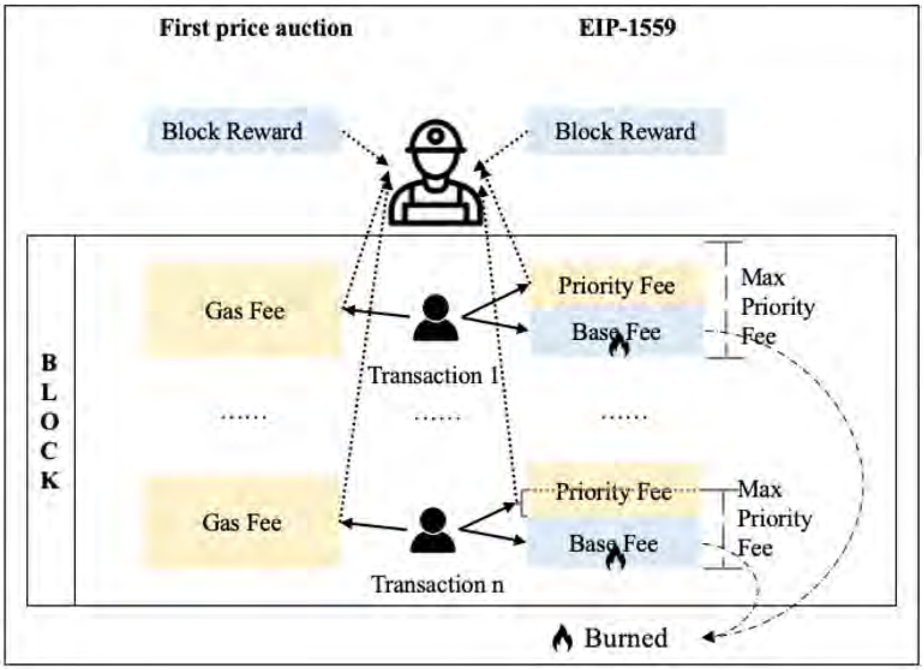



(a) Daily Price of Ether


(b) Rolling Volatility of Ether

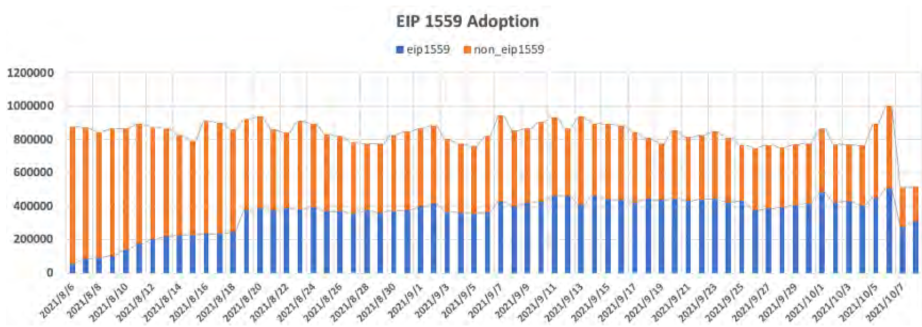
*Note:* This figure depicts the daily price and rolling volatility of ether. Panel A depicts the daily ether price from August 2015 to December 2020, with the y-axis representing the daily ether to US dollar exchange rate. Panel B depicts annualized volatility of ether from December 2017 to December 2020, using a rolling window of 183 days (half a year). The y-axis represents rolling volatility.

Figure 16. : Daily Price and Rolling Volatility of Ether

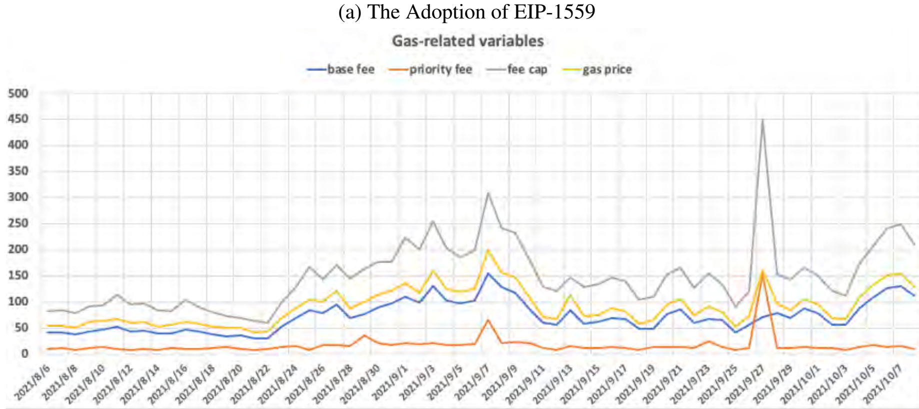



*Note:* This figure compares the transaction fee mechanism in the form of the first price auction before the launch of EIP-1559 with the transaction fee mechanism under EIP-1559.

Figure 17. : Comparison between EIP-1559 and First Price Auction



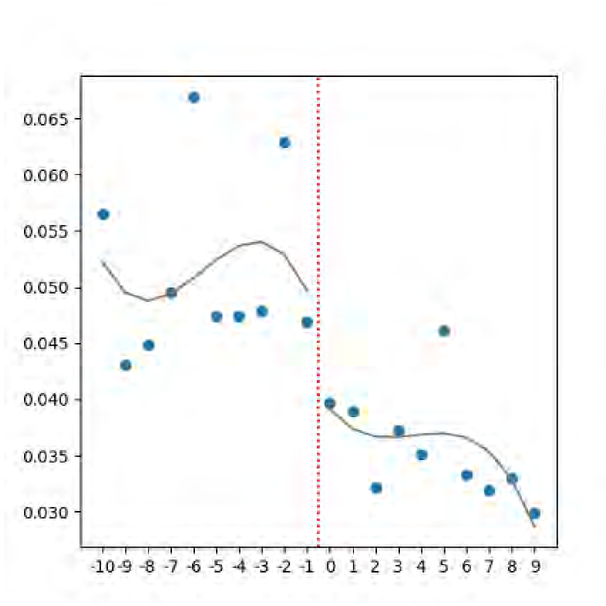

(a) The Adoption of EIP-1559



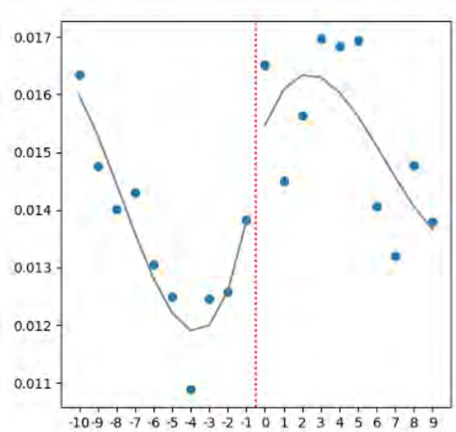

(b) Gas-related Variables under EIP-1559

*Note:* This figure depicts transaction fee under EIP-1559 mechanism. Panel A depicts the adoption of EIP-1559 from August 2021 to October 2021, with the y-axis representing the number of transactions, and the x-axis representing date. The blue bar indicates the number of transactions using EIP-1559, and the orange bar indicates the number of transactions not using EIP-1559. Panel B depicts gas-related variables under EIP-1559, with the y-axis representing price (in gwei), and the x-axis representing date. Four different colored lines represent base fee, priority fee, max fee and gas price separately.

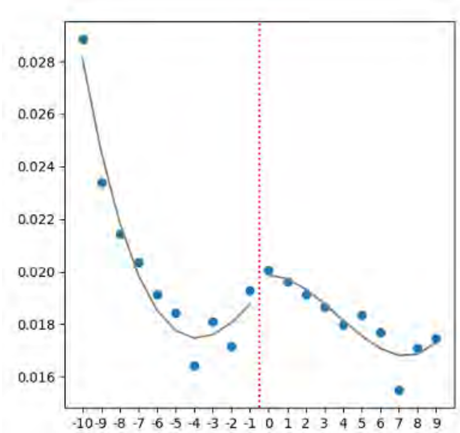
Figure 18. : EIP-1559 Adoption and Gas-related Variables under EIP-1559




(a) The Log of Weekly Mining Rewards



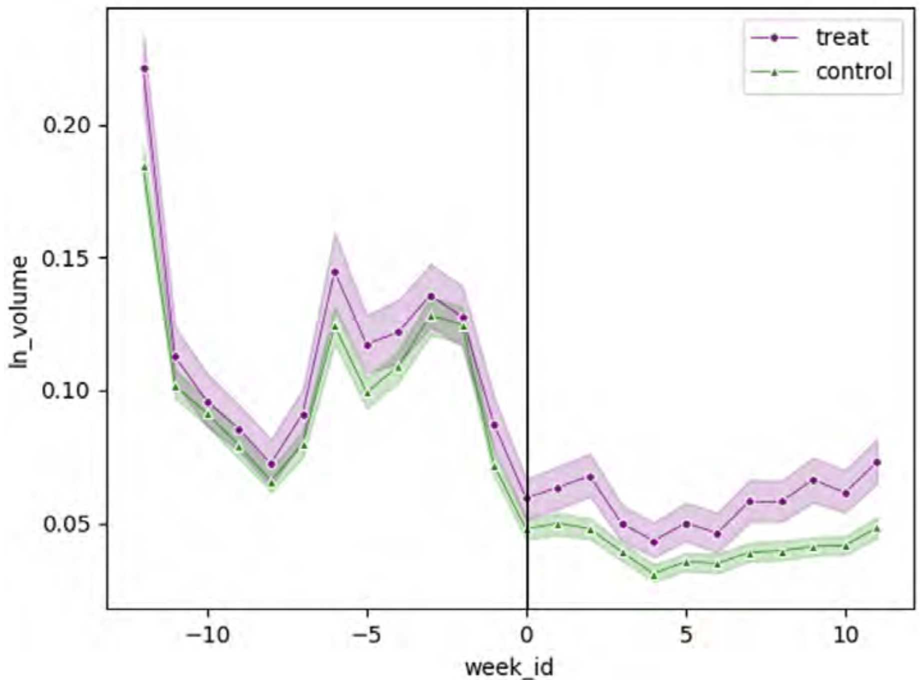

(b) The Log of Weekly Transaction Volume




(c) The Log of Number of Weekly used DApps

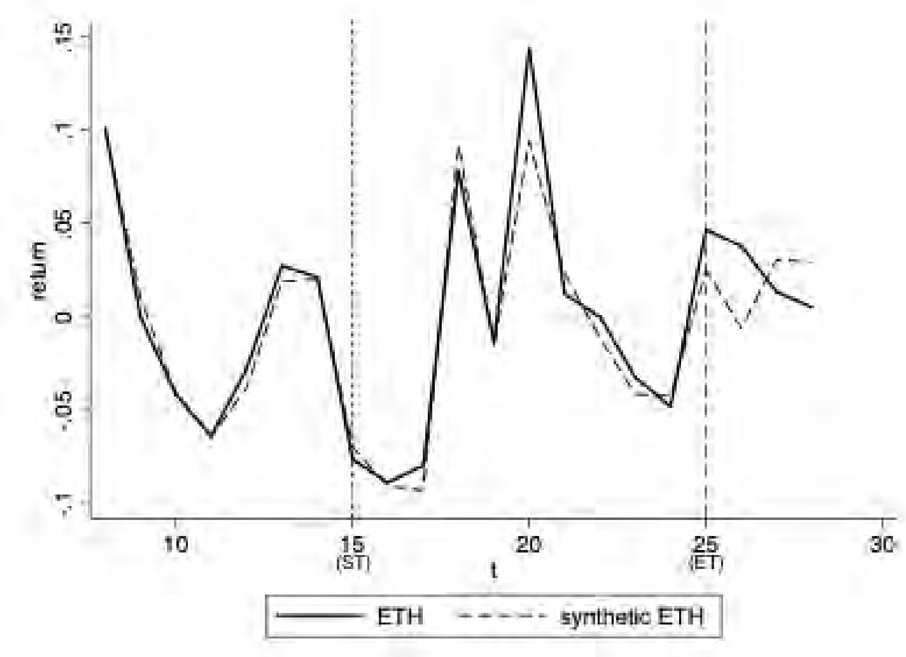
*Note:* Panel A, B, and C depict the average log of miners' weekly mining rewards, users' weekly transaction volume, and the number of DApps users used per week, respectively.

Figure 19. : Discontinuity in Mining and Trading Around EIP1559




*Note:* This figure reports the parallel trends of the treatment group and control group with a 90% confidence interval bar.

Figure 20. : Visual Checks of Parallel Trends




*Note:* This figure depicts the native token return of Ethereum and "synthetic Ethereum". The vertical axis represents the return, and the horizontal axis represents the date. Day 15 is the start of the Omisego airdrop and day 25 is the end. The solid line represents Ethereum and the dashed line represents "synthetic Ethereum".

Figure 21. : Trends in Native Cryptocurrency Return: Ethereum vs. Synthetic Ethereum

## APPENDIX

Table A1—: Annualized Volatility of Ether and 157 Ethereum-related Token

| Token | TokenAddress | Volatility 2018 | Volatility 2019 | Volatility 2020 | Volatility 3 years | Average Rolling volatility |
|---|---|---|---|---|---|---|
| ETH | 0 | 107% | 79% | 93% | 163% | 91% |
| STX | 0x006bea43baa3f7a6f765f14f10a1a1b08334ef45 | 174% | 150% | 292% | 372% | 180% |
| KCS | 0x039b5649a59967e3e936d7471f9c3700100ee1ab | 195% | 101% | 72% | 231% | 101% |
| CAPP | 0x04f2e7221fdb1b52a68169b25793e51478ff0329 | 208% | 130% | 179% | 303% | 152% |
| DLT | 0x07e3c70653548b04f0a75970c1f81b4cbbfb606f | 193% | 178% | 113% | 286% | 153% |
| EDG | 0x08711d3b02c8758f2fb3ab4e80228418a7f8e39c | 136% | 136% | 183% | 265% | 140% |
| DCN | 0x08d32b0da63e2c3bcf8019c9c5d849d7a9d791e6 | 272% | 249% | 338% | 500% | 255% |
| TNT | 0x08f5a9235b08173b7569f83645d2c7fb55e8ccd8 | 201% | 159% | 170% | 308% | 166% |
| DNT | 0x0abdace70d3790235af448c88547603b945604ea | 189% | 102% | 238% | 321% | 139% |
| PLBT | 0x0affa06e7fbe5bc9a764c979aa66e8256a631f02 | 198% | 276% | 230% | 410% | 230% |
| DATA | 0x0cf0ee63788a0849fe5297f3407f701e122cc023 | 154% | 137% | 379% | 431% | 210% |
| BAT | 0x0d8775f648430679a709e98d2b0cb6250d2887ef | 151% | 95% | 101% | 205% | 111% |
| AVT | 0x0d88ed6e74bbfd96b831231638b66c05571e824f | 202% | 269% | 262% | 427% | 245% |
| POE | 0x0e0989b1f9b8a38983c2ba8053269ca62ec9b195 | 183% | 106% | 217% | 303% | 140% |
| MANA | 0x0f5d2fb29fb7d3cfee444a200298f468908cc942 | 179% | 100% | 124% | 239% | 126% |
| GVT | 0x103c3a209da59d3e7c4a89307e66521e081cfdf0 | 184% | 95% | 138% | 249% | 126% |
| NMR | 0x1776e1f26f98b1a5df9cd347953a26dd3cb46671 | 191% | 127% | 287% | 368% | 196% |
| CDT | 0x177d39ac676ed1c67a2b268ad7f1e58826e5b0af | 181% | 128% | 146% | 266% | 144% |
| REP | 0x1985365e9f78359a9b6ad760e32412f4a445e862 | 131% | 102% | 133% | 213% | 118% |
| BCDN | 0x1e797ce986c3cff4472f7d38d5c4aba55dfefe40 | 263% | 344% | 131% | 453% | 246% |
| BNT | 0x1f573d6fb3f13d689ff844b4ce37794d79a7ff1c | 110% | 82% | 160% | 212% | 109% |
| PRO | 0x226bb599a12c826476e3a771454697ea52e9e220 | 217% | 108% | 226% | 332% | 171% |
| RDN | 0x255aa6df07540cb5d3d297f0d0d4d84cb52bc8e6 | 158% | 109% | 159% | 249% | 139% |
| PKT | 0x2604fa406be957e542beb89e6754fcde6815e83f | 238% | 233% | 269% | 428% | 220% |
| WABI | 0x286bda1413a2df81731d4930ce2f862a35a609fe | 191% | 143% | 132% | 272% | 149% |
| SKIN | 0x2bdc0d42996017fce214b21607a515da41a9e0c5 | 172% | 306% | 211% | 409% | 237% |
| OST | 0x2c4e8f2d746113d0696ce89b35f0d8bf88e0aeca | 198% | 106% | 240% | 329% | 149% |
| VIB | 0x2c974b2d0ba1716e644c1fc59982a89ddd2ff724 | 175% | 111% | 119% | 238% | 129% |
| DICE | 0x2e071d2966aa7d8decb1005885ba1977d6038a65 | 179% | 136% | 296% | 372% | 165% |
| REV | 0x2ef52ed7de8c5ce03a4ef0efbe9b7450f2d7edc9 | 170% | 109% | 86% | 219% | 112% |
| MORE | 0x305de070488c8469dfac957226c9c900c4bfba22 | 188% | 144% | 205% | 313% | 174% |
| EVR | 0x3137619705b5fc22a3048989f983905e456b59ab | 263% | 713% | 622% | 984% | 548% |
| VEE | 0x340d2bde5eb28c1eed91b2f790723e3b160613b7 | 184% | 6718% | 170% | 6722% | 2024% |
| DENT | 0x3597bfd533a99c9aa083587b074434e61eb0a258 | 241% | 125% | 124% | 299% | 155% |
| PRIX | 0x3adfc4999f77d04c8341bac5f3a76f58dff5b37a | 301% | 296% | 391% | 575% | 307% |
| RVT | 0x3d1ba9be9f66b8ee101911bc36d3fb562eac2244 | 199% | 437% | 252% | 543% | 297% |
| MGO | 0x40395044ac3c0c57051906da938b54bd6557f212 | 182% | 219% | 274% | 395% | 221% |
| SALT | 0x4156d3342d5c385a87d264f90653733592000581 | 158% | 150% | 233% | 320% | 164% |
| DRGN | 0x419c4db4b9e25d6db2ad9691ccb832c8d9fda05e | 175% | 124% | 163% | 269% | 145% |

Table A1 Annualized Volatility of Ether and 157 Ethereum-related Token (Continued)

| | | | | | | |
|---|---|---|---|---|---|---|
| FUN | 0x419d0d8bdd9af5e606ae2232ed285aff190e711b | 159% | 99% | 119% | 223% | 118% |
| CVC | 0x41e5560054824ea6b0732e656e3ad64e20e94e45 | 144% | 97% | 204% | 268% | 129% |
| MNE | 0x426ca1ea2406c07d75db9585f22781c096e3d0e0 | 302% | 458% | 626% | 833% | 460% |
| SPANK | 0x42d6622dece394b54999fbd73d108123806f6a18 | 345% | 173% | 769% | 861% | 359% |
| OPT | 0x4355fc160f74328f9b383df2ec589bb3dfd82ba0 | 866% | 472% | 243% | 1017% | 550% |
| ELTCOIN | 0x44197a4c44d6a059297caf6be4f7e172bd56caaf | 361% | 671% | 350% | 838% | 475% |
| TIME | 0x485d17a6f1b8780392d53d64751824253011a260 | 214% | 147% | 227% | 345% | 191% |
| XAUR | 0x4df812f6064def1e5e029f1ca858777cc98d2d81 | 142% | 138% | 161% | 255% | 140% |
| LINK | 0x514910771af9ca656af840dff83e8264ecf986ca | 163% | 133% | 125% | 244% | 132% |
| MDA | 0x51db5ad35c671a87207d88fc11d593ac0c8415bd | 188% | 137% | 124% | 264% | 144% |
| BLUE | 0x539efe69bcdd21a83efd9122571a64cc25e0282b | 274% | 602% | 1455% | 1604% | 734% |
| SMT | 0x55f93985431fc9304077687a35a1ba103dc1e081 | 198% | 97% | 151% | 267% | 133% |
| POWR | 0x595832f8fc6bf59c85c527fec3740a1b7a361269 | 147% | 90% | 133% | 218% | 118% |
| VGX | 0x5af2be193a6abca9c8817001f45744777db30756 | 190% | 125% | 177% | 289% | 160% |
| PST | 0x5d4abc77b8405ad177d8ac6682d584ecbfd46cec | 242% | 197% | 183% | 361% | 205% |
| B2B | 0x5d51fcced3114a8bb5e90cdd0f9d682bcbcc5393 | 328% | 163% | 234% | 434% | 209% |
| MYB | 0x5d60d8d7ef6d37e16ebabc324de3be57f135e0bc | 287% | 307% | 484% | 641% | 311% |
| LOC | 0x5e3346444010135322268a4630d2ed5f8d09446c | 198% | 99% | 129% | 256% | 129% |
| ITC | 0x5e6b6d9abad9093fdc861ea1600eba1b355cd940 | 235% | 166% | 322% | 432% | 215% |
| RLC | 0x607f4c5bb672230e8672085532f7e901544a7375 | 181% | 124% | 152% | 267% | 139% |
| QASH | 0x618e75ac90b12c6049ba3b27f5d5f8651b0037f6 | 138% | 97% | 124% | 209% | 112% |
| GAME | 0x63f88a2298a5c4aee3c216aa6d926b184a4b2437 | 140% | 207% | 128% | 281% | 155% |
| MDS | 0x66186008c1050627f979d464eabb258860563dbe | 194% | 132% | 139% | 273% | 142% |
| WINGS | 0x667088b212ce3d06a1b553a7221e1fd19000d9af | 150% | 146% | 215% | 300% | 169% |
| GNO | 0x6810e776880c02933d47db1b9fc05908e5386b96 | 133% | 95% | 119% | 203% | 105% |
| DPY | 0x6c2adc2073994fb2ccc5032cc2906fa221e9b391 | 177% | 198% | 166% | 313% | 181% |
| GNX | 0x6ec8a24cabdc339a06a172f8223ea557055adaa5 | 154% | 156% | 204% | 299% | 163% |
| OAX | 0x701c244b988a513c945973defa05de933b23fe1d | 173% | 224% | 184% | 338% | 181% |
| WRC | 0x72adadb447784dd7ab1f472467750fc485e4cb2d | 244% | 548% | 769% | 976% | 515% |
| NGC | 0x72dd4b6bd852a3aa172be4d6c5a6dbec588cf131 | 142% | 167% | 185% | 287% | 160% |
| SNT | 0x744d70fdbe2ba4cf95131626614a1763df805b9e | 166% | 82% | 139% | 232% | 111% |
| ERO | 0x74ceda77281b339142a36817fa5f9e29412bab85 | 215% | 530% | 342% | 667% | 387% |
| IFT | 0x7654915a1b82d6d2d0afc37c52af556ea8983c7e | 264% | 443% | 194% | 552% | 321% |
| ATL | 0x78b7fada55a64dd895d8c8c35779dd8b67fa8a05 | 227% | 314% | 388% | 548% | 276% |
| ZSC | 0x7a41e0517a5eca4fdbc7fbeba4d4c47b9ff6dc63 | 155% | 119% | 193% | 275% | 146% |
| SAN | 0x7c5a0ce9267ed19b22f8cae653f198e3e8daf098 | 168% | 121% | 131% | 245% | 135% |
| CAG | 0x7d4b8cce0591c9044a22ee543533b72e976e36c3 | 186% | 125% | 297% | 372% | 186% |
| GNT | 0x7dd9c5cba05e151c895fde1cf355c9a1d5da6429 | 158% | 82% | 143% | 229% | 119% |
| DAT | 0x81c9151de0c8bafcd325a57e3db5a5df1cebf79c | 188% | 223% | 134% | 321% | 183% |
| VOISE | 0x83eea00d838f92dec4d1475697b9f4d3537b56e3 | 256% | 587% | 5711% | 5761% | 971% |
| IETH | 0x859a9c0b44cb7066d956a958b0b82e54c9e44b4b | 468% | 324% | 247% | 620% | 308% |
| JET | 0x8727c112c712c4a03371ac87a74dd6ab104af768 | 605% | 290% | 447% | 806% | 391% |
| UQC | 0x8806926ab68eb5a7b909dcaf6fdbe5d93271d6e2 | 276% | 209% | 226% | 414% | 243% |
| PRE | 0x88a3e4f35d64aad41a6d4030ac9afe4356cb84fa | 227% | 259% | 217% | 406% | 209% |
| PTOY | 0x8ae4bf2c33a8e667de34b54938b0ccd03eb8cc06 | 145% | 135% | 187% | 273% | 149% |
| AMM | 0x8b1f49491477e0fb46a29fef53f1ea320d13c349 | 254% | 293% | 213% | 442% | 253% |

Table A1 Annualized Volatility of Ether and 157 Ethereum-related Token (Continued)

| | | | | | | |
|---|---|---|---|---|---|---|
| SUB | 0x8d75959f1e61ec2571aa72798237101f084de63a | 170% | 213% | 144% | 308% | 168% |
| FYP | 0x8f0921f30555624143d427b340b1156914882c10 | 341% | 304% | 344% | 572% | 322% |
| VERI | 0x8f3470a7388c05ee4e7af3d01d8c722b0ff52374 | 178% | 184% | 234% | 347% | 193% |
| REQ | 0x8f8221afbb33998d8584a2b05749ba73c37a938a | 160% | 110% | 155% | 249% | 133% |
| PRA | 0x9041fe5b3fdea0f5e4afdc17e75180738d877a01 | 171% | 347% | 562% | 684% | 363% |
| REAL | 0x9214ec02cb71cba0ada6896b8da260736a67ab10 | 343% | 490% | 306% | 672% | 361% |
| SNM | 0x983f6d60db79ea8ca4eb9968c6aff8cfa04b3c63 | 162% | 146% | 159% | 269% | 149% |
| QSP | 0x99ea4db9ee77acd40b119bd1dc4e33e1c070b80d | 161% | 103% | 142% | 238% | 128% |
| DRT | 0x9af4f26941677c706cfecf6d3379ff01bb85d5ab | 197% | 296% | 415% | 547% | 277% |
| DBET | 0x9b68bfae21df5a510931a262cecf63f41338f264 | 243% | 294% | 762% | 855% | 444% |
| MKR | 0x9f8f72aa9304c8b593d555f12ef6589cc3a579a2 | 130% | 87% | 117% | 195% | 106% |
| ANT | 0xa117000000f279d81a1d3cc75430faa017fa5a2e | 143% | 109% | 151% | 235% | 126% |
| TFL | 0xa7f976c360ebbed4465c2855684d1aae5271efa9 | 171% | 188% | 203% | 325% | 176% |
| INXT | 0xa8006c4ca56f24d6836727d106349320db7fef82 | 543% | 243% | 336% | 683% | 351% |
| TKN | 0xaaaf91d9b90df800df4f55c205fd6989c977e73a | 177% | 189% | 135% | 291% | 167% |
| DOV | 0xac3211a5025414af2866ff09c23fc18bc97e79b1 | 260% | 207% | 258% | 421% | 229% |
| ADX | 0xade00c28244d5ce17d72e40330b1c318cd12b7c3 | 187% | 167% | 160% | 298% | 169% |
| SNGLS | 0xaec2e87e0a235266d9c5adc9deb4b2e29b54d009 | 177% | 112% | 187% | 281% | 134% |
| 1ST | 0xaf30d2a7e90d7dc361c8c4585e9bb7d2f6f15bc7 | 173% | 210% | 218% | 349% | 183% |
| MTH | 0xaf4dce16da2877f8c9e00544c93b62ac40631f16 | 194% | 155% | 134% | 282% | 155% |
| COB | 0xb2f7eb1f2c37645be61d73953035360e768d81e6 | 253% | 292% | 299% | 488% | 267% |
| EVC | 0xb62d18dea74045e822352ce4b3ee77319dc5ff2f | 441% | 294% | 285% | 602% | 333% |
| MCO | 0xb63b606ac810a52cca15e44bb630fd42d8d1d83d | 154% | 90% | 156% | 237% | 113% |
| STORJ | 0xb64ef51c888972c908cfacf59b47c1afbc0ab8ac | 139% | 178% | 155% | 274% | 147% |
| WTC | 0xb7cb1c96db6b22b0d3d9536e0108d062bd488f74 | 174% | 106% | 132% | 243% | 127% |
| PAY | 0xb97048628db6b661d4c2aa833e95dbe1a905b280 | 156% | 123% | 122% | 233% | 134% |
| SWT | 0xb9e7f8568e08d5659f5d29c4997173d84cdf2607 | 165% | 304% | 327% | 476% | 250% |
| HGT | 0xba2184520a1cc49a6159c57e61e1844e085615b6 | 433% | 396% | 201% | 620% | 336% |
| LRC | 0xbbbbca6a901c926f240b89eacb641d8aec7aeafd | 175% | 113% | 141% | 252% | 130% |
| STMX | 0xbe9375c6a420d2eeb258962efb95551a5b722803 | 264% | 87% | 135% | 309% | 136% |
| ELF | 0xbf2179859fc6d5bee9bf9158632dc51678a4100e | 175% | 95% | 194% | 278% | 136% |
| HVN | 0xc0eb85285d83217cd7c891702bcbc0fc401e2d9d | 180% | 186% | 261% | 368% | 202% |
| KICK | 0xc12d1c73ee7dc3615ba4e37e4abfdbddfa38907e | 188% | 143% | 287% | 372% | 202% |
| XUC | 0xc324a2f6b05880503444451b8b27e6f9e63287cb | 90% | 90% | 195% | 233% | 113% |
| NIOX | 0xc813ea5e3b48bebeedb796ab42a30c5599b01740 | 306% | 457% | 2483% | 2549% | 814% |
| ORMEUS | 0xc96df921009b790dffca412375251ed1a2b75c60 | 188% | 1041% | 188% | 1074% | 451% |
| TRST | 0xcb94be6f13a1182e4a4b6140cb7bf2025d28e41b | 147% | 178% | 212% | 314% | 170% |
| HMQ | 0xcbcc0f036ed4788f63fc0fee32873d6a7487b908 | 142% | 134% | 165% | 256% | 143% |
| BON | 0xcc34366e3842ca1bd36c1f324d15257960fcc801 | 219% | 302% | 252% | 450% | 250% |
| ADT | 0xd0d6d6c5fe4a677d343cc433536bb717bae167dd | 309% | 423% | 932% | 1074% | 427% |
| DTR | 0xd234bf2410a0009df9c3c63b610c09738f18ccd7 | 162% | 173% | 87% | 253% | 127% |
| ONG | 0xd341d1680eeee3255b8c4c75bcce7eb57f144dae | 351% | 335% | 373% | 612% | 324% |
| CND | 0xd4c435f5b09f855c3317c8524cb1f586e42795fa | 204% | 106% | 118% | 258% | 126% |
| PPT | 0xd4fa1460f537bb9085d22c7bccb5dd450ef28e3a | 159% | 116% | 148% | 247% | 127% |
| SCL | 0xd7631787b4dcc87b1254cfd1e5ce48e96823dee8 | 321% | 2807% | 364% | 2849% | 1060% |
| USDT* | 0xdac17f958d2ee523a2206206994597c13d831ec7 | 10% | 8% | 11% | 17% | 9% |

**Table A1 Annualized Volatility of Ether and 157 Ethereum-related Token (Continued)**

| | | | | | | |
|---|---|---|---|---|---|---|
| KNC | 0xdd974d5c2e2928dea5f71b9825b8b646686bd200 | 151% | 117% | 126% | 229% | 127% |
| BMC | 0xdf6ef343350780bf8c3410bf062e0c015b1dd671 | 149% | 142% | 474% | 517% | 242% |
| DGD | 0xe0b7927c4af23765cb51314a0e0521a9645f0e2a | 163% | 120% | 98% | 226% | 119% |
| SUR | 0xe120c1ecbfdfea7f0a8f0ee30063491e8c26fedf | 184% | 241% | 942% | 990% | 367% |
| PLR | 0xe3818504c1b32bf1557b16c238b2e01fd3149c17 | 192% | 178% | 153% | 302% | 169% |
| ZRX | 0xe41d2489571d322189246dafa5ebde1f4699f498 | 163% | 86% | 119% | 220% | 116% |
| LA | 0xe50365f5d679cb98a1dd62d6f6e58e59321bcddf | 166% | 151% | 190% | 294% | 149% |
| DAY | 0xe814aee960a85208c3db542c53e7d4a6c8d5f60f | 329% | 225% | 246% | 468% | 249% |
| VIBE | 0xe8ff5c9c75deb346acac493c463c8950be03dfba | 472% | 125% | 134% | 506% | 159% |
| UFR | 0xea097a2b1db00627b2fa17460ad260c016016977 | 245% | 304% | 388% | 550% | 308% |
| TIX | 0xea1f346faf023f974eb5adaf088bbcdf02d761f4 | 173% | 354% | 625% | 740% | 347% |
| FUEL | 0xea38eaa3c86c8f9b751533ba2e562deb9acded40 | 168% | 136% | 337% | 401% | 182% |
| EBTC | 0xeb7c20027172e5d143fb030d50f91cece2d1485d | 273% | 336% | 1306% | 1379% | 557% |
| MLN | 0xec67005c4e498ec7f55e092bd1d35cbc47c91892 | 168% | 123% | 171% | 270% | 149% |
| FLIXX | 0xf04a8ac553fcedb5ba99a64799155826c136b0be | 251% | 176% | 302% | 430% | 220% |
| ENG | 0xf0ee6b27b759c9893ce4f094b49ad28fd15a23e4 | 170% | 123% | 168% | 269% | 142% |
| EVX | 0xf3db5fa2c66b7af3eb0c0b782510816cbe4813b8 | 171% | 201% | 120% | 290% | 153% |
| SNC | 0xf4134146af2d511dd5ea8cdb1c4ac88c57d60404 | 188% | 187% | 152% | 306% | 164% |
| MTL | 0xf433089366899d83a9f26a773d59ec7ecf30355e | 154% | 116% | 115% | 225% | 127% |
| ENJ | 0xf629cbd94d3791c9250152bd8dfbdf380e2a3b9c | 173% | 195% | 116% | 285% | 152% |
| TNB | 0xf7920b0768ecb20a123fac32311d07d193381d6f | 168% | 113% | 125% | 238% | 128% |
| DAM | 0xf80d589b3dbe130c270a69f1a69d050f268786df | 171% | 399% | 721% | 842% | 424% |
| IND | 0xf8e386eda857484f5a12e4b5daa9984e06e73705 | 118% | 1215% | 493% | 1319% | 636% |
| RCN | 0xf970b8e36e23f7fc3fd752eea86f8be8d83375a6 | 162% | 151% | 119% | 252% | 145% |
| LUN | 0xfa05a73ffe78ef8f1a739473e462c54bae6567d9 | 193% | 110% | 164% | 276% | 136% |
| IXT | 0xfca47962d45adfdfd1ab2d972315db4ce7ccf094 | 210% | 395% | 701% | 834% | 405% |
| ART | 0xfec0cf7fe078a500abf15f1284958f22049c2c7e | 536% | 328% | 802% | 1019% | 444% |

Table A2—: Transaction fee using SWIFT

| Financial | Incoming domestic | Outgoing domestic | Incoming International | Outgoing International |
|---|---|---|---|---|
| Median | $15 | $25 | $15 | $49 |
| Bank of America | $15 | $30 | $16 | 35$ sent in foreign currency; 45$ sent in U.S. dollars. |
| Fidelity (Intermediary charge fees) | $0 | $0 | $0 | 3% of amount in foreign currency; 0% sent in U.S. dollars. |
| Citibank | $15 | $25 | $15 | $35 |
| U.S. Bank | $20 | $30 | $25 | $50 |
| Associated Bank | $15 | $25-$28 | $15 | $45, $60 or $85; varies by processing method |
| HSBC Bank | $12 | Varies; fee may be waived for eligible accounts | Varies; fee may be waived for eligible accounts | Varies; fee may be waived for eligible accounts |
| Capital One 360 | $0 | $30 | $0 | Only available in-branch for eligible accounts |
| USAA | $0 | $20 | $0 | $45 |
| Chase | $15 ($0 if coming from Chase) | $25 online; $35 with banker assistance | $15 ($0 if coming from Chase) | $5 sent in foreign currency (or $0 for transfers of $5,000 or more); $40 sent in U.S. dollars (or $50, with banker assistance) |
| Wells Fargo | $15 | $30 | $16 | $35 sent in foreign currency; $45 sent in U.S. dollars. |

Table A3—: Variables Description in the analysis of EIP-1559

| Variables | Description |
|---|---|
| ***Dependent Variables*** | |
| LnRewards | The log of weekly mining rewards received by miners (in ether) |
| LnVolume | The log of weekly transaction volume in ether made by miners/users |
| LnTransactions | The log of weekly number of transactions made by miners/users |
| LnDApps | The log of weekly number of used DApps by miners/users |
| ***Independent Variables*** | |
| Burning | A dummy variable indicating the event of EIP-1559. Burning equals to one after 2021.08.05, and 0 otherwise. |
| LnPercentBlocks | The log of the percentage of blocks mined by the mining pool to which the miner belongs between February 5, 2021 and August 5, 2021 in the total number of blocks. |
| LnBeforeRewards | The log of total mining rewards received by miners between February 5, 2021 and August 5, 2021. |
| LnBeforeTransactions | The log of total number of transactions made by users between February 5, 2021 and August 5, 2021. |
| LnBeforeBalance | The log of average balance of users between February 5, 2021 and August 5, 2021. |
| ***Control Variables*** | |
| LnGasPrice | The log of weekly median gas price. |
| LnDeviantGasPrice | The log of weekly deviant of gas price. |
| LnEtherPrice | The log of weekly exchange rate of ether to dollar. |
| LnDifficulty | The log of weekly difficulty of mining blocks. |
| LnCongestion | The log of weekly average number of transactions. |
| LnMiners | The log of total number of miners who have received mining rewards from the mining pool. |

Table A4—: Variables Description in the Analysis of Airdrop

| Variables | Description |
|---|---|
| ***Dependent Variables*** | |
| LnRewards | The log of weekly mining rewards received by miners (in ether) |
| LnVolume | The log of weekly transaction volume in ether made by miners/users |
| ***Independent Variables*** | |
| Airdrop | A dummy variable indicating the event of OmiseGo Airdrop. Airdrop equals to one if he/she received the airdrop, and 0 otherwise. |
| After | A dummy variable indicating the time before or after OmiseGo airdrop. After equals to one after he/she received the airdrop, and 0 otherwise. |
| After*Airdrop | The interaction term of variable After and variable Airdrop. |
| ***Control Variables*** | |
| LnGasPrice | The log of weekly median gas price. |
| LnEtherPrice | The log of weekly average exchange rate of ether to dollar. |
| LnOmgPrice | The log of weekly average exchange rate of OMG token to dollar. |
| LnDifficulty | The log of weekly average difficulty of mining blocks. |
| LnHashRate | The log of weekly average hash rate. |
| LnTransactions | The log of weekly average number of transactions. |
| LnBlocks | The log of weekly average daily number of blocks mined. |
| Byzantium | A dummy variable indicating the event of Byzantium hard fork. Byzantium equals to one after Byzantium hard fork, and 0 otherwise. |
| OMG | A dummy variable indicating the issuance of tokens. OMG equals to one after the first day of the token issuance, and 0 otherwise. |
| Announcement | A dummy variable indicating the date on which OmiseGo airdrop announcement published. Announcement equals to one after the day of the announcement, and 0 otherwise. |

Table A5—: The effect of EIP-1559 on different groups of users' transaction volume

| | Group 1 | | | | Group 2 | | | | Group 3 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| VARIABLES | 12 weeks | 12 weeks | 24 weeks | 24 weeks | 12 weeks | 12 weeks | 24 weeks | 24 weeks | 12 weeks | 12 weeks | 24 weeks | 24 weeks |
| burning | -0.088*** | -0.275*** | -0.077*** | -0.214*** | -0.072*** | -0.165*** | -0.082*** | -0.067*** | 0.026*** | 0.024*** | 0.029*** | 0.094*** |
| | (0.002) | (0.003) | (0.002) | (0.004) | (0.002) | (0.002) | (0.001) | (0.003) | (0.001) | (0.001) | (0.001) | (0.002) |
| Observations | 5,679,264 | 5,679,264 | 11,358,528 | 11,358,528 | 6,201,624 | 6,201,624 | 12,403,248 | 12,403,248 | 4,695,816 | 4,695,816 | 9,391,632 | 9,391,632 |
| R-squared | 0.006 | 0.010 | 0.052 | 0.056 | 0.008 | 0.010 | 0.030 | 0.033 | 0.012 | 0.013 | 0.007 | 0.008 |
| Number of users | 236,636 | 236,636 | 236,636 | 236,636 | 258,401 | 258,401 | 258,401 | 258,401 | 195,659 | 195,659 | 195,659 | 195,659 |
| Controls | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Miners FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Month FE | NO | YES | NO | YES | NO | YES | NO | YES | NO | YES | NO | YES |

Table A6—: The effect of EIP-1559 on different groups of users' use of DApps

| | Group 1 | | | | Group 2 | | | | Group 3 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| VARIABLES | 12 weeks | 12 weeks | 24 weeks | 24 weeks | 12 weeks | 12 weeks | 24 weeks | 24 weeks | 12 weeks | 12 weeks | 24 weeks | 24 weeks |
| burning | -0.070*** | -0.237*** | -0.038*** | -0.205*** | -0.066*** | -0.195*** | -0.069*** | -0.117*** | 0.031*** | -0.023*** | 0.044*** | 0.037*** |
| | (0.002) | (0.002) | (0.001) | (0.003) | (0.001) | (0.002) | (0.001) | (0.002) | (0.001) | (0.001) | (0.001) | (0.002) |
| Observations | 5,679,264 | 5,679,264 | 11,358,528 | 11,358,528 | 6,201,624 | 6,201,624 | 12,403,248 | 12,403,248 | 4,695,816 | 4,695,816 | 9,391,632 | 9,391,632 |
| R-squared | 0.008 | 0.012 | 0.051 | 0.055 | 0.008 | 0.011 | 0.030 | 0.034 | 0.010 | 0.013 | 0.006 | 0.008 |
| Number of users | 236,636 | 236,636 | 236,636 | 236,636 | 258,401 | 258,401 | 258,401 | 258,401 | 195,659 | 195,659 | 195,659 | 195,659 |
| Controls | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Miners FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Month FE | NO | YES | NO | YES | NO | YES | NO | YES | NO | YES | NO | YES |