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

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Abstract

Web3 and DeFi are widely advocated as innovations for greater financial inclusion and democratization. We assemble (and share) the most comprehensive dataset to date about the largest Web3 ecosystem and use one of the largest-scale computing in the economics literature to investigate the claim. We document Ethereum's network structure, time trends, and distributions of transactions, mining, and ownership. Mining income and Ether ownership are concentrated in a few nodes, even after excluding exchange and mining pool wallets, with inequalities more exacerbated than observed in the real economy. Network activities are dominated by large transactions, shifting from peer-to-peer to user-DApps/DeFi interactions, and from Ether-based to ERC-20-token-based. High percentage transaction fees, congestion-induced gas-price fluctuation, suboptimal reserve setting, and large return volatility of tokens disproportionally harm small, unsophisticated, and new nodes, with high failure rates hurting all users. Finally, we present causal evidence that prominent programs such as EIP-1559 base-fee burning mechanism and OmiseGo airdrop promote inclusion and equality through monetary redistribution.

Keywords: Blockchains, Financial Innovation, Inequality, Large-Scale Computing, Smart Contracts, Transaction Fees

JEL Codes: D63, E50, G29, H23, L14

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1. Introduction

How financial innovations facilitate financial inclusion and democratic access to financial services is a central topic for policy discussions and applied research (World Bank Group, 2016; Philippon, 2019). Blockchain, the foundation for Web3 technologies, has spurred many innovations in digital financial services and decentralized finance (DeFi).[1] One oft-cited advantage of blockchains over traditional systems entails reduced centralization and intermediation costs, because open consensus protocols and smart contracts ensure distributed recordkeeping and transaction executions (Cong and He, 2019; John et al., 2023). Furthermore, open access, transparency, and increasing interoperability conceptually can enable DeFi to provide financial services to under-served groups and billions of unbanked people around the globe (Harvey et al., 2020; Zhao et al., 2022).[2]

These technical possibilities offer serious contentions to traditional financial services and are too big to ignore. In a way, Web3 and DeFi represent (financial) innovations that treat users builders and owners of digitally assets and ecosystems, "a fundamentally new approach to corporate governance, value creation and stakeholder participation with pari passu interests" (the World Economic Forum 2022 Annual Meeting). The aggregate market cap of crypto assets once approached U.S. $3 trillion and still hovered above 1.2 trillion us dollars as of late Feb 2023, with transaction volumn multiple times that of the equity market, according to statista.com. Despite the collapse of Terra-Luna, the bankruptcy of cryptocurrency lending firms Three Arrows Capital and Celsius, and the infamous implosion of FTX, institutional venture funding for blockchain and web3 startups still amounted to more than U.S. $29 billions in 2022, according to Coin Telegraph. Yet, it is far from clear whether Web3 and DeFi's facilitate financial inclusion, equality, and democratization in reality, despite the given ethos of their enthu-

[1] Web3, a term coined by Gavin Wood in 2014, is a collective concept of a new iteration of the Internet to incorporate decentralized ledgers, smart contracting, and token-based economics (see, e.g., Fenwick and Jurcys, 2022); similarly, DeFi is a catch-all term for any provision of financial services through a permissionless blockchain and smart contracting, which includes lending, stablecoins, decentralized exchanges, etc.

[2] Many argue that the dramatic failure of the FTX exchange is due to centralization and the lack of transparency, for which DeFi offers potential remedies. Note that blockchain-based platforms or distributed networks are not the only options for greater financial inclusion, as alternative digital payment and FinTech platforms have developed by leaps and bounds, especially in emerging economies (Botta and Nadeau, 2022). That said, these alternatives typically do not give the ownership and governance rights to the users and face antitrust issues (Cong and Mayer, 2023).

siasts and advocates.[3] Admittedly, financial inclusion and democratization can have many definitions and interpretations.[4] To sharpen the economic questions we study, we focus on a few well-specified dimensions that are often negatively associated with the general concepts of financial inclusion, equality, and democratization: income inequality, wealth inequality, high fees for the underserved, and transaction risks.[5] In particular, while digitization and decentralization encourage competition and innovation, they do not necessarily benefit consumers and users if the costs and failure rates of financial services are high.

We use big data from the Ethereum ecosystem and large-scale computing to systematically examine the first-order questions on whether Web3 and DeFi platforms benefit the underserved and small players in a digital network, promote economic equality and democratic access to the system, and offer reliable services to all users involved. Ethereum is by far the most dominant Web3 platform with smart contracting functionalities (Schär, 2021), boasting the second largest native cryptocurrency by market capitalization and hosting 93% of all well-known DeFi projects by number and over 60% in the total value locked (TVL) as of 2021

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

[4]The world bank defines financial inclusion to mean that "individuals and businesses have access to useful and affordable financial products and services that meet their needs – transactions, payments, savings, credit and insurance – delivered in a responsible and sustainable way. " (https://www.worldbank.org/en/topic/financialinclusion/overview). When speaking of them being potentially enabled by Web3 and DeFi, people typically mean that those who are unserved or underserved by the traditional financial systems now have access to functional financial services such as payments, and that the systems allow more equal distribution of income and wealth. This is so for several reasons and based on observations from the real economy and conventional (digital) marketplaces. For example, observations that decentralization helps to redistribute wealth and recources and empower marginalized regions and populations (Yeo et al., 2022). Democracy is expected to increase redistribution and reduce inequality (e.g., Acemoglu et al., 2015) and income inequality is hypothesized to negative impact a country's level of democracy over time because extreme inequality generates class conflicts that are incompatible with stable democracies (Boix and Stokes, 2003; Bollen and Jackman, 1995). Empirically, some argue that autocrat and developing economies tend to feature greater wealth and income inequalities, which may fall after successful democratization Miller (2021).

[5]We do not take a strong stand on these associations though. Nonetheless, specifying these dimensions clearly is important for avoiding rendering our subjects of discussion "Chameleons" (Pfleiderer, 2020)—items whose meanings shift with the application at hand—and preempting sweeping dismissals by purists who cannot tolerate any use of industry terminology or buzzwords in academic writings even though the economic contributions and messages are clear.

(Browne, 2021), and the shares continue growing.[6] Therefore, we assemble, analyze, and share to our knowledge the most comprehensive datasets to date on the Ethereum blockchain and its associated DeFi applications.[7] We complement on-chain data with several other online sources and apply one, to our knowledge, the largest-scale computation in the economics literature 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, indicating an even greater inequality than conventional systems, (ii) show how small players are marginalized and excluded due to high percentage fees, failure rates, and token return volatility, and (iii) demonstrate how the recently implemented EIP-1559 mechanism and airdropping mitigate these inequality and exclusion 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 understanding the early landscape of the ecosystem and evaluating future changes to researchers, policymakers, and practitioners.[8]

We start by describing 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% of mining pools (about 3 to 5 mining pools) receive about 60% of block rewards, and the top 0.5% of individual miners receive 30-50% of the rewards overall. The rewards are distributed to individual miners and subsequently sent by miners primarily through centralized exchanges. Ether (ETH) ownership has grown in concentration over time, with the top 0.1% (10%) of the nodes owning more

[6]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 (https://defiprime.com/ethereum), 235 listed DeFi projects are listed and 219 are proposed on Ethereum in 2021.

[7]Data used in our analyses are available through the public data repository we built.

[8]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/. It is worth noting that an "identification police" may jump to the hasty conclusion that our main contribution is (iii). We emphasize that (i) and (ii) are equally significant because the descriptive and correlational findings form the basis for further studies of this large market.

than 80% (90%) in the second half of our sample. The concentration remains severe when we focus on individual user accounts (excluding exchange-related or DApp nodes). Overall, this concentration of income and ownership is significantly higher than that of the income and wealth shares in the United States (Saez and Zucman, 2020). Equity aside, the concentration may also harm the security of both focal and related networks, and thus token valuation and stability (e.g., Bonneau, 2019; Ao et al., 2022). Moreover, we find that 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% since 2020. Importantly, token transfers and smart contracting are concentrated at nodes with higher on-chain wealth and larger transactions.

We recognize that transactions (including both simple token transfers and execution of smart contracts) and network utilization provide direct litmus on how inclusive and democratic a platform is. We first explain that any activity on Ethereum requires a transaction fee, known as gas fee, which depends on the computing resources consumed, as well as users' willingness to pay (Zarir et al., 2021). Gas fees incentivize miners to maintain 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 to analyze how transactions fee mechanisms affect inclusion and equality. For a financial system to be inclusive and democratic, it must be functional, efficient, fair, and affordable to small, under-served groups (Corrado and Corrado, 2017). A recent 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 disporportionally high for smaller 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 et al. (2019), we find that congestion of the network creates significant fluctuations of gas prices, not to mention the Ether returns themselves feature high volatility. Coupled with users' limited knowledge and lack of experience (and consequently suboptimal gas parameter setting), this causes a large fraction of transactions to fail, incurring significant losses for users.

Despite the aforementioned challenges, recent programs intentionally or unintentionally improve financial inclusion through redistributing income and wealth across network nodes. The EIP-1559 fee mechanism change alleviates congestion through an adjustable block gas limit, and dynamically moderates and burns base fees based on supply and demand. While transaction fees for small players can still be high (Roughgarden, 2020), the burning of base fees collected from large players benefits all token holders, 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, miners with larger shares of mining income or belonging to smaller mining pools experience greater reductions in mining income, while smaller and less wealthy users conduct more transactions in the network in terms of both frequency and amount. Exploiting the first major airdrop on Ethereum of OmiseGo tokens, we also demonstrate how airdrops can serve as redistributive policies to improve financial inclusion. In particular, airdrops disproportionally encouraged less active and poorer users to utilize the network. Promoting OMG as an alternative and somewhat competing token within the ecosystem actually boosted Ether valuation.

Our study adds to the literature on transaction fees in blockchain-based systems (see Chung and Shi, 2021, for a survey). Easley et al. (2019) and Huberman et al. (2021) are the earliest to analyze transaction fees and relate congestion to transaction fees and system stability. Ilk et al. (2021) discuss self-regulation of fees in Bitcoin, while Basu et al. (2019) and Lavi et al. (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 et al. (2022) argue that increases in fees can increase DEX trading volume; using data from Ethereum, Capponi et al. (2022b) show that traders bid high fees on DEXs primarily to reduce the execution risk of their orders; Barbon and Ranaldo (2021) document that CEX transactions are often less costly than DEX transactions and that the most significant component of DEC trading costs arises due to fees paid to blockchain validators. More recently, Lehar et al. (2022) show that the significant fixed cost when liquidity providers on Uniswap interact with the liquidity pool's smart contract can lead to liquidity fragmentation on DEXs. We are the first to analyze transaction fees in 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) 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 analysis 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, which thus far has emphasized security and scaling issues more than financial inclusion and democratization.[9] John et al. (2023) describe the implementation, benefits, and limitations of smart contracts on the Ethereum blockchain. Other extant studies are either theoretical (Chen and Bellavitis, 2020; Harvey et al., 2020; Schär, 2021) or focus on specific DeFi applications such as Decentralized Exchanges and automated market-making (e.g., Capponi and Jia, 2021; Park, 2021; Augustin et al., 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 et al., 2018; Capponi et al., 2021; Roşu and Saleh, 2021). Capponi et al. (2022a) and Auer et al. (2022) examine miner/maximal Extractable values.

Our study adds to recent efforts to assemble large datasets and utilize high-power computation 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 et al. (2019) and Cong et al. (2021a, 2022b,a) apply forensic finance to cryptocurrency big data 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 the first comprehensive doc-

[9]A related literature examines token valuation and users' and miners' behaviors under game-theoretical settings (e.g., Cong et al., 2021b; Han and Makarov, 2021; Choi and Jarrow, 2022). A number of studies also point to the limitations of blockchains. Hinzen et al. (2022) 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 et al., 2019; Gonzalez-barahona, 2021) have been widely recognized.

umentation of the Ethereum network structure, ownership distribution, mining activities, transaction landscape, and programs such as fee mechanism changes and airdrops. Our study also represents one of the largest non-GPU-based computating effort in economic studies.

Also closely related is Zhang et al. (2022) highlighting the lack of research concerning blockchain decentralization from the transaction aspects — exactly the gap that our study bridges. Ao et al. (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 highlight the redistributive effects of fee mechanisms and airdrops, adding to recent studies on the monetary policy of crypto-tokens (e.g., Cong et al., 2020b), airdrops (Froewis et al., 2021; Liebi, 2021), and redistribution through staking (John et al., 2021; Cong et al., 2020a), which are either theoretical or descriptive without causal identification.

Finally, our study broadly relates to digitization and financial inclusion. While the literature has mostly focused on the differential impact of FinTech and digital technologies on the digital and non-digital populations (e.g., Philippon, 2016; Zhongming et al., 2021; Jiang et al., 2022), or informational frictions that lead to 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 evidence from Kenya and Mexico. We use the Web3 setting to demonstrate that even among the digitally savvy, high fixed transaction fees preclude financial democratization and inclusion.

The remainder of the paper is organized as follows. Section 2 provides the institutional background before introducing our data and computing setup. Section 3 describes the general network structure and distributions of token ownership, mining, and transactions. Section 4 highlights the implications of transaction fees on financial democratization and inclusion. Sections 5 and 6 document the redistributive effect of the transaction fee reform and airdrops. Section 7 concludes. The Online Appendix contains additional figures, tables, and analyses.

2. Institutional Background, Data, and Computation

2.1. 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 on-chain (Szabo et al., 1994; Lauslahti et al., 2018; Cong and He, 2019). 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 et al., 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. The three key parameters of 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 Ether transfer between two wallets requires 21,000 gas units, with variations dependent on the bytecode operations of the activities (Wood et al., 2018).

The gas fee for a transaction is simply the gas used multiplied by the gas price, with the caveat that a user needs to reserve a gas fee limit in their 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 in auction-like processes (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, her transaction fee on Bitcoin is deterministic, 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 if 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.

2.2. *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 August 2015 (hen Ethereum was founded) 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 regarding the total amount of Ether transferred, the block hash the transaction was recorded (indicating the time the transaction was completed), the gas used, the 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 ERC-20 and ERC-721 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.

Our computing architecture involves 14 servers with dual Xeon E5 CPUs, 128G memory, and 48TB hard disks. The first server runs an Ethereum node exclusively 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 large servers, each with Hadoop, Hbase, Spark, and Yarn installed.[10]

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, DApponline, and Ethercan.[11] 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 1b 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 the distributed processing of transaction-level data, Gephi for mapping the various networks, and Spark's machine learning library for performing linear and logistic regressions. We make available the data used in the

[10]To be concrete, it takes approximately 30 days to process the original Ethereum data and convert them into the variables used in the analyses. An average regression using Spark takes between 10 minutes to 1 hour. The visualization of mining reward tracing, including data processing and rendering, requires approximately one month to generate, while the visualization of the Ethereum activities network takes approximately one day.

[11]See, https://DAppradar.com, https://DApponline.io, https://etherscan.io/, respectively.

analyses through a public repository for other researchers, practitioners, and policymakers.

2.3. Key Variables

We take every external transaction as an observation unit, and also use information on internal transactions, token transfers, logs, etc., for the construction of variables. Table 3 constains a detailed list.

Transaction fee and extra gas reserved. The transaction fees in units of ETH and USD are calculated, respectively, as:

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

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

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 gas used :

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

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

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

Transaction value. We define the value of a DeFi transaction as the total number of ERC-20 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 ERC-20 involved in this transaction (instead of the sum of all ERC-20 tokens).

Token returns and volatility. The return of ETH ($EthReturn_t$) and the return of Ethereum-related tokens ($TokenReturn_{it}$) are also calculated, respectively, as:

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

$$TokenReturn_{it} = \frac{Price_{it} - Price_{it-1}}{Price_{it-1}}, \tag{6}$$

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:

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

and the daily exchange rate volatility of Ether is:

$$EtherVolatility_t = \sqrt{\frac{\sum_{j=1}^{n}\left(EtherPrice_{tj} - EtherPrice_t\right)^2}{n-1}} \times \sqrt{n}, \tag{8}$$

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.[12]

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:

$$FailureRate_t = \frac{\#Failure_t}{\#Transactions_t} \times 100\%. \tag{9}$$

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. The failure rate is higher than that for credit

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

card transactions.[13]

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 ETH). In addition, we use $LnVolume_{it}$ and $LnDApps_{it}$ to denote the log of total transaction volume in ETH and the 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 on a certain day t:

$$NetworkUtilization_t = \frac{TotalGasUsed_t}{TotalBlockGasLimit_t} \times 100\%. \tag{10}$$

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.[14] 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 1a). 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.

[13]The decline rate of credit card transactions is higher mostly for security reasons and anti-fraud effort, which are not about the smart contract executions.

[14]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).

3. The Ethereum Ecosystem

We start by describing basic patterns and trends in the ecosystem, focusing on the distribution of mining, ETH ownership, transactions, and network structure derived from on-chain data.

3.1. Network Structure and Activities

Ethereum represents a complex network and our first task is to map out network activities. Figure 2a reveals that Ether flows among DApps and exchanges are dominated by 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 (also used in Makarov and Schoar, 2022) reflects its importance. For DApp i, it is the largest solution (λ) to the equation $Ax = \lambda x$, where matrix elements A_{ij} are the total Ether flows from DApp i to j over 2015-2022. Figure 2b depicts the top 25 DApps and exchanges with the highest network centrality and their total received ETH. Again, exchanges and DeFi applications dominate.[15]

Next, we describe how various categories of DApps compete or complement. Figure OA.1 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.[16]

Finally, we can demonstrate any network of Ethereum-related activity centered on DApp. The cluster of the sphere in Figure OA.2 represents a DApp and its users, with the center of the cluster as the DApp, and surrounding points as users.

[15]Center nodes in the DApps network do not necessarily receive the most ETH (from other DApp/exchange nodes, suggesting that some nodes (e.g., Uniswap) receive ETH mainly from users.

[16]Sushiswap is a DApp that replicates Uniswap codes and firght for Uniswap users through marketing campaigns.

The color of the sphere represents its category. Lines in different colors 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.

Overall, these illustrations demonstrate how the data we assemble allows visualization of various network structure and can be useful to other researchers. We also learn that DeFi apps also play central roles in the network.

3.2. Distribution of Mining and Rewards

Ethereum miners (now stakers after the Merge) 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 OA.3, 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 3a is similar to that in Bitcoin (e.g., top 6 mining pools get 60% of block rewards Makarov and Schoar, 2022). Figure OA.3b 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 OA.3a uses Shannon Entropy to quantify the randomness 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 et al. (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. We use on-chain transactions to trace mining rewards from mining pools to the individuals participating in the pools. Figure OA.4 illustrates this tracing process using Ethermine pool. The top layer in the figure represents the nodes of the mining pool (gold-colored dots). Though the block rewards of Ethermine mining pool rarely flow directly to exchanges, its miners and miners' "friends" mainly transfer ETH to exchanges, indicating that centralized nodes are still important.

The shares of received mining rewards for different percentiles of miners (excluding exchanges) is given in Figure 3b. 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 economy, based on evidence from the Ethereum ecosystem.

3.3. Distribution of Token Ownership

If Ethers are owned by a selected few, it is hard to imagine that the network mitigates wealth inequality and enables inclusive DeFi for the masses. Figure 4 shows the ownership distribution. As shown in Panel 4a, the vast majority (about 80%) of Ethers in circulation are still held by EOAs, but the percentage has been decreasing over time. Figure OA.5 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 the Ethereum ecosystem. Furthermore, as shown in Figure 4c and Figure 4d, the top 0.1% of accounts, both for all addresses and EOAs, own more than 80% of the Ethers and top 10% own almost 100%. 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 own 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' off-line 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 possibility (Ferreira et al., 2022), but the "Merge" to switch to Proof-of-Stake (PoS) may alter the situation, which constitutes interesting future research.

3.4. Distribution of Transactions

We compute and show in Figure 5 the daily transaction volume (covering both ETH and other tokens) between October 16, 2017 and October 3, 2022.[17] Figure 5a-5b display the distributions of transaction volume (in dollars) among Ether and tokens on Ethereum, and Figure 5c-5d display the distributions of transaction volume (in dollars) among stakeholders on Ethereum ecosystem.

Transaction volume in the Ethereum ecosystem peaked in late 2017 to early 2018 and in the second half of 2020 to 2022. In the early years, transaction volume mainly entailed the native cryptocurrency ETH. But in recent years, ERC-20 tokens have become dominant. Moreover, transactions have gradually shifted from peer-to-peer to be between users and DApps. In particular, about 90% of the 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 the transaction volume in 2017.

4. 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, and is worth emphasizing also because of they differ from those in 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

[17] October 16, 2017 marks the date of Ethereum's Byzantine fork, the success or failure status of external transactions is only recorded from this date onwards. As such, the analyses on the distribution of transactions and transaction fees have samples start from October 16, 2017. 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.

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 compute a percentage transaction fee as the transaction fee divided by the value transferred:

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

Table OA.2 provides this fee rate of two types of received addresses (EOA and contract acctouns), two types of cryptocurrencies (Ether and ERC-20 tokens on Ethereum) and DApps and others. Panel A shows the percentage transaction fee for transactions with EOA and contract accounts, Panel B concerns ETH transactions and token transactions, and Panel C covers transactions with DApps and others. Figure OA.6 further illustrates the median percentage transaction fee for the aforementioned types of transactions.

Figure OA.7 reports the distribution of transaction value by transaction types. Transactions with EOAs are typically under \$100, while transactions with contract accounts are typically over \$1000. Transactions using Ether are typically under \$100, while transactions using tokens on Ethereum are typically over \$100, or even \$1,000. Most transactions with DApps are over \$1000, while other transactions are usually under \$100.

Moreover, the median percentage transaction fee for different groups varies from 0.25% to 0.37%, but is overall cheaper than the transaction of major banks in the SWIFT system (Table OA.3 in the online appendix).[18] 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

[18] The sample contains outliers, as 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. Median is therefore a better metric in our analysis.

domestic transactions and a 5% transaction fee for international transactions.[19] In contrast, the percentage transaction fee for small amount transactions using DeFi is too high and volatile for inclusive finance.[20] 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 OA.8 shows, transaction delays are negatively correlated with gas prices, consistent with previous studies on Bitcoin (Easley et al., 2019; Ilk et al., 2021). Using recommended gas prices, we show that users are willing to pay higher gas prices for quicker transactions in response to network congestion. We also investigate the relationships between gas prices and delay times and between gas prices and network utilization, to better understand the effects of congestion.

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:

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

y_i^* is the latent variable, and μ_i is the error 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 OA.4a 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 α_1, α_2, α_3 are -2.40, -1.20, -0.02 respectively in Equation (13). Table OA.4b 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

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

[20] 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.

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 report in OA.4 results using Probit and OLS models, and find them consistent with the logistic model.

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

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

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 ETH exchange rate in $t-1$.

Table OA.5 reports the transaction-level regression results for different types of activities. The first column shows that the utilization of the network has a significantly positive correlation with 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 et al., 2019; Ilk et al., 2021). For control variables, the return of ETH exchange rate has a significant positive correlation with 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 association with gas prices for all 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 get processed first, 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 OA.9, 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 OA.6a 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 OA.6b.

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

The network utilization and median gas price have a significantly positive impact on the variable *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, ETH returns, block rewards, and the popularity of Ehtereum are negatively correlated with *ExtraGasReserved*. As ETH rises in value, users are more likely to transact using it rather than saving it in their wallets in the form of transaction fees.

Recall that gas prices increase in network congestion and dollar value of Ether, this section shows that on top of gas price increases, positive ETH return and network congestion tend to increase extra gas reserved, incurring additional costs to users.

Transaction Failures. 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" which entails 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" which is caused by errors in smart contract codes.

The average daily failure rate, as Table 1c and Figure OA.10 show, is 2.03%. As shown in Table 1, 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 failed (5.56% of such types of transactions), with a total gas fee of 31,367,076 dollars.

In addition, Table 1e 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.[21]

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 a linear-probability regression at the transaction level:

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

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 OA.7 shows that in general if the user reserves extra gas when initiating a transaction, the probability of a failing transaction drops by 0.67%.[22] 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 correlations with transaction failures. 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, ETH return, and network utilization show negative correlation with transaction failures.

Token Exchange Rate Risk. As shown in Table OA.1 and Figure OA.11, the high price volatility of ETH (about 163% for 3 years) and ERC-20 tokens exclude users

[21] 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.

[22] 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.

with low risk tolerance and creating other frictions for adoption (Harvey et al., 2020). Moreover, the high volatility 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 longer.

Our data allow a further investigation into the drivers of the high exchange-rate volatilities of ETH and ERC-20 tokens. Table OA.9 reports the findings. Higher network utilization, block rewards, and Ethereum popularity positively correlates with comtemporaneous ETH exchange rate volatility and predicts higher future volatility, while higher failure rate, median gas price have negative contemporaneous correlation and prediction. For token exchange rate, median gas price and Ethereum popularity are positively correlated with and predict exchange rate volatility of other ERC-20 tokens, while block reward and network utilization exhibit weakly negative correlation with token exchange rate volatility.

In addition, we also study the link between ETH returns with relative returns of ERC-20 tokens. 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 fees of these tokens is in ETH, the high ETH exchange rate tends to increase the transaction cost of these tokens, and hence decrease their prices. Therefore, the correlation between other ERC-20 tokens and ETH is weakened by high ETH price. Formally, we perform the following regression:

$$TokenReturn_{it} = \beta_0 + \beta_1 EthReturn_t + \beta_2 EthReturn_t^2 + \varepsilon_{it} \tag{17}$$

We include the square of *EthReturn* to the model to study the influence of ether returns 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 OA.8. Ether returns indeed have a negative effect (β_2) on the Ether-token correlations.

5. Redistributive Effect of the EIP-1559 Fee Mechanism

We now examine a major fee mechanism change in the ecosystem and how it has, intentionally or unintentionally, created redistribution across various participants in the ecosystem. While there are many other changes in the system that could have affected transactions and income distribution in the ecosystem, the EIP-1559 fee change is arguably the largest major change before Ethereum's switch to Proof-of-Stake, and is one that is not designed to mitigate the inclusion problem, thus serving as a perfect exogenous shock.

5.1. 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 was an overhaul of the original transaction fee mechanism to address the problems of high fee volatility, network congestion, and overpayments due to fee unpredictability.[23] Figure OA.12 illustrates the primary adjustments of the EIP-1559 fee mechanism. One of the critical changes is the new "base fee burning" scheme. Base fee is the minimum gas price that a transaction needs to pay to enter the block, which follows a pre-specified formula:

$$BaseFee_{h+1} = BaseFee_h \times \left(1 + \frac{1}{8} \times \frac{GasUsed_h - GasTarget}{GasTarget}\right). \tag{18}$$

The gas target is constant at 15 million. As part of transaction fee, the base fee is no longer awarded to miners but is removed from ETH circulation forever, i.e., burned by sending to invalid wallet addresses. The second adjustment in EIP-1559 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 OA.13 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 OA.13a 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.[24]

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[23] 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.

[24] The lack of immediate full adoption is likely due to that most users use metamask wallets, some of which do not imeediately support the EIP-1559 protocol. Note that EIP-1559 is retained even after Ethereum's switch to PoS.

5.2. Empirical Strategy

We study the implications 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, 2021 as the threshold. Then, we extend the specification to consider the heterogeneity of miners and users using a difference-in-difference approach.

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 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 because for them PercentBlock is not well-defined.[25] These filters leave us 135,414 miner addresses associated with 102 separate mining pools. Table OA.11a 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 construct user samples in two ways. 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 method of grouping Bitcoin users. 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,

[25]In additional tests not included here, we find that the results are robust when we use the largest and the average values for these miners.

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 OA.11b provides the summary statistics on users' transaction activities before and after the launch of EIP-1559.[26]

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

$$y_{it} = \alpha + \beta Burning_{it} + \gamma f\left(date_{it}\right) + \delta X_{it} + \varepsilon_{it}. \tag{20}$$

For miners, y_{it} refers to the mining rewards received by miner i in 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 ε_{it} and the date. X_{it} denotes a set of additional control variables described in Table OA.10.

Burning base fees resembles consumption taxation. It effectively redistributes wealth from the most active players to all token holders. We use the following difference-in-difference specifications to test the heterogeneous effects formally:[27]

$$\begin{aligned} y_{mt} &= \beta ln\left(PercentBlock_m\right) \times Burning_t + \omega X_{mt} + \lambda_m + \gamma_t + \varepsilon_{mt}, & (21)\\ y_{mt} &= \beta \ln\left(BeforeRewards_m\right) \times Burning_t + \omega X_{mt} + \lambda_m + \gamma_t + \varepsilon_{mt}, & (22)\end{aligned}$$

[26] Table OA.13a and OA.13b in the online appendix contain the analyses using the second user sample for robustness check.

[27] The results remain robust when we run a difference-indifferences regression utilizing the previous year's statistics as a control sample (assuming parallel trends). This additional analysis controls for potential seasonality (see Kaiser, 2019), though empirically the cryptocurrency market is still in transition and has not exhibited clear seasonal patterns.

$$y_{it} = \beta \ln(BeforeTransactions_i) \times Burning_t + \omega X_{it} + \lambda_i + \gamma_t + \varepsilon_{it}, \quad (23)$$
$$y_{it} = \beta \ln(BeforeBalance_i) \times Burning_t + \omega X_{it} + \lambda_i + \gamma_t + \varepsilon_{it}. \quad (24)$$

Equations (21) and (22) test the influence 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 5, 2021. $BeforeRewards_m$ is the total mining rewards received by miner *m* between February 5, 2021, and August 5, 2021.

Equations (23) and (24) test the effects 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.

5.3. Empirical Results

We start with mining. Figure OA.14a plots the average log of weekly mining rewards received by miners for a 20-week window straddling the introduction of EIP-1559. The log of weekly mining rewards averages around 0.05 ahead of the launch but drops discontinuously to 0.04 after the launch. Table 4a shows an overall negative effect of the EIP-1559 fee mechanism on miners' mining rewards.[28] 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 5 reports the results of the heterogeneous effect of EIP-1559 on miners. Columns 1 and 3 in Table 5 indicate that miners belonging to larger mining pools experienced a smaller decrease in weekly mining rewards following the launch of EIP-1559. Moreover, Columns 2 and 4 in Table 5 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 gap among individual miners.

Moving to network usage, Table 4 shows an overall positive effect of the EIP-1559 fee mechanism on users' transaction volume and the number of used DApps. Figures OA.14b and OA.14c plot the average log of users' transaction volume and

[28]Though unreported here, we find using synthetic control (Abadie and Gardeazabal, 2003; Abadie et al., 2010, see Section VI.B for details) that EIP-1559 has insignificant effect on ETH exchange rate with dollars, so the numbers in USD would be just a noiser version due to the unpredictable Ether exchange rate fluctuations.

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. Tables 6 and OA.12 contain the results of heterogeneous effects of EIP-1559 on users. In particular, the significant negative coefficients of the interaction terms indicate that users with a lower frequency of transactions or ETH balance benefit more from EIP-1559.

Our results demonstrate that the EIP-1559 fee mechanism reform significantly impacts both mining and transactions on Ethereum. Through the "deflationary" fee-burning, this policy effectively taxes agents with more and larger transactions to redistribute wealth. Consequently, it encourages participation of small, new, and inactive users in the network. Due to many subsequent changes in the ecosystem and the limited time-series data, we cannot draw a conclusion about the long-run effects given the confounding factors.

6. Inclusion and Democracy Through Airdropping

Airdrops are often considered marketing strategies for expanding userbase (Froewis et al., 2021; Li et al., 2021a). 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; Zhao et al., 2022). In addition, if some tokens are distributed to inactive users, they become illiquid or permanently lost.

The extant literature mainly focuses on the effects 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.[29] Arguably, many other airdrop programs can be similarly studied. Our main contribution is to conceptually clarify how airdrops constitute redistributive monetary policy and to illustrate their impact on financial inclusion and democratization.

[29] 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.

6.1. Background: OmiseGo Airdropping

OmiseGo is a wallet and payment network that allows people to send and transfer money to other accounts without a bank. It implemented the first airdrop on Ethereum, which remains as one of the most prominent airdrops to date. The airdrop dispenses 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.[30] For example, an address with the account balance of 1 ETH would receive 0.075 OMG.

The announcement date of OmiseGo airdrop was August 17, 2017, while the snapshot date was July 7, 2017. This snapshot date, which is earlier 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, 2017. During this period, the daily exchange rate of OMG was around 10 dollars.

6.2. Empirical Strategy

We first adopt the identification strategy of difference-in-difference with the 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. We perform weighted local linear regression on the RD sample within the bandwidth, with a simple weighting scheme:

$$y_{it} = \beta \left(After_{it} \times Airdrop_i \right) + \omega X_{it} + \lambda_i + \gamma_t + \varepsilon_{it}; \tag{25}$$

weight$_i$=1-$\left| \frac{balance_i - 0.1}{bandwidth} \right|$,(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 OA.10), λ_i, user fixed effect, and γ_t, time fixed effect. $weight_i$ represents the weight assigned to user i, $balance_i$ denotes the account balance of user i, and $bandwidth$ corresponds to the utilized bandwidth.

[30]The block height 3,988,888 corresponds to July $7^{th}, 2017, 04:36:56$.

In addition, we use synthetic control (SCM, e.g., Abadie and Gardeazabal, 2003; Abadie et al., 2010) to verify the impact of airdropping on the return of relevant native cryptocurrency. Since a perfect control blockchain of Ethereum cannot be found, we constructed a "synthetic ETH" by linearly combining 14 blockchains with 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 ETH" 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 exchange rate of ETH 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 ETH" 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.

6.3. Empirical Results

Impact of airdropping on users' transaction volume. Figure 6 provides a visual image showing the parallel trends and post-treatment dynamics, and Table 7 presents the regression results. The airdrop has a significantly positive influence on users' transaction volume. These results illustrate that airdrop improves the transaction volume of those who received airdropped tokens, even among less wealthy users with an account balance of around 0.1 ETH.[31]

Impact of airdropping on native cryptocurrency exchange rate. The issuers of airdrops typically understand the direct cost of giving tokens away. But they do not fully internalize the externality of airdrops on the usage and valuation of the native token ETH. In fact, Liebi (2021) points out that native token returns may decrease following an airdrop for the simple reason that introducing a new token crowds out the usage of the base layer token.

The weight of each blockchain in the control group is illustrated in Table 8a. Before the launch of OmiseGo airdrop, the trend of Ether return is best represented

[31] For discussions of the long-term effects of airdrops, see, e.g., Zhang and Zhang (2023) and Zhang et al. (2023).

by the combination of Bitcoin, Ethereum Classic, Litecoin, Peercoin and Waves, in which Bitcoin occupies the highest weight. Table 8b further shows a similar trend of mean values of predictors between ETH and synthetic ETH.

The estimated effects are shown in Figure 7 and Table 8c. Different from (Liebi, 2021), we do not find an immediate negative effect of the start of OmiseGo airdropping on its native token return using SCM. Instead, 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.

7. 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, with on-chain income and wealth inequalities no better than those in economies such as the United States. 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 and new 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 the opportunity costs of additional gas limit reservations, cause high rates of failures. Financial inclusivity and democratization ought be taken seriously in the next iterations of Web3/DeFi systems.

Proposals (e.g., 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. Combining our data and data from OmiseGo, we demonstrate airdrops are also redistributive policies that potentially improve financial inclusion. Given that protocol updates and token distribution for user acquisition likely remain in the long run, the causal evidence we provide has general validity and implications.

The full potential of DeFi and Web3 may be realized only after a long, iterative process. Our paper is an initial attempt to understand the landscape, mechanisms, and limitations of the current design, so as to inform future research and design. The data platform developed for our study also allows other researchers public access to blockchain and DeFi big data. Note that the switch to PoS (the Merge) can alter the Ethereum ecosystem dramatically.[32] Nevertheless, the issues we document remain because the Merge does not reduce transaction fees directly, although it opens up the possibility for further reforms, including sharding and third-party and Layer-2 roll-ups. Overall, our findings can serve as a useful benchmark to evaluate the future evolution of Web3 and DeFi.

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[32]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.

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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*). Panel B describes network dependent variables (i.e., *NetworkUtilization*, *#Transaction*, *BlockRewards*, and *EthPopularity*). Panel C reports the daily failure rate and failure number. Panel D 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 E summarizes the gas fee incurred due to different failed reasons. The sample period of panel A-E is from October 2017 to August 2021, spanning a total number of 1,389 days and covering 748,738,026 unique transactions. Panel F lists the summary statistics of gas price at the 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 of 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
NetworkUtilization (%)	86.742	89.680	79.070	96.680	10.802
#Transaction	839601.885	757712.000	611188.000	1096582.000	279352.418
BlockRewards	2.571	2.115	2.089	3.309	0.636
EthPopularity	14.089	6.000	4.000	14.000	17.936

Table 1: Summary Statistics (continued)

(c) Failure-related Variables

	mean	median	25%	75%	standard deviation	Obs
Failure	0.071	0.000	0.000	0.000	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

(d) 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%

(e) 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%

(f) 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. It shows the overall statistics of percentage transaction fees 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. Table OA.2a (EOAs and contract accounts), Table OA.2b (Ether and token on Ethereum) and Table OA.2c (DApps and others) list the summary statistics of six categories of percentage transaction fees at different transaction value levels separately, which are reported in the online appendix. The sample period is from October 2017 to August 2021.

	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 3: Key Variables and Correspondence with Sections and Formulas

This table delineates the correspondence between key variables and formulas mentioned in Sections 2.3 and 4, and provides data sources for variable constructions.

Variables	Data Sources	Corresponding Equation	Corresponding Section
GasPrice	On-chain data	1-2, 4, 11, 14, 16, 19,	2.3, 4
GasUsed	On-chain data	1-4, 11	2.3, 4
GasLimit	On-chain data	3-4	2.3
GasFee	On-chain data	1-2	2.3
EtherPrice	CoinMarketCap	2, 4, 5, 8	2.3
ExtraGasReserved	On-chain data	3, 15	2.3, 4
ExtraGasFee	On-chain data	4	2.3
EtherReturn	CoinMarketCap	5, 17	2.3, 4
TokenReturn	CoinMarketCap	6, 17	2.3, 4
ReturnVolatility	CoinMarketCap	7	2.3
EtherVolatility	CoinMarketCap	8	2.3
FailureRate	On-chain data	9, 16	2.3, 4
NetworkUtilization	On-chain data	10, 15	2.3
PercentageTransactionFee	On-chain data, CoinMarketCap	11	4
Value	On-chain data, CoinMarketCap	11	4
RecommendedGasPrice	ETH Gas Station	12	4
DelayTime	ETH Gas Station	13	4

Table 4: The Overall Effects of EIP-1559 on Miners' Mining Rewards and Users Trading Behavior

This table reports the estimated effect of the launch of EIP-1559 mechanism on both miners' mining rewards and users' trading behavior. Panel A 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 (fifth) and forth (last) columns systematically exclude one (two) week(s) before and after the launch of EIP-1559. All columns include miner fixed effect and a set of controls. Panel B describes the linear regression results with the log of weekly transaction volume (*LnVolume*) as dependent variable. Standard errors are reported in parentheses. The sample period is from February 2021 to February 2022 which covers a total of 135,469 miner addresses and 252,112 user addresses.

(a) Weekly Mining Rewards

	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
Month FE	NO	NO	NO	NO	NO	NO

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

Table 4: The Overall Effects of EIP-1559 on Miners' Mining Rewards and Users Trading Behavior

(b) 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
Month FE	NO	NO	NO	NO	NO	NO

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

Table 5: 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) 20 weeks	(2) 20 weeks	(3) 10 weeks	(4) 10 weeks
LnPercentBlocks*Burning	0.043***		0.001	
	(0.003)		(0.002)	
LnBeforeRewards*Burning		-0.055***		-0.022***
		(0.001)		(0.001)
LnMiners	0.010***	0.009***	0.018***	0.016***
	(0.001)	(0.001)	(0.001)	(0.001)
LnGasprice	0.014***	0.014***	-0.002***	-0.002***
	(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)
EthReturn	0.024***	0.028***	0.041***	0.054***
	(0.003)	(0.003)	(0.010)	(0.010)
LnDifficulty	-0.078***	-0.080***	-0.019***	-0.02***
	(0.002)	(0.002)	(0.002)	(0.002)
LnTransactions	0.010***	0.011***	0.054***	0.057***
	(0.001)	(0.001)	(0.004)	(0.004)
Observations	5,418,760	5,418,760	2,709,380	2,709,380
R-squared	0.060	0.145	0.021	0.045
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 6: DID—Heterogenous Effects of EIP-1559 on users' Trading behavior

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.

	(1)	(2)	(3)	(4)
VARIABLES	20 weeks	20 weeks	10 weeks	10 weeks
LnBeforeTransactions*Burning	-0.032***		-0.001	
	(0.001)		(0.001)	
LnBeforeBalance*Burning		-0.037***		0.001
		(0.002)		(0.002)
LnGasprice	0.004***	0.004***	0.002***	0.002***
	(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)
EthReturn	0.014***	0.014***	0.013*	0.013*
	(0.004)	(0.004)	(0.006)	(0.006)
LnDifficulty	-0.002	-0.002***	0.003*	0.003*
	(0.001)	(0.002)	(0.002)	(0.002)
LnTransactions	0.011***	0.011***	0.014**	0.014***
	(0.002)	(0.002)	(0.005)	(0.005)
Observations	10,091,600	10,091,600	5,045,800	5,045,800
R-squared	0.008	0.145	0.000	0.00
Number of users	252,290	252,290	252,290	252,290
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 7: The Effect 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 bandwidths. The first two columns use a bandwidth of 0.015 to divide the RD sample, the third and fourth columns use a bandwidth of 0.01 to divide the RD sample, and the last two columns use a 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 8: The Effect of OMG Airdrop on Native Token (ETH) Returns

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

(a) Blockchain Weights in the Synthetic Ethereum

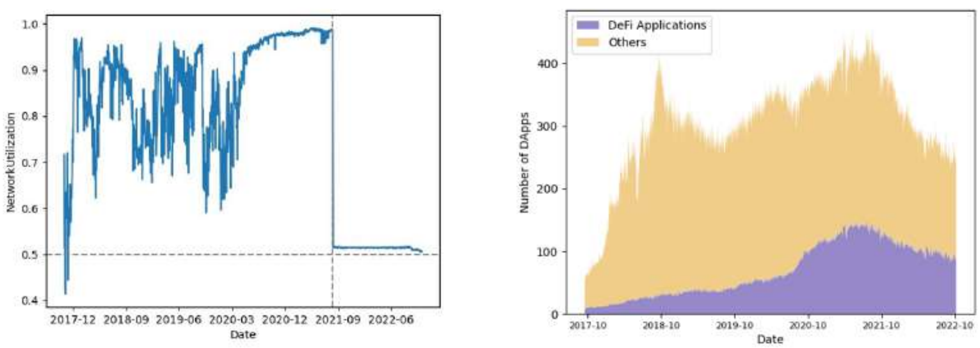
Blockchain	Weight	Blockchain	Weight
Bitcoin	0.713	Neo	0
Bitcoin Cash	0	Peercoin	0.116
Binance Smart Chain	0	SpreadCoin	0
Dash	0	Steem	0
Ethereum Classic	0.032	Waves	0.04
Litecoin	0.099	Monero	0
Zclassic	0	Zcash	0

(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

(c) Post-Treatment Effects with Placebo Test

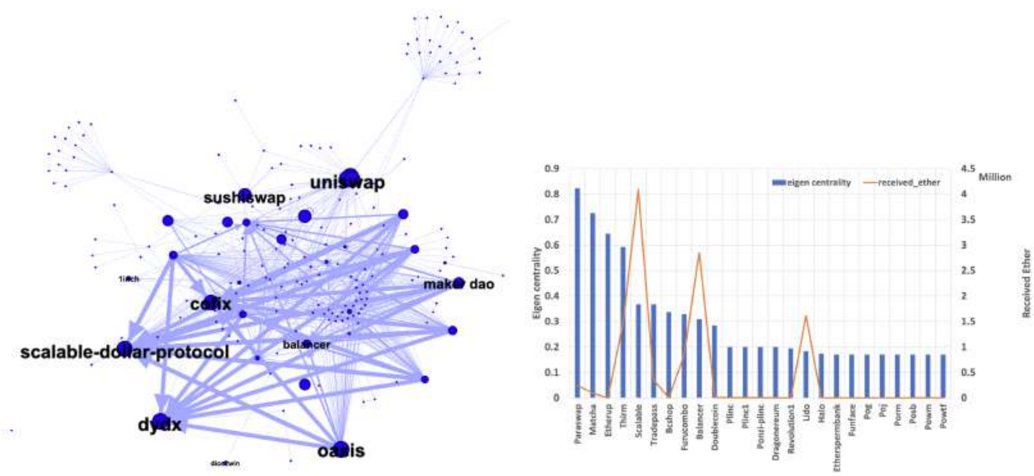
Post Day	Estimates	Pvals-std	Post Day	Estimates	Pvals-std
c1	-0.007	0.429	c8	0.011	0.429
c2	0.005	0.643	c9	0.008	0.286
c3	0.012	0.429	**c10 (end day)**	-0.004	0.714
c4	-0.013	0.286	c11	0.021	0.000
c5	0.005	0.357	c12	0.044	0.000
c6	0.052	0.000	c13	-0.017	0.214
c7	-0.009	0.500	c14	-0.024	0.000



(a) Network Utilization (b) Daily Active DeFi Applications

This figure depicts the development of the Ethereum ecosystem. Panel A shows 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). Panel B shows the evolvement of daily active DeFi applications and other DApps, with the y-axis representing the number of active DApps.

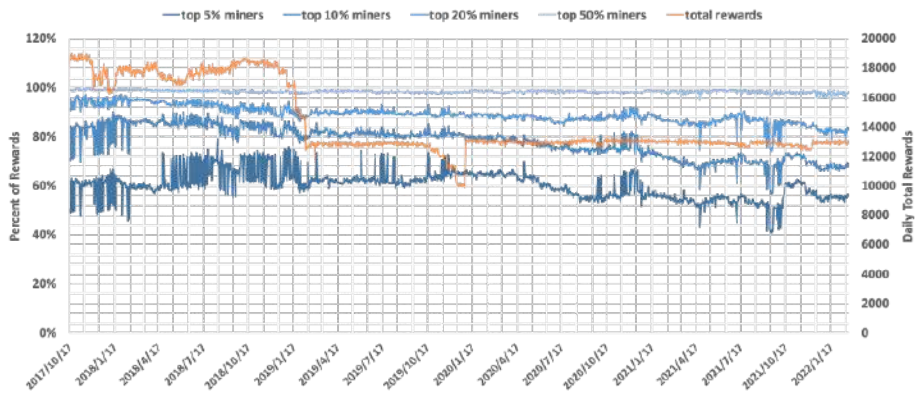
Figure 1: Ethereum Ecosystem



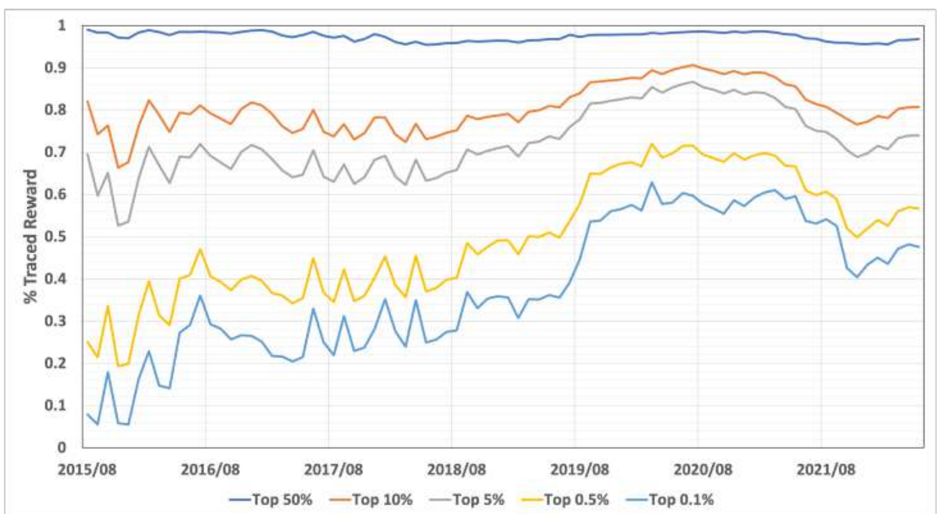
(a) Network (b) Enginevector Centrality of DApps

This figure depicts the flow of ETH among DApps and exchanges on Ethereum from 2015 to 2022. Panel B reports the the enginevector centrality and total received Ether of each DApps. The primary y-axis represents the centrality, the secondary y-axis represents DApps' total received Ether, and the x-axis represents DApps.

Figure 2: Ether Network among Exchanges and DApps



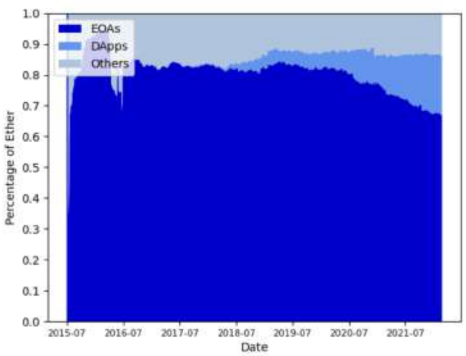
(a) Mining Rewards Received by Mining Pools



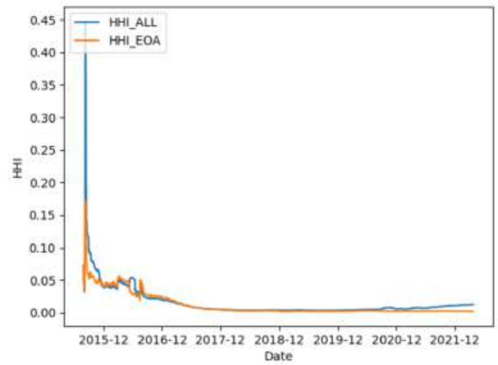
(b) Traced Mining Rewards for Miners

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 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.

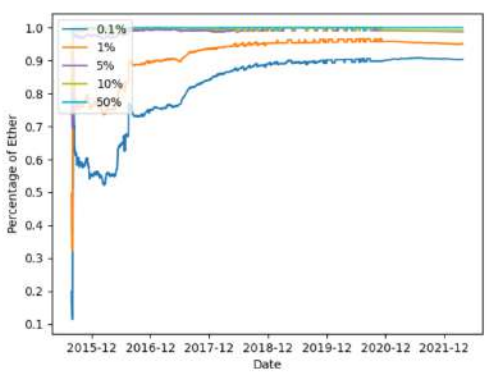
Figure 3: The Concentration of Mining Capacity



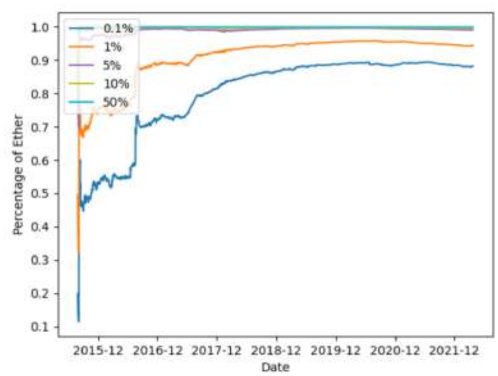
(a) Distribution of Ether between Users and Other Stakeholders



(b) Herfindahl–Hirschman Index



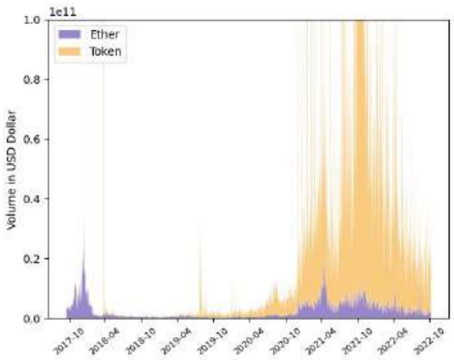
(c) The Concentration of All Addresses



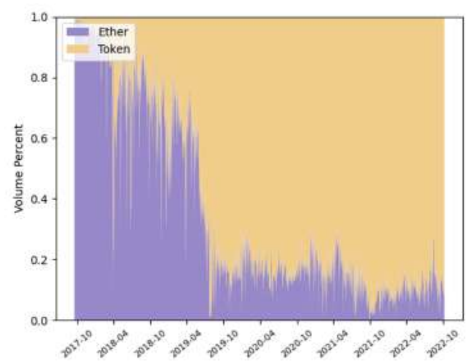
(d) The Concentration of EOAs

Ownership 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 depicts the Herfindahl–Hirschman Index (HHI) of the distribution of ether tokens among all addresses and EOAs. 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 (non-DApps and non-exchange related EOAs), denoted using the percentage share of all ETH held by these EOAs.

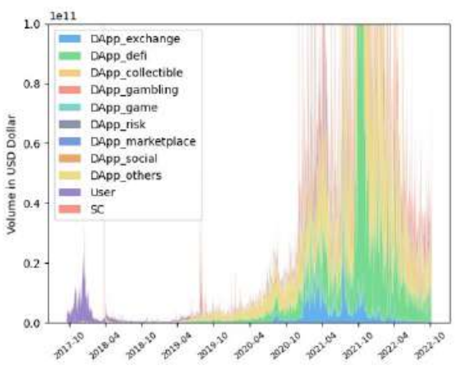
Figure 4: Ownership of Ether



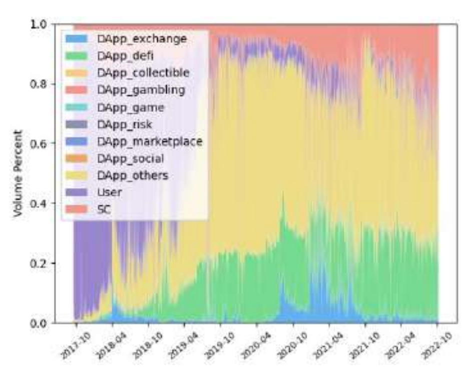
(a) Ether and token



(b) Ether and token



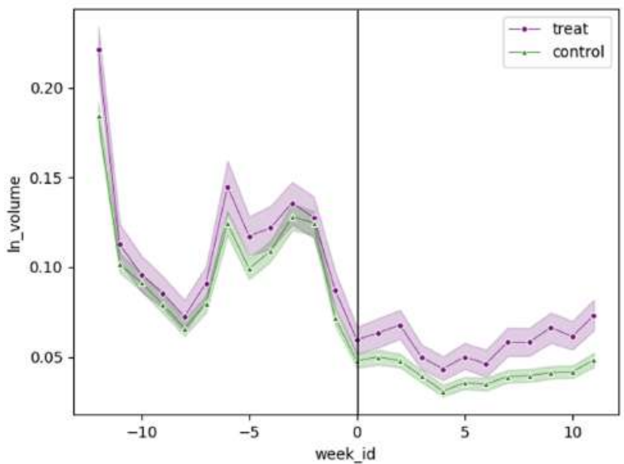
(c) DApps, EOAs and SCs



(d) DApps, EOAs and SCs

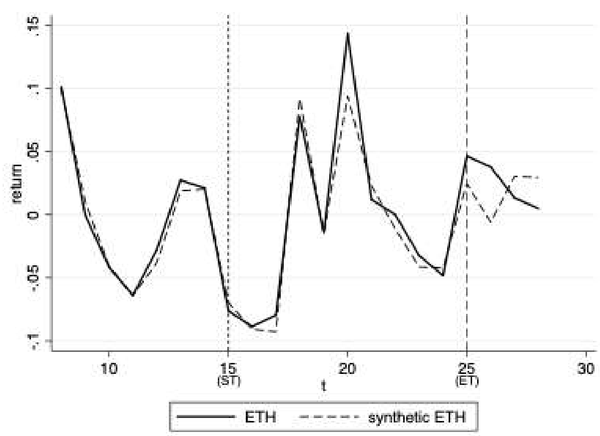
This figure depicts the daily transaction volume on Ethereum and its composition. The two pictures at the top illustrate the transaction volume using Ether and transaction volume using ERC-20 tokens on Ethereum. The two pictures at the bottom illustrate the transaction volume of 9 categories of DApps, users and other contracts. Transaction volume is calculated in dollars. For the visibility of figure, we exclude data on 2017.11.03 and 2018.04.24 due to two extremely high transaction values of token-related transactions.

Figure 5: Decomposition of Transaction Volume



This figure reports the parallel trends of the treatment group and control group with a 90% confidence interval bar. The y-axis is the log of Ether transaction volume.

Figure 6: Visual Checks of Parallel Trends



This figure depicts the return dynamics of Ether and "synthetic Ether." The vertical axis represents the returns, and the horizontal axis represents the date. Day 15 is the start of the OmiseGo airdrop and day 25 is the end.

Figure 7: Trends in Native Cryptocurrency Return: Ethereum vs. Synthetic Ethereum

Online Appendix

Table OA.1: Annualized Volatility of Ether and 157 ERC-20 Tokens (Dec 2017 - Dec 2020)

Token Symbol	Volatility 2018	Volatility 2019	Volatility 2020	Volatility 3 years	Average Rolling volatility
ETH	107%	79%	93%	163%	91%
STX	174%	150%	292%	372%	180%
KCS	195%	101%	72%	231%	101%
CAPP	208%	130%	179%	303%	152%
DLT	193%	178%	113%	286%	153%
EDG	136%	136%	183%	265%	140%
DCN	272%	249%	338%	500%	255%
TNT	201%	159%	170%	308%	166%
DNT	189%	102%	238%	321%	139%
PLBT	198%	276%	230%	410%	230%
DATA	154%	137%	379%	431%	210%
BAT	151%	95%	101%	205%	111%
AVT	202%	269%	262%	427%	245%
POE	183%	106%	217%	303%	140%
MANA	179%	100%	124%	239%	126%
GVT	184%	95%	138%	249%	126%
NMR	191%	127%	287%	368%	196%
CDT	181%	128%	146%	266%	144%
REP	131%	102%	133%	213%	118%
BCDN	263%	344%	131%	453%	246%
BNT	110%	82%	160%	212%	109%
PRO	217%	108%	226%	332%	171%
RDN	158%	109%	159%	249%	139%
PKT	238%	233%	269%	428%	220%
WABI	191%	143%	132%	272%	149%
SKIN	172%	306%	211%	409%	237%
OST	198%	106%	240%	329%	149%
VIB	175%	111%	119%	238%	129%
DICE	179%	136%	296%	372%	165%
REV	170%	109%	86%	219%	112%
MORE	188%	144%	205%	313%	174%
EVR	263%	713%	622%	984%	548%

VEE	184%	6718%	170%	6722%	2024%
DENT	241%	125%	124%	299%	155%
PRIX	301%	296%	391%	575%	307%
RVT	199%	437%	252%	543%	297%
MGO	182%	219%	274%	395%	221%
SALT	158%	150%	233%	320%	164%
DRGN	175%	124%	163%	269%	145%
FUN	159%	99%	119%	223%	118%
CVC	144%	97%	204%	268%	129%
MNE	302%	458%	626%	833%	460%
SPANK	345%	173%	769%	861%	359%
OPT	866%	472%	243%	1017%	550%
ELTCOIN	361%	671%	350%	838%	475%
TIME	214%	147%	227%	345%	191%
XAUR	142%	138%	161%	255%	140%
LINK	163%	133%	125%	244%	132%
MDA	188%	137%	124%	264%	144%
BLUE	274%	602%	1455%	1604%	734%
SMT	198%	97%	151%	267%	133%
POWR	147%	90%	133%	218%	118%
VGX	190%	125%	177%	289%	160%
PST	242%	197%	183%	361%	205%
B2B	328%	163%	234%	434%	209%
MYB	287%	307%	484%	641%	311%
LOC	198%	99%	129%	256%	129%
ITC	235%	166%	322%	432%	215%
RLC	181%	124%	152%	267%	139%
QASH	138%	97%	124%	209%	112%
GAME	140%	207%	128%	281%	155%
MDS	194%	132%	139%	273%	142%
WINGS	150%	146%	215%	300%	169%
GNO	133%	95%	119%	203%	105%
DPY	177%	198%	166%	313%	181%
GNX	154%	156%	204%	299%	163%
OAX	173%	224%	184%	338%	181%
WRC	244%	548%	769%	976%	515%
NGC	142%	167%	185%	287%	160%

SNT	166%	82%	139%	232%	111%
ERO	215%	530%	342%	667%	387%
IFT	264%	443%	194%	552%	321%
ATL	227%	314%	388%	548%	276%
ZSC	155%	119%	193%	275%	146%
SAN	168%	121%	131%	245%	135%
CAG	186%	125%	297%	372%	186%
GNT	158%	82%	143%	229%	119%
DAT	188%	223%	134%	321%	183%
VOISE	256%	587%	5711%	5761%	971%
IETH	468%	324%	247%	620%	308%
JET	605%	290%	447%	806%	391%
UQC	276%	209%	226%	414%	243%
PRE	227%	259%	217%	406%	209%
PTOY	145%	135%	187%	273%	149%
AMM	254%	293%	213%	442%	253%
SUB	170%	213%	144%	308%	168%
FYP	341%	304%	344%	572%	322%
VERI	178%	184%	234%	347%	193%
REQ	160%	110%	155%	249%	133%
PRA	171%	347%	562%	684%	363%
REAL	343%	490%	306%	672%	361%
SNM	162%	146%	159%	269%	149%
QSP	161%	103%	142%	238%	128%
DRT	197%	296%	415%	547%	277%
DBET	243%	294%	762%	855%	444%
MKR	130%	87%	117%	195%	106%
ANT	143%	109%	151%	235%	126%
TFL	171%	188%	203%	325%	176%
INXT	543%	243%	336%	683%	351%
TKN	177%	189%	135%	291%	167%
DOV	260%	207%	258%	421%	229%
ADX	187%	167%	160%	298%	169%
SNGLS	177%	112%	187%	281%	134%
1ST	173%	210%	218%	349%	183%
MTH	194%	155%	134%	282%	155%
COB	253%	292%	299%	488%	267%

EVC	441%	294%	285%	602%	333%
MCO	154%	90%	156%	237%	113%
STORJ	139%	178%	155%	274%	147%
WTC	174%	106%	132%	243%	127%
PAY	156%	123%	122%	233%	134%
SWT	165%	304%	327%	476%	250%
HGT	433%	396%	201%	620%	336%
LRC	175%	113%	141%	252%	130%
STMX	264%	87%	135%	309%	136%
ELF	175%	95%	194%	278%	136%
HVN	180%	186%	261%	368%	202%
KICK	188%	143%	287%	372%	202%
XUC	90%	90%	195%	233%	113%
NIOX	306%	457%	2483%	2549%	814%
ORMEUS	188%	1041%	188%	1074%	451%
TRST	147%	178%	212%	314%	170%
HMQ	142%	134%	165%	256%	143%
BON	219%	302%	252%	450%	250%
ADT	309%	423%	932%	1074%	427%
DTR	162%	173%	87%	253%	127%
ONG	351%	335%	373%	612%	324%
CND	204%	106%	118%	258%	126%
PPT	159%	116%	148%	247%	127%
SCL	321%	2807%	364%	2849%	1060%
USDT	10%	8%	11%	17%	9%
KNC	151%	117%	126%	229%	127%
BMC	149%	142%	474%	517%	242%
DGD	163%	120%	98%	226%	119%
SUR	184%	241%	942%	990%	367%
PLR	192%	178%	153%	302%	169%
ZRX	163%	86%	119%	220%	116%
LA	166%	151%	190%	294%	149%
DAY	329%	225%	246%	468%	249%
VIBE	472%	125%	134%	506%	159%
UFR	245%	304%	388%	550%	308%
TIX	173%	354%	625%	740%	347%
FUEL	168%	136%	337%	401%	182%

EBTC	273%	336%	1306%	1379%	557%
MLN	168%	123%	171%	270%	149%
FLIXX	251%	176%	302%	430%	220%
ENG	170%	123%	168%	269%	142%
EVX	171%	201%	120%	290%	153%
SNC	188%	187%	152%	306%	164%
MTL	154%	116%	115%	225%	127%
ENJ	173%	195%	116%	285%	152%
TNB	168%	113%	125%	238%	128%
DAM	171%	399%	721%	842%	424%
IND	118%	1215%	493%	1319%	636%
RCN	162%	151%	119%	252%	145%
LUN	193%	110%	164%	276%	136%
IXT	210%	395%	701%	834%	405%
ART	536%	328%	802%	1019%	444%

Table OA.2: Percentage Transaction Fee (continued)

(a) 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

(b) Ether and Tokens on Ethereum

value	Percentage transaction fee of transactions with Ether						Percentage transaction fee of transactions with tokens					
	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	$6.866*10^{22}$	248,677,706

Table OA.2: Percentage Transaction Fee (continued)

(c) DApps and Others

value	Percentage transaction fee of transactions with DApps						Percentage transaction fee of transactions with others					
	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 OA.3: 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 OA.4: 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 2021. 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 R^2	3.8%	3.7%	7.3% (R^2)

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

	Ologit (1) dy/dx	Oprobit (2) 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 OA.5: The Effect of Congestion on Gas Price

This table reports OLS regression results of the log of gas price $ln(GasPrice)$ on both the log of network utilization with a lag of one day $L.ln(NetworkUtilization)$ and the log of network utilization $ln(NetworkUtilization)$ at transaction-level. We employ a generalized linear regression model in Spark Machine Learning (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.

(a) One Day Lag Prediction

Ln(GasPrice)	All (1)	Token (2)	EOA (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	$1.935*10^9$	$3.908*10^8$	$1.290*10^9$	$1.178*10^8$

(b) Contemporaneous Regression

Ln(GasPrice)	All (1)	Token (2)	EOA (3)	SC (4)
Ln(NetworkUtilization)	7.835***	9.693***	6.432***	7.195***
	(0.001)	(0.002)	(0.001)	(0.003)
EthReturn	-0.033***	-0.138***	0.027***	-0.095***
	(0.001)	(0.001)	(0.001)	(0.003)
ln(BlockRewards)	-1.481***	-1.768***	-1.074***	-1.293***
	(0.000)	(0.001)	(0.000)	(0.001)
ln(EthPopularity)	0.356***	0.241***	0.400***	0.409***
	(0.000)	(0.000)	(0.000)	(0.00)
Obs.	748,738,026	248,677,706	448,145,174	51,915,146
AIC	$2.602*10^9$	$7.188*10^8$	$1.638*10^9$	$1.704*10^8$
Null Deviance	$1.935*10^9$	$3.908*10^8$	$1.290*10^9$	$1.178*10^8$

Table OA.6: 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 the 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 the 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)	Lag (1)	Contemporaneous (2)
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	
ln(NetworkUtilization)		1.095***
		0.005
EthReturn		-0.358***
		0.003
ln(MedianGasPrice)		0.060***
		0.000
ln(BlockRewards)		-0.954***
		0.001
ln(EthPopularity)		-0.096***
		0.004
Obs.	748,738,026	748,738,026
AIC	$4.622*10^{9}$	$4.622*10^{9}$
Null Deviance	$2.043*10^{10}$	$2.043*10^{10}$

Table OA.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 a generalized linear regression model in Spark ML library to estimate transaction-level regression, and set the series parameters including Family, Link, MaxIter and RegParam as "binomial", "logit", 10, and 0.3 respectively.

	Lag		Contemporaneous	
Failure	All (1)	Token (2)	All (3)	Token (4)
GasExtra	-0.670***	-0.877***	-0.670***	-0.877***
	(0.000)	(0.000)	(0.000)	(0.000)
Ln(GasPrice)	-0.247***	-0.421***	-0.250***	-0.418
	(0.000)	(0.000)	(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)		
ln(MedianGasPrice)			-0.114***	-0.310***
			(0.000)	(0.000)
EthReturn			-0.007***	-0.008***
			(0.000)	(0.001)
ln(NetworkUtilization)			-0.033***	-0.005***
			(0.000)	(0.001)
ln(BlockRewards)			0.201***	0.301***
			(0.000)	(0.000)
ln(EthPopularity)			0.079***	0.012***
			(0.002)	(0.003)
Obs.	319,679,841	267,764,695	319,679,841	267,764,695
AIC	$1.484*10^8$	$8.842*10^7$	$1.485*10^8$	$8.856*10^7$
Null Deviance	$1.614*10^8$	$1.104*10^8$	$1.614*10^8$	$1.104*10^8$

Table OA.8: Relative Token Returns

This table reports the coefficient and R square of Ethereum-related token returns 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)
$EthReturn^2$	-0.826***	-0.802***
	(0.052)	(0.278)
Observations	171,758	1,094
R-squared	2.1%	64.6%
Number of tokens	157	

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

Table OA.9: The Determinants of Token Exchange Rate Volatility

This table reports the determinants of Ether exchange rate and Ether-related ERC-20 token exchange rate. The first two columns report the OLS regression results of the log of daily Ether exchange rate volatility on the lag of average Ether exchange rate (*L.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), while the last two columns report the regression results of the log of daily Token Exchange Rate Volatility with token fixed effect. The sample period is October 2017 to August 2021.

	Ether Exchange Rate Volatility		Token Exchange Rate Volatility	
	Lag	Contemporaneous	Lag	Contemporaneous
L.ln(NetworkUtilization)	1.724***		0.018	
	(0.190)		(0.030)	
L.ln(FailureRate)	-2.564*		0.397***	
	(1.339)		(0.091)	
L.ln(MedianGasPrice)	-0.103***		0.044***	
	(0.026)		(0.003)	
L.ln(BlockRewards)	0.571***		-0.129***	
	(0.128)		(0.034)	
L.ln(Popularity)	1.237***		0.132***	
	(0.028)		(0.011)	
L.EthReturn	-0.495		-0.008	
	(0.337)		(0.006)	
ln(NetworkUtilization)		4.145***		-0.053
		0.421		0.064
ln(FailureRate)		-3.976**		0.017
		1.236		(0.089)
ln(MedianGasPrice)		-0.109***		0.046***
		0.025		(0.003)
ln(BlockRewards)		0.747***		-0.093**
		0.124		(0.034)
ln(Popularity)		1.237***		0.131***
		0.027		(0.011)
EthReturn		-0.769		-0.193***
		(0.469)		0.011
Observations	1,388	1,388	782,974	782,974
R-squared	0.711	0.731	0.081	0.082
Number of Tokens	1	1	1,297	1,297
Tokens FE	NO	NO	YES	YES
Month and Year FE	NO	NO	YES	YES

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

Table OA.10: Variables Description in the Analysis of EIP-1559 and OmiseGo 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
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.
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.
LnDeviantGasPrice	The log of weekly deviant of gas price.
EthReturn	The average daily return of Ether exchange rate.
LnDifficulty	The log of weekly difficulty of mining blocks.
LnTransactions	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. LnHashRate
The log of weekly average hash rate.	
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 OA.11: 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 (168.514)	53.810 (2048.037)	1.645 (2.907)	5.745 132.336	24.559 (1212.136)	0.993 (2.411)	236,636	236,636
Group2	1.493 (16.865)	4.016 (195.298)	0.772 (1.355)	1.111 (25.213)	2.706 (249.256)	0.501 (1.303)	2,588,965	258,401
Group3	0.716 (1.154)	1.323 (188.411)	0.152 (0.633)	0.638 (5.846)	1.374 (167.762)	0.237 (0.866)	9,786,208	195,659
All	4.796 (99.304)	20.313 (1209.112)	0.896 (2.013)	2.565 (79.075)	9.816 (731.239)	0.594 (1.713)	12,614,467	693,916

Table OA.12: DID—Heterogenous Effects of EIP-1559 on Users' Number of DApps Used Per Week

VARIABLES	(1) 20 weeks	(2) 20 weeks	(3) 10 weeks	(4) 10 weeks
LnBeforeTransactions*Burning	-0.029***		-0.009***	
	(0.001)		(0.001)	
LnBeforeBalance*Burning		-0.006***		0.002
		(0.001)		(0.001)
LnGasprice	-0.001***	-0.001***	-0.001*	-0.001*
	(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)
EthReturn	-0.003	-0.003	-0.013*	-0.013*
	(0.003)	(0.001)	(0.005)	(0.005)
LnDifficulty	0.009***	0.009***	0.012***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)
LnTransactions	0.003*	0.003*	0.023***	0.023***
	(0.001)	(0.001)	(0.005)	(0.005)
Observations	10,091,600	10,091,600	5,045,800	5,045,800
R-squared	0.010	0.002	0.001	0.045
Number of users	252,290	252,290	252,290	252,290
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 OA.13: The Effect of EIP-1559 on the Trading Behavior of Users with Different Trading Frequency

(a) Weekly 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

(b) The Number of DApps Used Per Week

	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

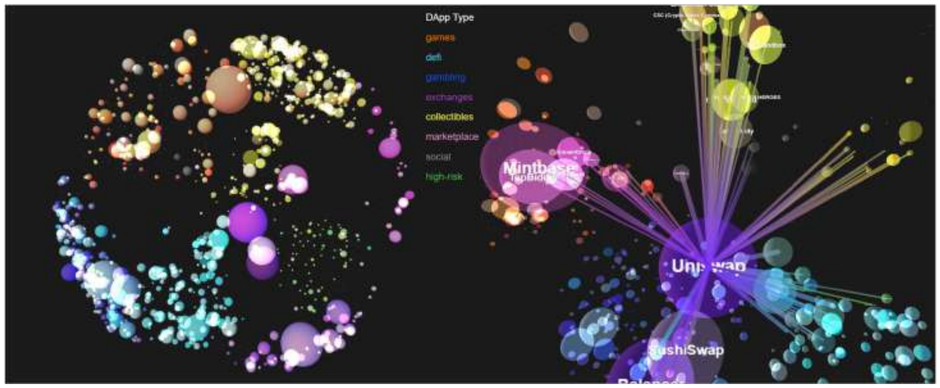
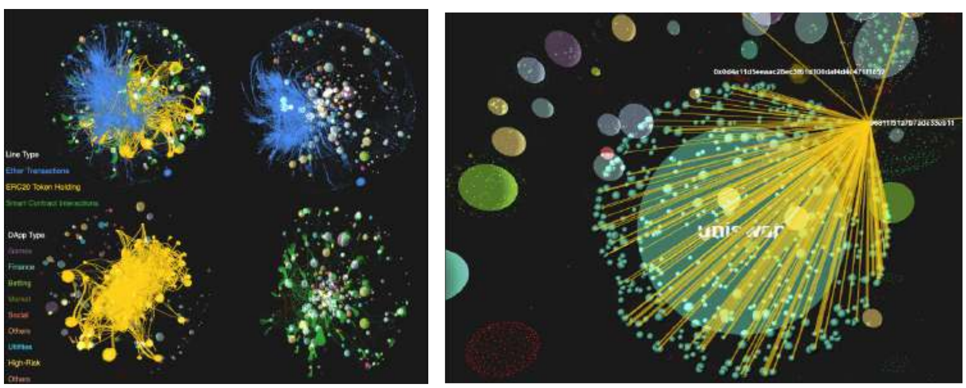


Figure OA.1: User Network among Exchanges and DApps

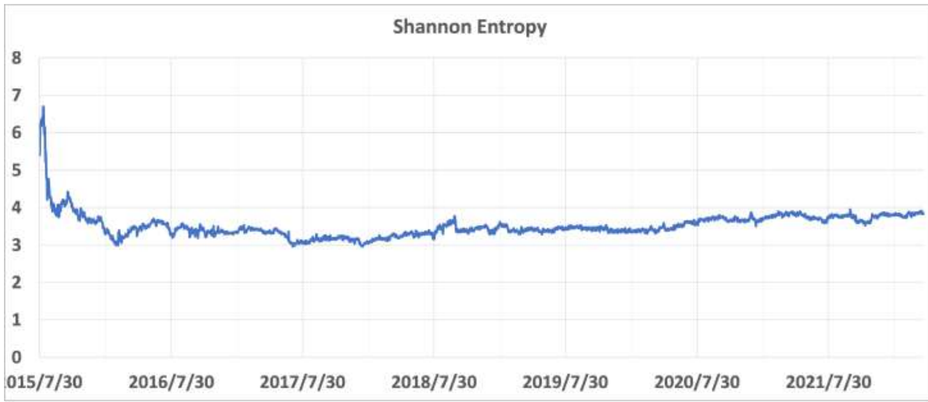


(a) Overall network

(b) Uniswap as an example

This figure shows various types of activities on Ethereum, i.e., Ether 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 colors represent different Ethereum-related activities. The blue line represents trading activities using 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 produced using the Inddigo platform (http://inddigo.io).

Figure OA.2: Ethereum-related activities network

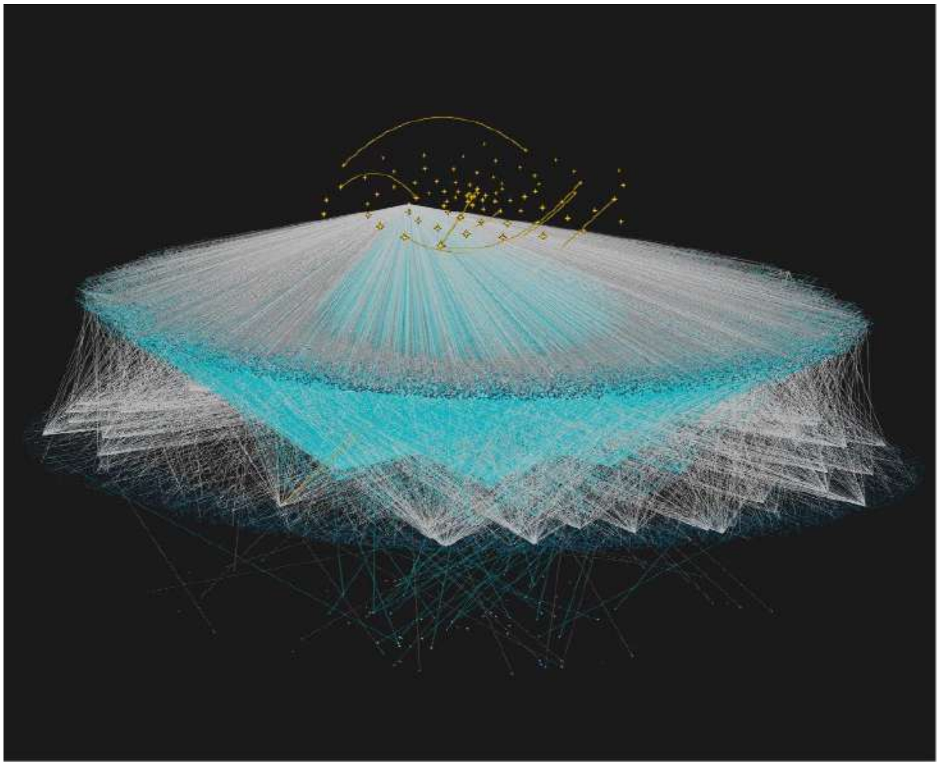


(a) Shannon Entropy for Mining Pools

(b) Gini for Mining Pools

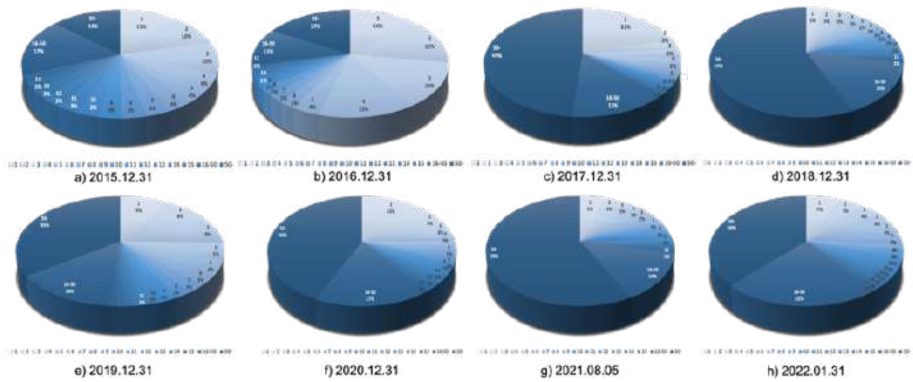
This figure shows the concentration of mining capacity on Ethereum. Panel A and B the daily Gini coefficients and Shannon entropy coefficients at the mining pool's level respectively.

Figure OA.3: The Concentration of Mining Capacity (Continued)



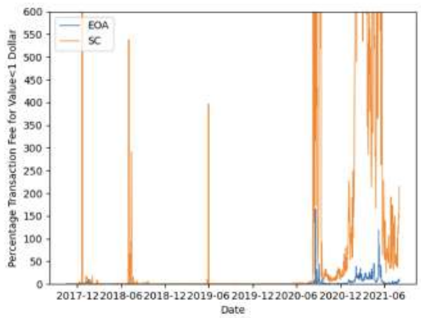
This figure visualizes the tracing process of mining rewards and contains a network of four layers. The lower three layers are miners, miners' primary trading network, and secondary trading network. The dark blue points represent EOA accounts, and the light blue points represent exchanges. The light blue line is the ether flow with EOA accounts, and the dark blue line is the ether flow with exchanges. For better rendering, all nodes of the second and third layer within the top 10,000 (sorted by mining rewards mined) are retained in the visualization, while every 100 EOAs after the top 10,000 are consolidated into a single point. This visualization is produced using the Inddigo platform (http://inddigo.io).

Figure OA.4: The Tracing Process of Mining Rewards

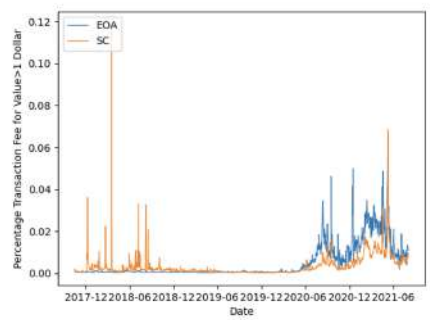


This figure illustrates the evolution of Ether ownership of Users from 2015 to 2022, which includes top 50 users and others ranking by balance.

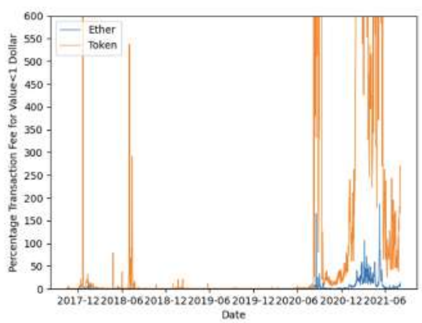
Figure OA.5: The Evolution of Ownership Concentration of Users



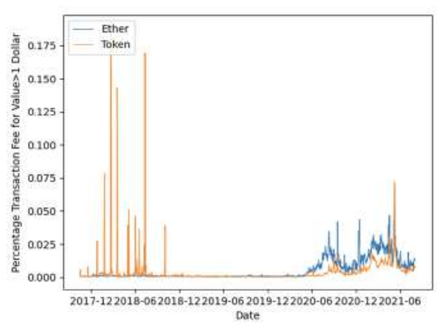
(a) EOA and SC: Value<1



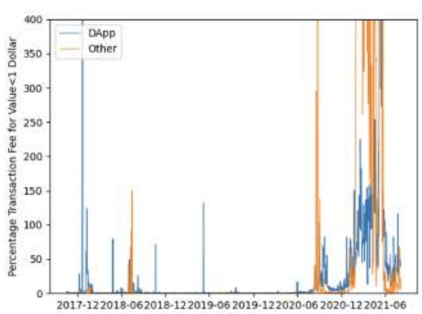
(b) EOA and SC: Value>1



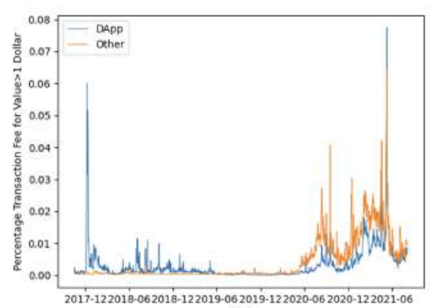
(c) Ether and Token: Value<1



(d) Ether and Token: Value>1



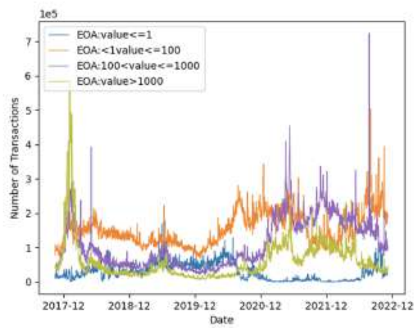
(e) DApp and Others: Value<1



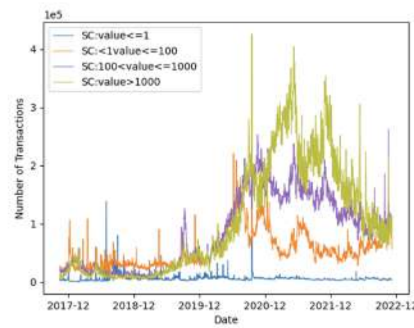
(f) DApp and Others: Value>1

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

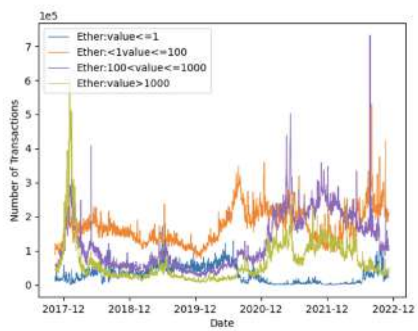
Figure OA.6: Median Percentage Transaction Fee



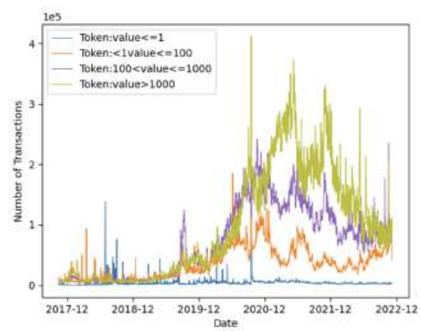
(a) Number of Transactions-EOA



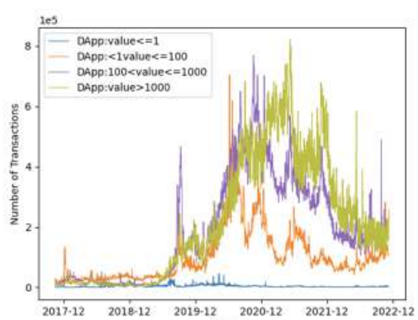
(b) Number of Transactions-SC



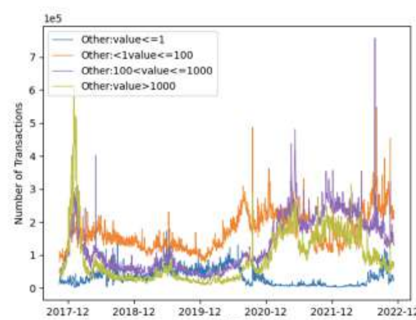
(c) Number of Transactions-Ether



(d) Number of Transactions-Token



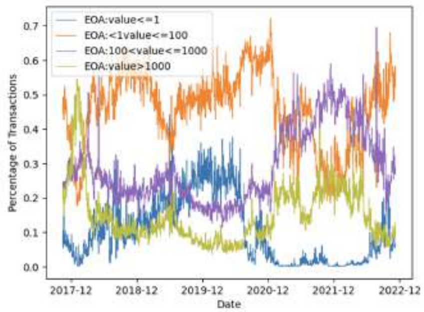
(e) Number of Transactions-DApp



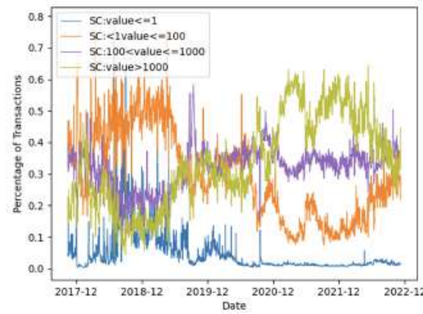
(f) Number of Transactions-Other

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.

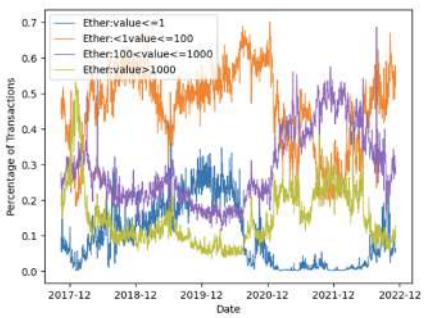
Figure OA.7: Distribution of Transactions by Value



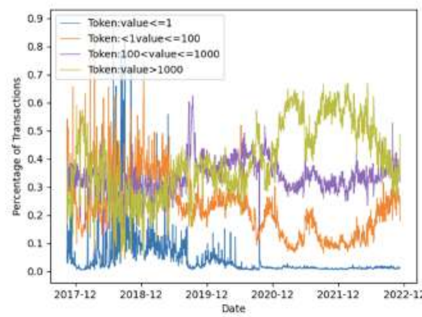
(g) Percentage of Transactions-EOA



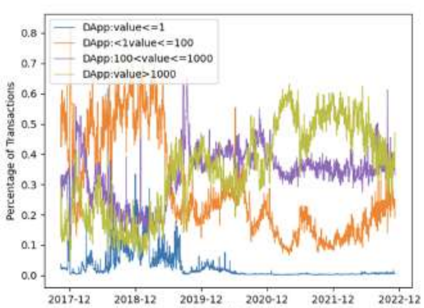
(h) Percentage of Transactions-SC



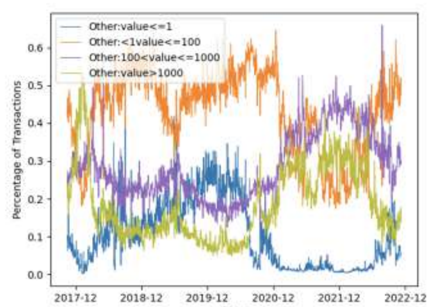
(i) Percentage of Transactions-Ether



(j) Percentage of Transactions-Token

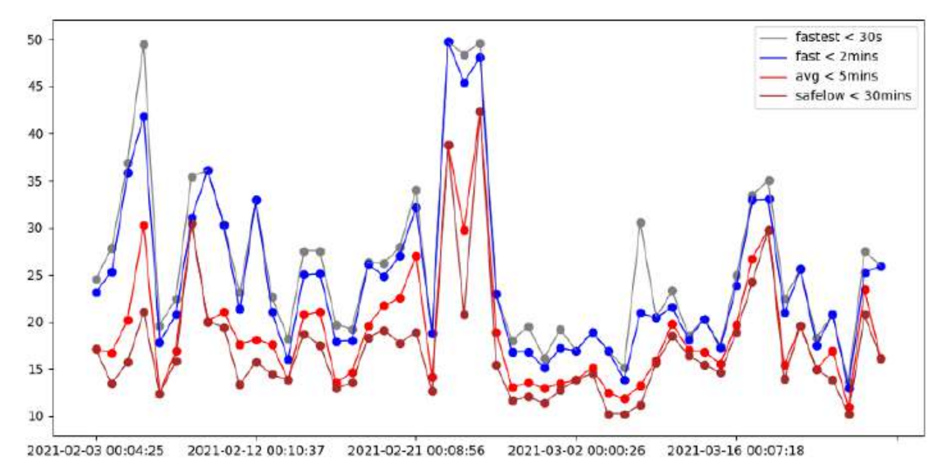


(k) Percentage of Transactions-DApp



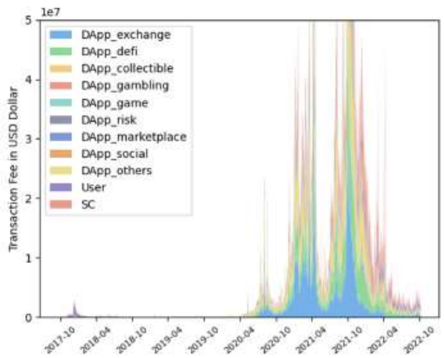
(l) Percentage of Transactions-Other

Figure OA.7: Distribution of Transactions by Value (Continued)

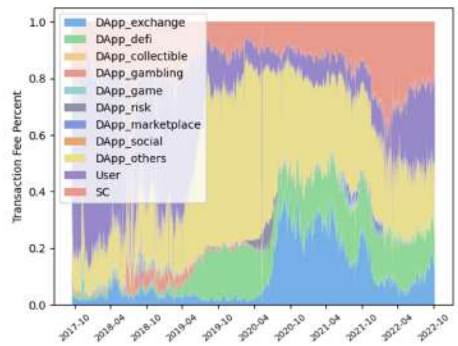


This figure shows the relationship between gas price and delay time. The y-axis represents gas price (gwei), and the x-axis represents date. Each line represents the minimum gas price that one must set in order to successfully complete a transaction within a specified amount of time (0.5, 2, 5, and 30 minutes).

Figure OA.8: Gas Price and Delay Time



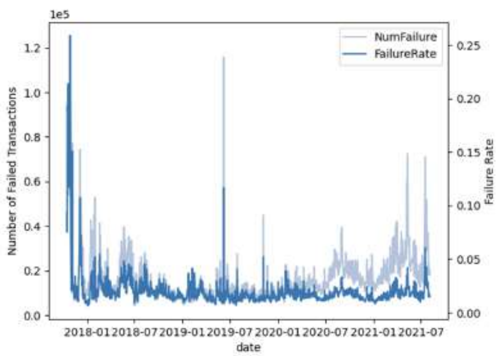
(a) Transaction Fee in USD Dollar



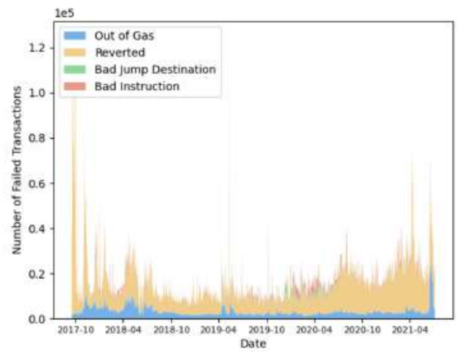
(b) Percentage of Transaction Fee

This figure depicts the 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 dollars.

Figure OA.9: Distribution of Transaction Fee



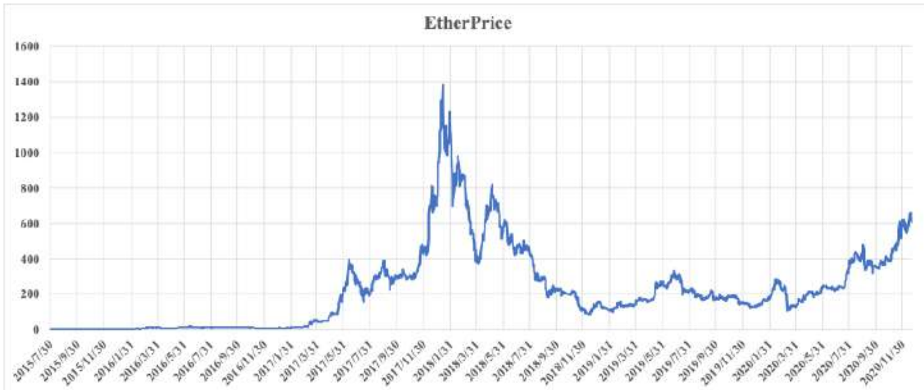
(a) Daily Failure Rate



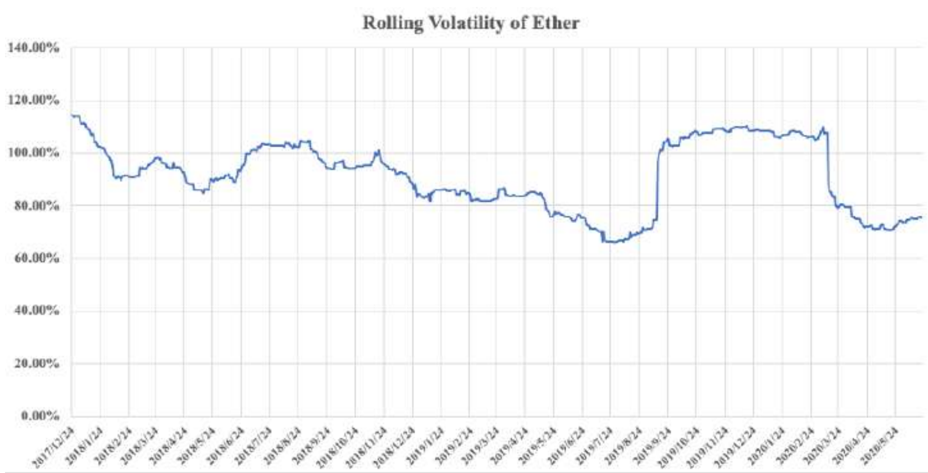
(b) Ratio of different reasons for transaction failure

This figure shows the daily failure rate with its reason for failure. Panel A illustrates daily failed transaction amounts and the failures 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 OA.10: Daily Failure Rate



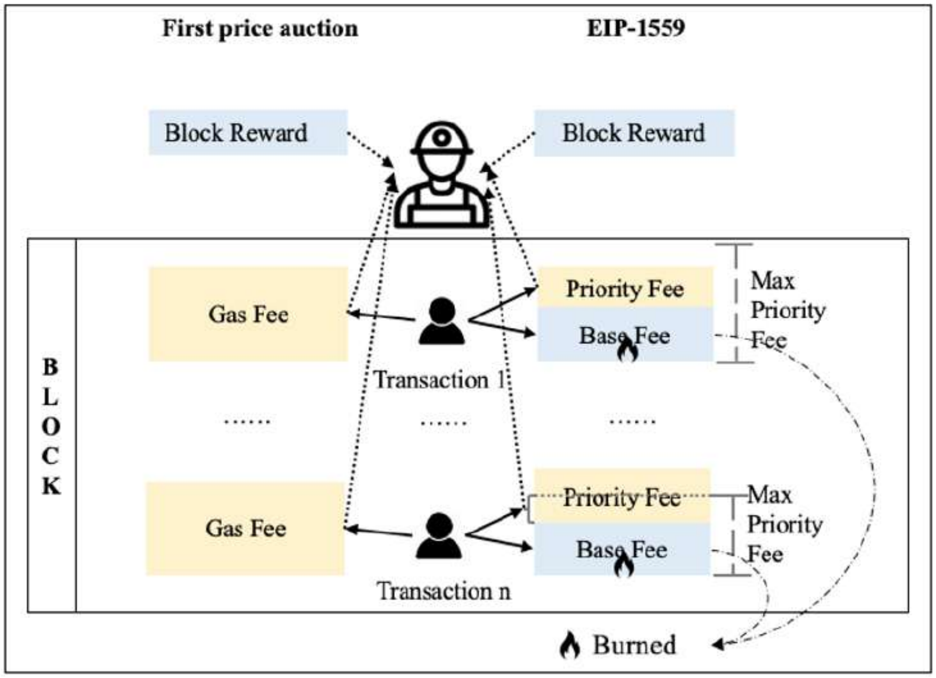
(a) Daily Price of Ether



(b) Rolling Volatility of Ether

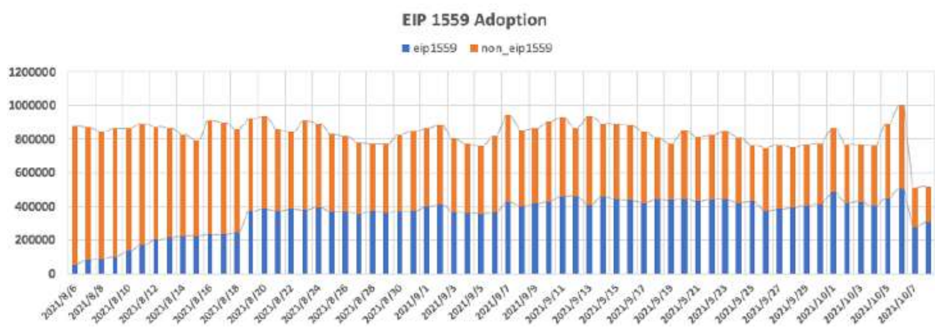
This figure depicts the daily price and rolling volatility of ether. Panel A depicts the daily ether price from August 2015 to December 2020, with the y-axis representing the daily Ether to US dollar exchange rate. Panel B depicts annualized volatility of ether from December 2017 to December 2020, using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

Figure OA.11: Daily Price and Rolling Volatility of Ether

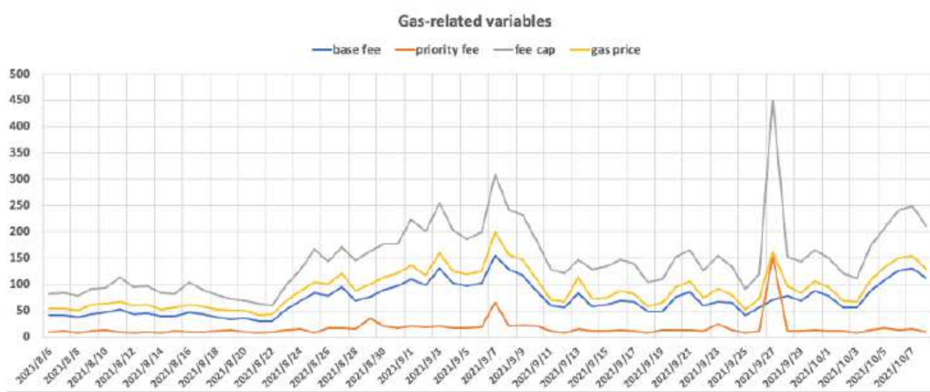


This figure compares the transaction fee mechanism in the form of the first price auction before the launch of EIP-1559 with the transaction fee mechanism under EIP-1559.

Figure OA.12: Comparison between EIP-1559 and First Price Auction



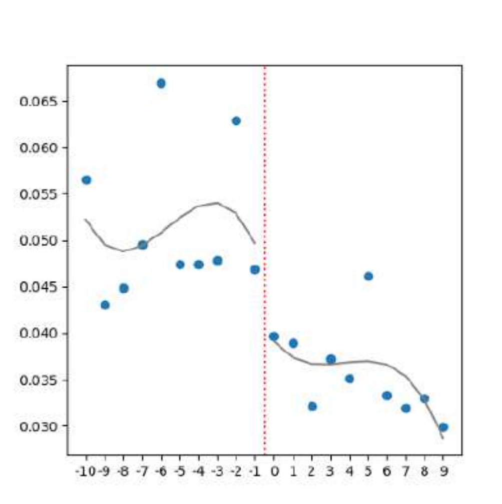
(a) The Adoption of EIP-1559



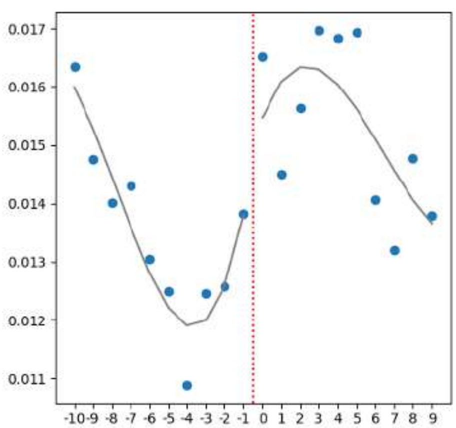
(b) Gas-related Variables under EIP-1559

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.

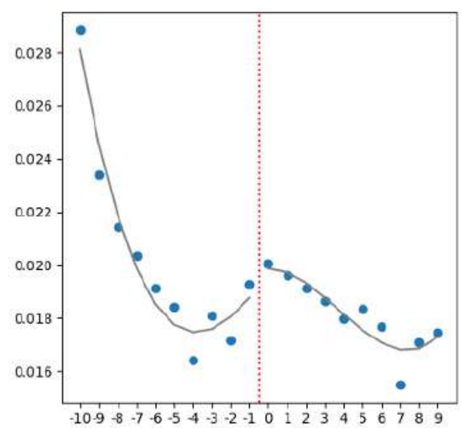
Figure OA.13: EIP-1559 Adoption and Gas-related Variables under EIP-1559



(a) The Log of Weekly Mining Rewards



(b) The Log of Weekly Transaction Volume



(c) The Log of Number of Weekly used DApps

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 OA.14: Discontinuity in Mining and Trading Around EIP1559