Non-native tokens and price discovery

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The unrelenting growth in blockchain functionality drives greater adoption and, therefore, ensures the security of transaction settlement. We show that the wider adoption carries its own risk for the blockchain. Specifically, when a large fraction of blockchain transactions involves non-native tokens, the cost of price discovery in the native cryptocurrency increases. This, in turn, leads to lower trade informedness and price efficiency. In a difference-in-differences setup, we find that a shock to non-native transactions typically leads to 1.25 bp of unrealized informed price movement and a 0.60% decrease in price efficiency in the underlying cryptocurrency. Our findings lend support to the theoretical literature arguing that multiple attack vectors on blockchain arise from native cryptocurrency mispricing.

Keywords: Blockchain, Non-native tokens, Price discovery, Decentralized exchange, NFT Airdrops

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1. Introduction

Decentralized ledgers enable the transfer of value in both native and non-native tokens. However, blockchain processing capacity is inherently constrained. These constraints lead to higher transaction costs and increased failure rates (e.g. Capponi et al. (2025) and Zhao (2024)). We demonstrate that such frictions hinder price discovery in native cryptocurrency markets, leading to less efficient pricing. Several theoretical studies argue that price discovery and price efficiency in the native cryptocurrency are essential for blockchain stability.[1] As such, our paper is the first to establish the link between the proliferation of non-native tokens and the blockchain vulnerability highlighted in the theory.

We utilize a comprehensive dataset of NFT airdrops on the Ethereum blockchain to show that non-native tokens can have a significant impact on the native cryptocurrency. We choose NFT tokens as our non-native asset class for our empirical investigation because, according to the digital art literature, their creation is primarily driven by social demand for memes, rather than being strategically timed in response to fluctuations in transaction costs associated with token distribution.

Tokenization of non-native cryptocurrencies constitutes a dramatic improvement in blockchain functionality. Compatibility with a versatile range of applications mitigates concerns about blockchain underadoption. Wide blockchain adoption facilitates validator consensus (Cong and He, 2019), enhances coordination among users (Li and Mann, 2024), increase cryptocurrency

[1] Cong, He, and Tang (2022), John, Rivera, and Saleh (2024), Hinzen, John, and Saleh (2022), Budish, Lewis-Pye, and Roughgarden (2024), Pagnotta (2022).

valuation (Cong, Li and Wang, 2021; Pagnotta, 2022; Cong, Tang, Wang and Zhao, 2023; Kogan, Makarov, Niessner and Schoar, 2024) and lowers its volatility (Lyandres, Palazzo and Rabetti, 2022). The intense adoption of blockchain, however, can make price discovery more costly. When non-native token transactions compete for execution with the native ones, the blockchain transaction fees increase. This increases the frictions for transactions executed on decentralized crypto exchanges. To the best of our knowledge, our paper is the first to empirically measure these negative externalities of blockchain over-adoption on native tokens.

Hinzen, John, and Saleh (2022) provide a theoretical argument that blockchain adoption has a limit when a marginal increase in fees leads to the exit of incumbent users. In line with this, Sokolov (2021) shows that ad hoc users create blockchain congestion and drive down participation by regular users, who are active over a long period of time. This may be an issue for a blockchain if equilibrium transaction fees are insufficient to reward block validators. The typical response to the adoption limit is to enhance the blockchain's functionality so that one can not only transact in the native cryptocurrency but also in non-native tokenized assets via smart contracts. In the models of Cong, Li, and Wang (2021) and Prat, Danos, and Marcassa (2025), the fundamental value of native cryptocurrency tokens is defined by transactional and speculative demand for these tokens. As such, a token suitable for a wide variety of applications should have greater value. There are, however, risks to increasing a blockchain's functionality. For example, Liebi (2021) shows that users may abandon the old blockchain if a new, more functional token becomes available through a chain fork. Furthermore, the substitution effect described by Gandal and Halaburda (2020) implies that wider cryptocurrency adoption for speculation may encourage cryptocurrency users to seek alternative cryptocurrencies for transaction purposes due to their lower cost.

We argue that adopting new functionality introduces an additional channel of risk for the original cryptocurrency. While Halaburda (2016) and Liebi (2021) suggest that the original cryptocurrency may be harmed when users abandon the old blockchain and migrate to a forked chain, we show that even without migration, non-native tokens on the original blockchain can impair price discovery in the native token.

Our empirical exploration involves three steps. First, we take advantage of the scalability difference between Ethereum and Polygon to demonstrate that NFT airdrops on the Ethereum blockchain contribute to congestion costs. While both Ethereum and Polygon blockchains allow deploying airdrops, Polygon is designed to scale more efficiently than Ethereum, and therefore, it is less prone to congestion.[2] We rely on this feature to conduct a difference-in-differences analysis. Our findings indicate that NFT airdrops increase transaction volume and transaction costs on the Ethereum blockchain. A one standard deviation shock in the number of NFT transactions leads to a total increase of Ethereum blockchain transactions by 2.04% per block, which results in a 4.72% spike in the average fee per block. Moreover, we observe that NFT airdrops lead to a higher number of transactions that failed. Specifically, NFT airdrop shocks increase the transaction failure rate by 0.05% (the unconditional failure rate is 2.95%). We also observe that NFT airdrop shocks lead to a higher number of pending blockchain transactions that end up bidding fees that are not competitive given the level of blockchain congestion.[3] All these results indicate that non-native transactions, such as NFT airdrops, increase blockchain transaction costs, both in the form of higher transaction fees and the number of transactions that fail.

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[2] Layer 2 Demystified: How Polygon Scales Ethereum
[3] We do not report this observation in the main analysis. The statistics are available on request.

We show that NFT airdrops on Ethereum reduce the trade informedness of the native cryptocurrency. When the NFT airdrop activity increases, the trades on decentralized exchanges become more costly. This is because Ethereum-based decentralized exchanges, such as Uniswap, have to compete with NFT airdrop transactions for space on the blockchain. Consistent with this, we observe that price impacts decline when NFT airdrop shocks occur. This effect remains visible up to five days. The total average decrease in price impact after one day of a one standard deviation NFT airdrop shock is 3.09 bp.

Capponi, Jia, and Yu (2025) find that public mempool orders with high-priority fees are more informed compared to orders bidding a lower-priority fee, and this finding is robust to the introduction of private mempools. We hypothesize that when the blockchain transaction costs increase, informed trading becomes more expensive. Informed trades with low time sensitivity and information content may become unprofitable. In this case, the users are less likely to rely on private mempools. Consistent with this, our findings indicate that NFT airdrops lead to a lower utilization of the private mempool.

Finally, we explore whether the decline in trade informedness leads to mispricing. If a significant amount of informed trading is not realized due to high blockchain fees, the prices on Uniswap may deviate from those on conventional centralized exchanges, such as Binance. Indeed, we find that NFT airdrops lead to a higher share of price discovery on centralized exchanges than on decentralized exchanges. Consistent with lower price informedness, the bursts of NFT airdrops lead to lower price efficiency of the Ethereum cryptocurrency as measured by the variance ratio and price delay. The average economic significance of a one standard deviation shock to the NFT airdrops is a 1.23 % decline in price efficiency.

2. Why does price discovery in native cryptocurrency matter?

Financial markets facilitate price discovery by allowing informed traders who trade based on superior knowledge about an asset's fundamental value to mix in with the uninformed ones who provide liquidity and trade for reasons unrelated to fundamental value, such as allocation motives, portfolio rebalancing, or noise trading (Kyle, 1985 and Glosten and Milgrom, 1985). O'Hara (2003) underscores that deviations from the fundamental price pose a concern for investors.[4] In cryptocurrency markets, price discovery is influenced not only by informed and uninformed traders but also by the security of the trustless consensus mechanism that underlies the blockchain network.

Multiple vectors of attack on blockchain arise from the native cryptocurrency mispricing. Cong, He, and Tang (2022) and John, Rivera, and Saleh (2024) emphasize that the ability to borrow a native token by an attacker is a vulnerability of proof-of-stake blockchains like Ethereum. For example, when the native token is undervalued, the cost of borrowing coins decreases, thereby increasing the likelihood of the attack. Wider blockchain adoption typically implies a higher price for the native cryptocurrency, and hence stronger security. However, our paper illustrates that the versatility of blockchain adoption for uses such as NFT airdrops may harm price discovery in the native token. Consistent with the literature, this may constitute a higher risk for the native token.

[4] Price discovery also affects corporate decisions, such as budgeting (Baker, Stein, and Wurgler, 2003, Chen, Goldstein, and Jiang, 2007) and managerial incentive structuring (Holmström and Tirole, 1993).

The quick reaction of the price of a native token to a double-spending attack is critical for the security of both proof-of-stake and proof-of-work blockchains (Budish, Lewis-Pye, and Roughgarden, 2024). If, however, the price discovery is limited, the attacker may be able to dispose of their holdings before the information about the attack is incorporated into the price. While a successful double-spending attack remains a hypothetical scenario involving a discrete price shock, weak price discovery can undermine blockchain security, particularly when the blockchain's security and the price of its native cryptocurrency are jointly determined, as in Pagnotta (2022). Consequently, if broader blockchain adoption impairs the price discovery of the native token, it may increase the blockchain's vulnerability to such attacks. In the following section, we describe the link between the Ethereum validation process, congestion caused by non-native tokens, and price discovery in the underlying cryptocurrency.

3. Stacking, congestion and price discovery

In this section, we describe the institutional details of Ethereum cryptocurrency price discovery and Ethereum blockchain functionality. Our sample starts in September 2022, after Ethereum blockchain migrated from proof-of-work to proof-of-stake validation mechanism. This transition affected both the underlying security mechanism and the type of participants in the Ethereum validation process.

At a glance, the process of incorporating transactions into the Ethereum blockchain takes the following steps. Under the proof-of-stake protocol, an Ethereum holder may commit the stake to the block validation process and thus become an Ethereum staker. The minimum amount staked is set at 32ETH, although the stakers often aggregate their holdings in the pools, which allow contributions in fractions of a minimum value. Then the new stakers have to enter the queue to become active validators. There is no limit on the number of active validators, yet the Ethereum protocol limits the number of stakers that can enter and exit the list of active validators per unit of time, called an epoch.

One epoch lasts 384 seconds and produces 32 new blocks with an interval of 12 seconds per block. The validators who are active during each epoch take two roles: attestors and proposers. The proposers are the 32 validators who are randomly selected at the beginning of an epoch to propose one block each. Another subset of validators is selected to become attestors. The proposer has the authority to determine the composition of the block, while the attestors take a limited role and only vote on the validity of the proposed block.

The proposers typically delegate the block construction to separate entities, called block builders. These builders are sensitive to transaction fee incentives that keep the Ethereum blockchain running. The more competitive the builders are, the higher their bids to proposers to include the block into the blockchain. This makes builders the central entities of our analysis. Although the role of validators is crucial in the proof-of-stake consensus mechanism, it has a mechanical nature. In contrast, builders stay at the forefront of biochanin technology running bots through the mempool in search of the most optimal transaction composition. Moreover, builders often maintain private mempools for users who prefer their transactions to remain undisclosed until they are included in a block. As such, our empirical analysis relies on the panel of builders rather than validators.

Once a proposer chooses a block with the winning bid, the builder relays the selected block to the proposer. The builder's bid goes to the proposer, and in return, the builder receives the sum of transaction fees as well as arbitrage and liquidation values extracted from Ethereum-based financial markets. The transaction fees are coming from users who incentivise builders to include their transactions in the block. The blockchain capacity constraints define the competition among users for space in the block. When demand for Ethereum transactions spikes, users have to attach higher fees to have their transactions picked up by builders and eventually relayed to the proposer. Since the transactions involving buying or selling Ethereum ERC-20 tokens on decentralized exchanges have to be recorded in the blockchain, the higher blockchain congestion may lead to a higher cost of price discovery in the underlying Ethereum cryptocurrency.

The proliferation of transactions involving non-native tokens on the Ethereum blockchain implies higher overall demand for transactions and thus has the potential to hinder price discovery and disrupt the price efficiency of the native token. One variety of non-native transactions is an NFT airdrop. The next section provides the rationale for using this particular type of transaction for studying the effect of non-native transactions on price discovery in the underlying cryptocurrency.

4. NFT airdrops

The main independent variable in our empirical setup is the number of NFT airdrops. NFTs are non-native tokens that serve as proof of ownership in digital art. In order to proceed with our empirical investigation, it is crucial to articulate that among all the non-native tokens, NFT is the best class of instruments to study the reaction of the native coin price discovery to the proliferation of the non-native tokens. This claim is supported by the literature, which shows that, like other forms of art, NFTs emerge in response to social demand for this medium of artistic expression rather than as an endogenous reaction to blockchain market frictions.

The vast scholarship on the inception of art rests on the concept of *the sublime*, the aesthetic greatness so intense that the human mind can not express it in a form other than art. In the metaphysical works of Burke and Kant, the sublime emerges when a human mind is confronted with an incomprehensible and overawing reality. In line with this, Serada, Sihvonen, and Harviainen (2021) and Dylan-Ennis (2024) argue that NFTs have a unique ludic culture that aims for creative experimentation. That is, airdrops are likely to occur when the community creates a collection of graphical images timed to express the sublime (for instance, in the form of a meme) rather than to the change in the distribution cost. Consistent with this, Borri, Liu and Tsyvinski (2023) find that NFT markets have limited exposure to common cryptocurrency and traditional asset price fluctuations. The social timing of NFTs provides an opportunity to test how the proliferation of non-native transactions, in the form of NFT airdrops, affects price discovery in the native token.

Indeed, NFTs have revealed their potential to disrupt the Ethereum blockchain and increase transaction costs. For example, CryptoKitties NFT at its peak popularity has led to a six-fold increase in transaction waiting time on the Ethereum blockchain (Kräussl and Tugnetti, 2024). This spike in popularity was caused by the cultural appeal of the NFT-based game rather than being timed to a low transaction cost. Consistent with this, another subclass of tokens, dynamic NFTs, has been developed to trigger minting based on the outcomes of sports events, election results and video games.[5]

To identify NFT airdrop activity, we examine the input field of blockchain transactions and find those that call smart contract functions commonly used by NFT airdrops. The largest and most prominent NFT marketplace is OpenSea, which uses a procedure called SeaDrop for NFT airdrops. According to SeaDrop's Github page, most essential smart contract functions for the procedure are *mintpublic*, *mintallowlist* and *mintseadrop*. Furthermore, NFT airdrops also heavily rely on the function *freemint*. Therefore, we search for transactions that call these four functions and classify them as NFT airdrops.

Figure 1.a shows an example of an NFT airdrop transaction that uses the *mintpublic* smart contract function on the Ethereum blockchain. This transaction carried an NFT from the '90s Kids collection.[6] The '90s Kids collection was inspired by the trends of the 1990s, 2000s and skateboard culture. Figure 2 shows the distribution of NFT airdrop transactions over the sample period. We discuss the sample construction and methodology in the next section.

[Figure 1]

[Figure 2]

5. Data and methodology

[5] https://cointelegraph.com/explained/what-are-dynamic-nfts-use-cases-and-examples
[6] 90's Kids 0.0042 ETH - Collection | OpenSea

Our sample period is from November 1, 2022, to May 31, 2023. We obtain blockchain data from Google's Blockchain Analytics hosted through BigQuery. Lyandres and Zaidelson (2024) compare Ethereum and Polygon blockchains and show that decentralized exchange market efficiency facilitates allocation of capital to its most profitable uses. We collect information for each block, transaction, and event on the Ethereum and Polygon blockchain from Google's database.

Polygon blockchain is a suitable match for the difference-in-differences setup because it experiences similar cycles of boom and busts in transactions as the Ethereum blockchain, yet it is designed to scale more efficiently than Ethereum, and therefore, it is less prone to congestion. Specifically, Ethereum 2.0 can handle a maximum of 119 transactions per second, whereas Polygon's capacity exceeds 65,000 transactions per second. Figure 3 illustrates that transaction intensity on Polygon and Ethereum follows a common trend. Thus, by matching builders on the Ethereum blockchain with those on the Polygon blockchain, we can estimate the difference-in-differences effect of an increase in non-native usage on the Ethereum blockchain.

[Figure 3]

We proceed by calculating the following variables to examine the impact of NFT airdrop intensity on on-chain transaction volume and costs. *Transactions* is the total number of blockchain transactions. *FeePerBlock* is the transaction fee per block. *FailRate* is the number of failed transactions divided by the total number of transactions.

We rely on Uniswap DEX transactions to measure price impacts. The primary reason for this choice is that traders on DEX incur blockchain costs to execute transactions (Capponi, Jia, and

Yu, 2024). Therefore, such trades will be the most susceptible to the overadoption mechanism described in the paper. The second reason is that trades on DEX tend to be more transparent, whereas trades reported by CEX are subject to manipulation (Cong, Li, Tang and Yang, 2023) and measurement errors (Schwenkler, Shah and Yang, 2025).

To examine price discovery, we calculate price impacts of swap transactions of non-native tokens. More specifically, we examine transactions and event data and identify on-chain token swaps. For each swap transaction, we calculate the price impact after time T as:

$$Price\ impact_T = D(Ln(Price_T) - Ln(Price_0))$$

where $Price_0$ is the token transaction price, $Price_T$ is the token price after time T, and D is an indicator variable that equals +1 if the token is swapped into the account and -1 if it is swapped out of the account. We calculate price impacts using a range of time intervals after the transaction.

We start by calculating the variables above for each block on the Ethereum and Polygon blockchains. Then, we aggregate the variables on the builder-day level for each blockchain. To construct the builder-day panel data for the difference-in-differences regressions, for each day during the sample period, we perform a one-to-one match between the most active builders on the Ethereum blockchain and the Polygon blockchain. Builders compete for blocks, and the most active builders mine the majority of all blocks. Our matched sample includes 147 miners who mined 89% of the blocks on the Ethereum blockchain and 95% on the Polygon blockchain. We then calculate the differences between each pair of builders for the variables.

Additionally, we use Uniswap data to calculate two control variables that capture the on-chain trading conditions of Ethereum. *EthVolatility* is the difference between the high and low prices, divided by the midpoint, for each block. *EthVolume* is the total trading volume during each block. Table 1 presents the summary statistics for the variables.

[Table 1]

6. Results

6.1 Non-native tokens, blockchain congestion and transaction costs

Non-native tokens occupy space on the blockchain and compete for the limited block capacity. Among these non-native tokens, NFTs satisfy society's demand for proof of ownership in digital art. The metaphysics of art presumes that the art emerges when a human mind experiences a spontaneous need for artistic expression. Therefore, the creation of NFTs would cause spontaneous spikes in the number of blockchain transactions. However, if the creation of NFTs is delayed to periods of time when the blockchain is less congested, the higher NFT activity would be accompanied by troughs in the total number of blockchain transactions. We, therefore, begin by examining whether NFT airdrops are causing a surge in the total number of transactions.

Specifically, we estimate the following difference-in-differences regression.

$$\Delta DepVar_{it} = \alpha + \beta_1 \Delta NFTAirdrop_{it} + \beta_2 EthVolatility_{it} + \beta_3 EthVolume_{it} + \varepsilon_{it}, \qquad (1)$$

where $\Delta DepVar_{it}$ is the difference between the number of transactions on Ethereum and Polygon blockchains, $\Delta NFTAirdrop_{it}$ is the difference between the number of NFT airdrops transactions on Ethereum and Polygon blockchains, and $EthVolatility_t$ and $EthVolume_t$ are control variables that capture the trading condition of Ethereum in the off-chain market. In the panel data, the subscript i corresponds to the cross-section of blockchain builders, and t corresponds to the date.

Table 2 shows that NFT airdrop activity increases the total number of transactions. A one standard deviation shock to the number of NFT airdrops typically increases the total number of transactions by 2.67 (2.04 %) per block. Figure 4 shows the effect of two standard deviation shocks to NFT airdrop activity on the number of transactions on the Ethereum blockchain. These results indicate that transactions with non-native instruments, such as NFT airdrops, cause an increase in the total number of transactions. This is consistent with the spontaneous nature of artistic expression, which is exogenous to the availability of space in the block. The NFT airdrop activity is defined by the social events that lead to artistic expression, while the demand for the native Ethereum cryptocurrency follows the economic trend.

[Figure 4]

[Table 2]

We proceed by exploring whether the spikes in transactions caused by NFT airdrops lead to higher transaction costs on the Ethereum blockchain. These costs may be observed in two forms. The first form is the transaction fee attached to transactions that are successfully included in a block. The higher number of pending transactions due to NFT airdrops increases the competition for space in a block and thus may raise the required fee for a transaction to be included in the block. The second form of the blockchain transaction cost is the number of failed transactions. As the congestion intensifies and the required transaction fee increases, more and more users will fall short of attaching the significant fee. This may result in a failed transaction record in the blockchain.

We follow the difference-in-differences specification (Equation 1) to test whether transaction costs increase during NFT airdrop spikes.

Table 3 presents the results on transaction fees. The estimated coefficients for the NFT airdrop variable in all specifications are positive and statistically significant, indicating that the higher NFT airdrop activity increases the required fee for a transaction to be included in a block. The estimated coefficient of 0.049 in specification (4) indicates that a one standard deviation positive shock to the number of NFT airdrops increases the average fee per block by 0.02 (4.72%) Ether.

[Table 3]

Table 4 shows that the results on transaction fail rate are in line with the results on transaction fees. Specifically, the estimated coefficient of 0.37 in specification (4) indicates that a one standard deviation positive shock to the number of NFT airdrops increases the fail rate by 0.05 % (the unconditional fail rate is 2.95 %). Therefore, our difference-in-differences analysis indicated that non-native transactions, such as NFT airdrops can make transactions on the native blockchain more costly.

[Table 4]

6.2 Non-native tokens and private transactions

We begin by examining whether spikes in NFT airdrops affect the number of private blockchain transactions. Such transactions originate from a private mempool that conceals sensitive price information from the public until the transaction is processed. We hypothesize that when the capacity constraints increase, informed trading becomes more expensive. As a result, the informed trades with low time-sensitivity and information content may become unprofitable. In this case, the users are less likely to rely on private mempools. Moreover, the binding capacity constraints may lower utilization of the private mempool because builders will prioritize public mempools over their private mempools when the fees on the public mempools increase. The less widespread use of private mempool during the surge of public mempool transaction costs is one of the mechanisms for decreased price discovery. This is because some of the informed transactions that would originate from the private mempool do not materialize.

The indication of an increased number of private transactions can be obtained from public mempool data and blockchain transactions. We identify private transactions by merging the public mempool data from Blocknative with the Ethereum blockchain data. These merged data contain all proposed transactions that entered the public mempool as well as all executed transactions. If an executed transaction on blockchain has never appeared in the public mempool, we assume that it is likely to be a private transaction. Since the data are only for the Ethereum blockchain, we cannot use the difference-in-differences approach. Table 5 shows the results. The estimated coefficients for the NFT variable in all specifications are negative. The coefficients for the NFT dummy in specification (4) are statistically significant, indicating that a higher NFT airdrop activity reduces the number of private transactions. This finding further confirms that the number of private transactions decreases when blockchain costs rise due to a surge in non-native transactions.

[Table 5]

6.3 Non-native tokens, price discovery and efficiency

In this section, we investigate whether non-native tokens, in the form of NFT airdrops, impact price discovery in the underlying native cryptocurrency. As the number of pending transactions increases, block builders are forced to prioritize those offering the highest fees. For example, arbitrage swaps (Capponi and Jia, 2025) and frontrunning transactions in decentralized exchanges (Capponi, Jia, and Wang, 2025) must compete for inclusion with all other transaction types. This congestion may deter informed traders from submitting transactions altogether or lead to outright settlement failures. As a result, price discovery in ERC-20 token swaps becomes less efficient. We hypothesize that non-native tokens can impede information revelation, hinder price discovery and lower price efficiency in the native token.

When the competition for the block space increases, it becomes more costly to enter a transaction into a block. This must affect price discovery on decentralized exchanges because token swaps have to be recorded on the blockchain. While high blockchain transaction fees are likely to affect both native and non-native token swaps, we focus on the swaps involving transactions in the native Ethereum token because of the implications of Cong, He, and Tang (2022) and John, Rivera, and Saleh (2024), who emphasize the vulnerability of the blockchain's security due to native cryptocurrency mispricing.

We rely on the difference-in-differences specification in Equation (1) to test whether the non-native tokens affect price impact in the underlying native cryptocurrency. Table 6 reports the results. The estimated coefficients become negative and statistically significant after 10 hours, implying that higher NFT activity leads to a decrease in price impacts and, therefore, less informed prices.[7] The economic effect is 3.18 bp within the first 10 hours after a one standard deviation NFT airdrop shock. This effect is 3.09 bp after one day and remains visible up to three days. The total average decrease in price impact after three days of a one standard deviation NFT airdrop shock is 2.54 bp. Recall that a one standard deviation shock to the number of NFT airdrops typically increases the total number of transactions by 2.04 % per block. A such, the reduction of capacity by 1% typically leads to 1.25 bp of unrealized informed price movement.

[Table 6]

To examine the impact of non-native tokens on price efficiency, we calculate the variance ratio and price delay measures using a token pair-day panel data. More specifically, we obtain intraday token pair price data from Binance for pairs that had over 100,000 transactions during our sample period. For each token pair-day, we calculate two measures of price efficiency for pairs that had over 100,000 transactions during the sample period. The variance ratio is calculated with the variances of intraday returns using different intervals.

$$Variance\,ratio = \left|1 - \frac{\sigma_{k\times l}^2}{k \times \sigma_l^2}\right|$$

where (l, $k \times l$) is (30s, 300s), (60s, 300s), or (150s, 300s). To calculate the price delay, we run the following regression:

[7] The long-lasting effect of high execution costs on price impacts is in contrast with the equity markets, where information revelation occurs in milliseconds. The decentralized exchanges do not rely on the limit order book, which makes the price discovery more spread out in time.

$$ret_l = \alpha + \beta ret_{m,l} + \sum_{\tau=1}^{10} \gamma_\tau ret_{m,l-\tau} + \varepsilon_l$$

where ret_l is the token pair return during the time interval l (in seconds) and $ret_{m,l}$ is the return of the S&P 500 index proxied by the ETF SPY. We define R_u^2 (R_c^2) as the R^2 from the above regression when estimated with (without) the lagged market returns. Then:

$$Price\ delay = 1 - \frac{R_c^2}{R_u^2}$$

Table 7 presents the results on price efficiency. The estimated coefficients for the NFT variable indicate that the more intense NFT airdrop activity decreases price efficiency. The average economic significance of all statistically significant estimates is that a one standard deviation positive shock to the number of NFT airdrops reduces price efficiency by 1.23%. This translates into a (1.2/2.04)=0.60% decrease in price efficiency per 1% increase in the transaction processing capacity constraint.

[Table 7]

The intensified use of non-native tokens on the Ethereum blockchain may make it more challenging to implement predatory trading. One notable example of such activity is frontrunning attacks in on-chain token-swap markets. When trader A detects trader B's trading intentions and conducts such an attack, A will first initiate a trade in the same direction as B's intention. Then, when B's transaction hits the market, the market price will be worse for B. At last, A does a reverse transaction and ends up with more tokens. We follow the methodology in Capponi, Jia, and Wang (2024) to identify these attacks. Because the method requires both attacking and victim transactions to be in the same liquidity pool of a swap market, we obtain token-swap transactions data on Ethereum from Uniswap. Since we do not have access to Uniswap data on the Polygon blockchain, we cannot use the difference-in-differences approach. Instead, we use only the Ethereum blockchain and create dummy variables that indicate a one or two standard deviation shocks to NFT airdrop activity. Table 8 shows the results. The estimated coefficients for the NFT dummies in all specifications are negative and statistically significant, indicating that more NFT airdrop activity reduces frontrunning attacks.

[Table 8]

To further examine the impact of non-native tokens on price discovery, we use the Hasbrouck (1995) method and calculate the information share of token swap transactions on the Ethereum blockchain versus off-chain swap transactions. Following Capponi, Jia, and Yu (2025), we match intraday swap transaction price movements on Uniswap (on-chain) with those on Binance (off-chain) for four token pairs: ETH-USDT, WBTC-ETH, LINK-ETH, and AAVE-ETH. We use 30-second and 60-second intraday intervals to match the price movements. We then calculate the information share of on-chain versus off-chain transactions at the token pair-day level. The Hasbrouck (1995) method produces an upper bound and a lower bound for the information share of each trading venue, and we also calculate the midpoint between the bounds. Table 9 presents the results of regressing the on-chain information share on NFT airdrop activity. The statistically significant negative coefficients in all regression specifications indicate that higher non-native usage of the Ethereum blockchain is detrimental to the on-chain price discovery process. Specifically, a one-standard-deviation shock to the number of NFT airdrops decreases the on-chain information share by 1.27–4.30%. As such, the 1% decrease of transaction processing capacity leads to a 0.62–2.11% decrease of the information share of the decentralized exchanges.

[Table 9]

7. Conclusion

We find that the proliferation of non-native tokens on the Ethereum blockchain has the potential to harm price discovery and price efficiency of the native Ethereum cryptocurrency. This finding illustrates that adopting new functionality introduces an additional channel of risk for the native cryptocurrency. This risk is in line with the theoretical research modeling the blockchain's vulnerability to mispricing of the underlying native cryptocurrency. Specifically, we show that non-native tokens on the original blockchain can impair price discovery in the native token. Using a difference-in-differences framework with Polygon as a benchmark, we find that NFT airdrops increase blockchain congestion, elevate transaction fees, and raise the likelihood of failed transactions. The evidence indicates that capacity constraints hinder informed participation and reduce the on-chain information share.

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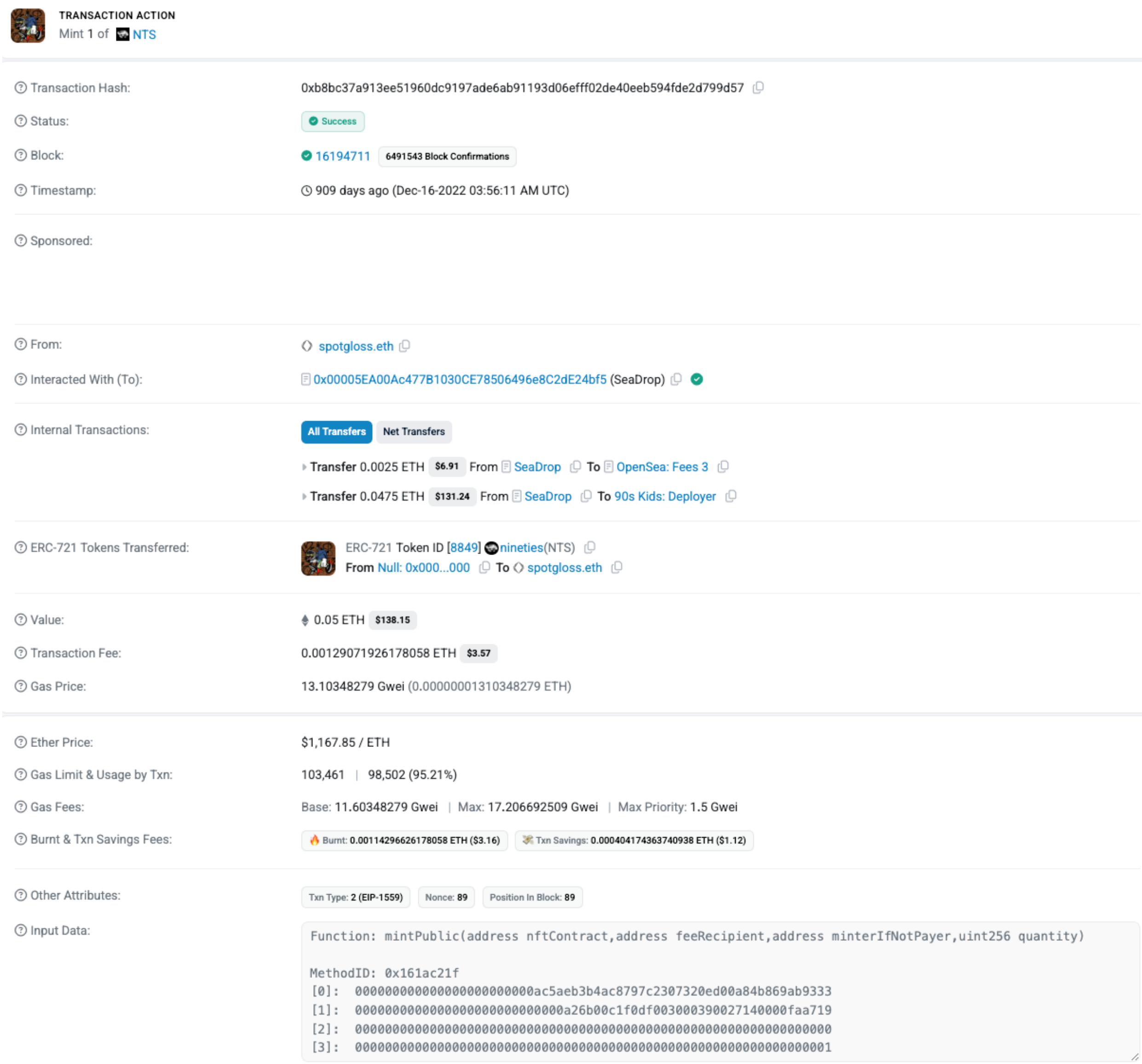

Figure 1. Example of NFT airdrop transaction on Ethereum. Transaction: https://etherscan.io/tx/0xb8bc37a913ee51960dc9197ade6ab91193d06efff02de40eeb594fde2d799d57. NFT (90's kids #8849) information: https://opensea.io/item/ethereum/0xac5aeb3b4ac8797c2307320ed00a84b869ab9333/8849.

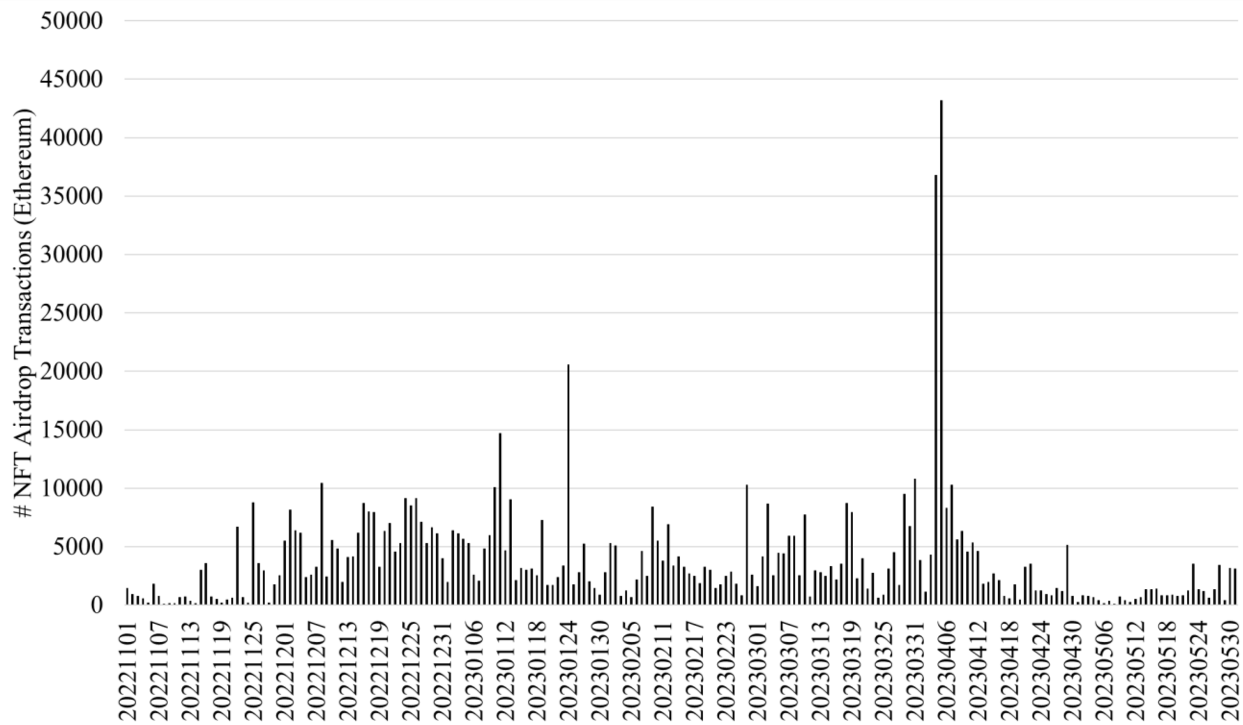

Figure 2: Number of NFT airdrop transactions on the Ethereum blockchain during the sample from November 1, 2022, to May 31, 2023.

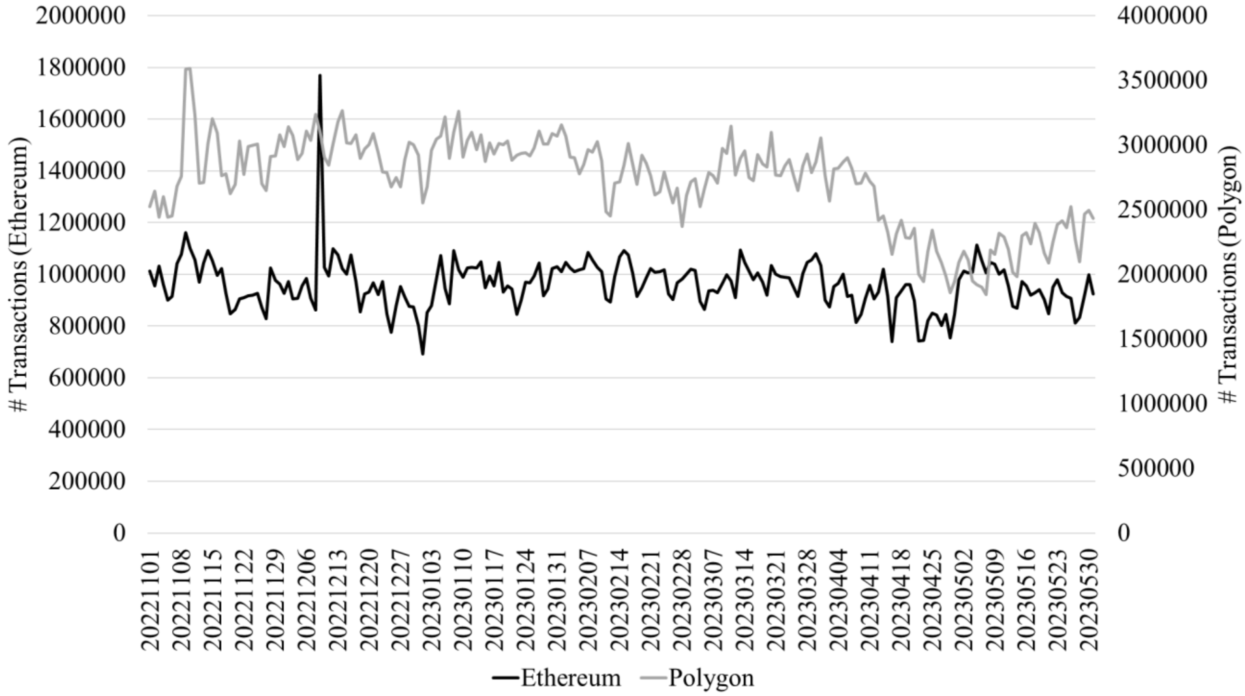

Figure 3: Total number of transactions on the Ethereum and Polygon blockchains during the sample from November 1, 2022, to May 31, 2023.

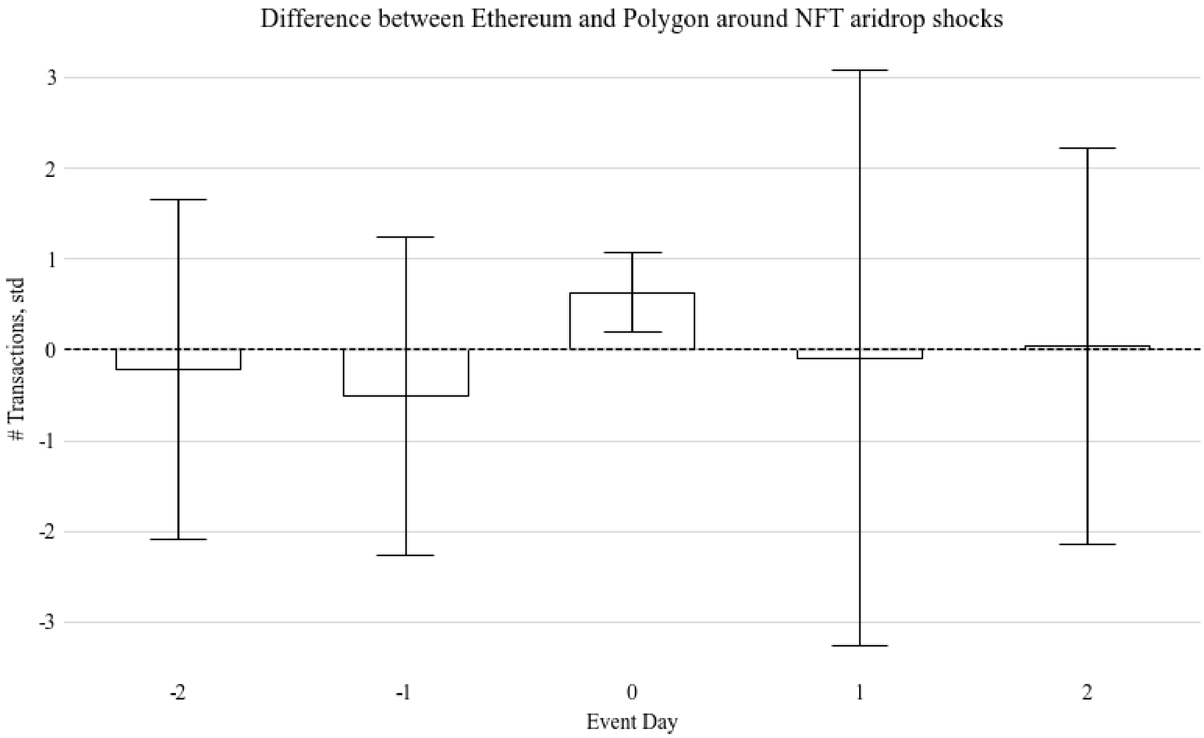

Figure 4: Effect of two standard deviation shocks to NFT airdrop activity on the difference between the number of transactions on the Ethereum and Polygon blockchains. The bars carry 95% confidence intervals.

Table 1: Summary statistics
This table reports descriptive statistics for the sample from November 1, 2022, to May 31, 2023. The variables are calculated for each block and averaged on the builder-day level. The statistics are then calculated using all builder-day observations. Number of NFT Airdrop transactions is the total number of NFT Airdrop transactions included in a block. Number of transactions is the total number of transactions. Fee per block is the transaction fee per block. Percentage of failed transactions is the number of failed transactions divided by the total number of transactions in a block. Ethereum volatility is calculated as the difference between the high and low prices divided by the midpoint for each block on Uniswap. Ethereum volume is the total trading volume for each block on Uniswap.

	Mean	Median	Std Dev	P25	P75
Panel A: Ethereum blockchain					
Number of NFT Airdrop transactions	0.4920	0.1429	1.5788	0.0348	0.4224
Number of transactions (in 10^3)	0.1309	0.1381	0.0424	0.1150	0.1549
Fee per block (in 10^{18})	0.4779	0.3807	0.4604	0.2501	0.5774
Percentage of failed transactions	0.0295	0.0271	0.0130	0.0212	0.0349
Ethereum volatility	0.0002	0.0002	0.0007	0.0000	0.0003
Ethereum volume (in 10^3)	0.0056	0.0018	0.0278	0.0007	0.0044
Number of private transactions	0.4744	0.0000	1.1048	0.0000	0.1667
Percentage of Frontrunning attacks (%)	0.0527	0.0000	0.9323	0.0000	0.0000
Panel B: Polygon blockchain					
Number of NFT Airdrop transactions	0.0046	0.0000	0.0178	0.0000	0.0040
Number of transactions (in 10^3)	0.0734	0.0727	0.0155	0.0644	0.0797
Fee per block (in 10^{18})	2.8469	2.4140	2.4392	1.3547	3.5291
Percentage of failed transactions	0.0436	0.0393	0.0201	0.0316	0.0499

Table 2: Total number of transactions
This table reports the results of the following regression:

$$\#ofTransactions_{it} = \alpha + \beta_1 NFTAirdrop_{it} + \beta_2 EthVolatility_{it} + \beta_3 EthVolume_{it} + \varepsilon_{it}$$

where $\#ofTransactions_{it}$ is the total number of transactions, $NFTAirdrop_{it}$ is the number of NFT Airdrops transactions, and $EthVolatility_{it}$ and $EthVolume_{it}$ are control variables that capture the trading condition of Ethereum on Uniswap. To construct the builder-day panel data for the regressions, for each day during the sample period from November 1, 2022, to May 31, 2023, we do a one-to-one match between the most active builders on the Ethereum blockchain and the Polygon blockchain. We then standardize $NFTAirdrop_{it}$ and the dependent variable and calculate the differences between the top 30 pairs of builders. Variables are defined in Table 1. P-values corresponding to double-clustered standard errors are in parentheses. *, ** and *** indicate significance at the 90th, 95th and 99th confidence levels.

	(1)	(2)	(3)	(4)
$NFTAirdrop$	0.139*** (0.00)	0.065*** (0.00)	0.120*** (0.00)	0.063*** (0.00)
$EthVolatility$			0.350*** (0.00)	0.132*** (0.00)
$EthVolume$			0.060 (0.25)	-0.006 (0.84)
Builder FE	No	Yes	No	Yes
# of builder pairs per day	30	30	30	30
# of days	212	212	212	212

Table 3: Transaction costs
This table reports the results of the following regression:

$$TransactionCosts_{it} = \alpha + \beta_1 NFTAirdrop_{it} + \beta_2 EthVolatility_{it} + \beta_3 EthVolume_{it} + \varepsilon_{it}$$

where $TransactionCosts_{it}$ is the average fee per block, $NFTAirdrop_{it}$ is the number of NFT Airdrops transactions, and $EthVolatility_{it}$ and $EthVolume_{it}$ are control variables that capture the trading condition of Ethereum on Uniswap. To construct the builder-day panel data for the regressions, for each day during the sample period from November 1, 2022, to May 31, 2023, we do a one-to-one match between the most active builders on the Ethereum blockchain and the Polygon blockchain. We then standardize $NFTAirdrop_{it}$ and the dependent variable and calculate the differences between the top 30 pairs of builders. Variables are defined in Table 1. P-values corresponding to double-clustered standard errors are in parentheses. *, ** and *** indicate significance at the 90th, 95th and 99th confidence levels.

	(1)	(2)	(3)	(4)
$NFTAirdrop$	0.106***	0.051***	0.092***	0.049***
	(0.00)	(0.00)	(0.00)	(0.00)
$EthVolatility$			0.240***	0.091***
			(0.00)	(0.01)
$EthVolume$			0.084	0.048
			(0.13)	(0.12)
Builder FE	No	Yes	No	Yes
# of builder pairs per day	30	30	30	30
# of days	212	212	212	212

Table 4: Fail rate
This table reports the results of the following regression:

$$FailRate_{it} = \alpha + \beta_1 NFTAirdrop_{it} + \beta_2 EthVolatility_{it} + \beta_3 EthVolume_{it} + \varepsilon_{it}$$

where $FailRate_{it}$ is the percentage of failed transactions, $NFTAirdrop_{it}$ is the number of NFT Airdrops transactions, and $EthVolatility_{it}$ and $EthVolume_{it}$ are control variables that capture the trading condition of Ethereum on Uniswap. To construct the builder-day panel data for the regressions, for each day during the sample period from November 1, 2022, to May 31, 2023, we do a one-to-one match between the most active builders on the Ethereum blockchain and the Polygon blockchain. We then standardize $NFTAirdrop_{it}$ and the dependent variable and calculate the differences between the top 30 pairs of builders. Variables are defined in Table 1. P-values corresponding to double-clustered standard errors are in parentheses. *, ** and *** indicate significance at the 90th, 95th and 99th confidence levels.

	(1)	(2)	(3)	(4)
$NFTAirdrop$	0.038**	0.037**	0.034*	0.037**
	(0.04)	(0.04)	(0.06)	(0.04)
$EthVolatility$			-0.002	0.008
			(0.96)	(0.82)
$EthVolume$			0.135***	0.079**
			(0.00)	(0.01)
Builder FE	No	Yes	No	Yes
# of builder pairs per day	30	30	30	30
# of days	212	212	212	212

Table 5: Private transactions

This table reports the regression results with the number of private transactions as the dependent variable. $NFTAirdrop1_{it}$ ($NFTAirdrop2_{it}$) is a dummy variable that equals 1 if the number of NFT Airdrops is at least one (two) standard deviation above the mean. The regressions are estimated using a builder-day panel data with the 300 most active builders on the Ethereum blockchain during the sample from November 1, 2022, to May 31, 2023. Control variables include volatility and volume of Ethereum trading activity on Uniswap. P-values corresponding to double-clustered standard errors are in parentheses. *, ** and *** indicate significance at the 90th, 95th and 99th confidence levels.

	(1)	(2)	(3)	(4)
$NFTAirdrop1$	-0.033 (0.16)	-0.110*** (0.00)	-0.110*** (0.00)	
$NFTAirdrop2$				-0.111*** (0.00)
$EthVolatility$			0.228 (0.36)	0.228 (0.36)
$EthVolume$			0.720** (0.04)	0.719** (0.04)
Builder FE	No	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
# of builders per day	300	300	300	300
# of days	212	212	212	212

Table 6: Price impacts
This table reports the results of the following regression:

$$PriceImpact_{it} = \alpha + \beta_1 NFTAirdrop_{it} + \beta_2 EthVolatility_{it} + \beta_3 EthVolume_{it} + \varepsilon_{it}$$

where $PriceImpact_{it}$ is the price impact of on-chain token swaps, $NFTAirdrop_{it}$ is the number of NFT Airdrops transactions, and $EthVolatility_{it}$ and $EthVolume_{it}$ are control variables that capture the trading condition of Ethereum on Uniswap. Price impacts are calculated using prices of various time windows after a transaction. We only report the estimated coefficient of the independent variable $NFTAirdrop_{it}$. To construct the builder-day panel data for the regressions, for each day during the sample period from November 1, 2022, to May 31, 2023, we do a one-to-one match between the most active builders on the Ethereum blockchain and the Polygon blockchain. We then standardize $NFTAirdrop_{it}$ and the dependent variable and calculate the differences between the top 30 pairs of builders. Variables are defined in Table 1. P-values corresponding to double-clustered standard errors are in parentheses. *, ** and *** indicate significance at the 90th, 95th and 99th confidence levels.

Time window of price impact	(1)	(2)	(3)	(4)
5 hours	-0.003	-0.006	-0.003	-0.006
10 hours	-0.032**	-0.037***	-0.033**	-0.036***
18 hours	-0.023*	-0.026**	-0.023*	-0.025**
1 day	-0.029**	-0.031***	-0.029***	-0.031***
2 days	-0.020*	-0.021*	-0.019*	-0.021*
3 days	-0.021*	-0.020	-0.021*	-0.019
Controls	No	No	Yes	Yes
Builder FE	No	Yes	No	Yes
# of builder pairs per day	30	30	30	30
# of days	212	212	212	212

Table 7: Price efficiency
This table reports the results of the following regression:

$$PriceEfficiency_{it} = \alpha + \beta_1 NFTAirdrop_{it} + \beta_2 EthVolatility_{it} + \beta_3 EthVolume_{it} + \varepsilon_{it}$$

where $PriceEfficiency_{it}$ is either variance ratio (Panel A) or price delay (Panel B), $NFTAirdrop_{it}$ is the number of NFT Airdrops transactions, and $EthVolatility_{it}$ and $EthVolume_{it}$ are control variables that capture the trading condition of Ethereum on Uniswap. Price efficiency measures are calculated using various return windows as indicated above the regression estimates. The regressions are estimated using a token pair-day panel data with pairs that had over 100,000 transactions during the sample period from November 1, 2022, to May 31, 2023. P-values corresponding to double-clustered standard errors are in parentheses. *, ** and *** indicate significance at the 90th, 95th and 99th confidence levels.

Panel A: Variance Ratio

	(30s, 300s)		(60s, 300s)		(150s, 300s)	
	(1)	(2)	(3)	(4)	(5)	(6)
$NFTAirdrop$	1.371 (0.17)	1.692 (0.12)	1.368* (0.09)	1.590* (0.07)	1.445*** (0.00)	1.386*** (0.00)
Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
# of token pairs	6	6	6	6	6	6
# of days	212	212	212	212	212	212

Panel B: Price Delay

	30s		150s		300s	
	(1)	(2)	(3)	(4)	(5)	(6)
$NFTAirdrop$	1.692*** (0.01)	1.695*** (0.01)	1.344*** (0.00)	1.289*** (0.0005)	0.582 (0.32)	0.541 (0.33)
Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
# of token pairs	6	6	6	6	6	6
# of days	212	212	212	212	212	212

Table 8: Frontrunning attacks

This table reports the regression results with the volume of Uniswap frontrunning attacks as a percentage of total Uniswap volume as the dependent variable. $NFTAirdrop1_{it}$ ($NFTAirdrop2_{it}$) is a dummy variable that equals 1 if the number of NFT Airdrops is at least one (two) standard deviation above the mean. The regressions are estimated using a builder-day panel data with the 300 most active builders on the Ethereum blockchain during the sample from November 1, 2022, to May 31, 2023. Control variables include volatility and volume of Ethereum trading activity. P-values corresponding to double-clustered standard errors are in parentheses. *, ** and *** indicate significance at the 90th, 95th and 99th confidence levels.

	(1)	(2)	(3)	(4)
$NFTAirdrop1$	-0.037** (0.02)	-0.068*** (0.00)	-0.069*** (0.00)	
$NFTAirdrop2$				-0.049*** (0.00)
$EthVolatility$			0.073 (0.62)	0.073 (0.63)
$EthVolume$			0.068 (0.80)	0.067 (0.80)
Builder FE	No	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
# of builders per day	300	300	300	300
# of days	212	212	212	212

Table 9: Information share
This table reports the results of the following regression:

$$InformationShare_{it} = \alpha + \beta_1 NFTAirdrop_{it} + \beta_2 EthVolatility_{it} + \beta_3 EthVolume_{it} + \varepsilon_{it}$$

where $InformationShare_{it}$ is the Hasbrouck (1995) information share of token swap transactions on the Ethereum blockchain (as opposed to off-chain swap transactions on Binance), $NFTAirdrop_{it}$ is the number of NFT Airdrops transactions, and $EthVolatility_{it}$ and $EthVolume_{it}$ are control variables that capture the trading condition of Ethereum on Uniswap. We use two intraday price movement intervals—30 seconds (Panel A) and 60 seconds (Panel B)—to calculate the upper bound, midpoint, and lower bound of daily information share. The regressions are estimated using a token pair-day panel data with four token pairs—ETH-USDT, WBTC-ETH, LINK-ETH, and AAVE-ETH—during the sample period from November 1, 2022, to May 31, 2023. P-values corresponding to double-clustered standard errors are in parentheses. *, ** and *** indicate significance at the 90th, 95th and 99th confidence levels.

	Upper bound		Midpoint		Lower bound	
Panel A: Intraday interval: 30 seconds						
	(1)	(2)	(3)	(4)	(5)	(6)
$NFTAirdrop$	-0.039** (0.03)	-0.030** (0.02)	-0.045** (0.02)	-0.037** (0.01)	-0.052*** (0.01)	-0.044*** (0.01)
Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
# of token pairs	4	4	4	4	4	4
# of days	212	212	212	212	212	212
Panel B: Intraday interval: 60 seconds						
	(1)	(2)	(3)	(4)	(5)	(6)
$NFTAirdrop$	-0.020*** (0.00)	-0.013* (0.09)	-0.025*** (0.01)	-0.018** (0.03)	-0.029*** (0.01)	-0.023** (0.03)
Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
# of token pairs	4	4	4	4	4	4
# of days	212	212	212	212	212	212

Appendix A1

Table A1: Information share summary statistics

This table reports the average Hasbrouck (1995) information share of token swap transactions on the Ethereum blockchain (as opposed to off-chain swap transactions on Binance) for four token pairs—ETH-USDT, WBTC-ETH, LINK-ETH, and AAVE-ETH—during the sample period from November 1, 2022, to May 31, 2023. We use two intraday price movement intervals—30 seconds and 60 seconds—to calculate the upper bound, midpoint, and lower bound of daily information share. The averages are calculated using token pair-day observations.

	30 seconds interval			60 seconds interval		
	Upper bound	Midpoint	Lower bound	Upper bound	Midpoint	Lower bound
AAVE-ETH	0.39	0.36	0.34	0.43	0.40	0.37
ETH-USDT	0.97	0.93	0.89	0.94	0.84	0.73
LINK-ETH	0.39	0.37	0.35	0.43	0.41	0.39
WBTC-ETH	0.28	0.24	0.20	0.25	0.22	0.19
Average	0.50	0.47	0.44	0.51	0.47	0.42