Liquidity Mechanisms in Decentralized Finance: Design, Fragmentation, and Arbitrage in Real-World Asset Markets

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Abstract

The tokenization of real-world assets (RWAs) promises to improve accessibility and tradability in traditionally illiquid markets. However, the question of whether digital asset markets can achieve sustained liquidity and efficient price discovery remains unresolved. In this study, we analyze three coexisting liquidity mechanisms—automated market makers (AMMs), peer-to-peer (P2P) marketplaces, and centralized buybacks—within a stylized framework that addresses the cost-efficiency trade-offs faced by liquidity demanders across these three mechanisms. Building on a dataset of 444,535 secondary market transactions of tokenized RWAs from 2019 to 2024, we document arbitrage-driven liquidity flows, market fragmentation, and varying investor sophistication as well as a different arbitrage susceptibility of the mechanisms during periods of instability. While AMMs provide continuous liquidity, their deterministic pricing enables arbitrage that systematically drains liquidity over time. P2P marketplaces support efficient price discovery, and buybacks offer stable but inflexible exits. Recognizing that each mechanism addresses distinct trading needs, our findings underscore the importance of hybrid liquidity models that integrate centralized and decentralized elements. However, without addressing current design limitations, RWA markets risk becoming fragmented digital search markets rather than efficient trading environments.

Keywords: Real-World Assets (RWA), Tokenization, Market Microstructure, Decentralized Finance (DeFi), Difference-in-Differences (DiD)

JEL: G10, G12, G14, O33, R30

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[1] *Conflicts of Interest:* One author bought and sold few digital tokens issued by the company RealT so that they could retrace the process and trading of tokenization. There is no current investment. The other authors have no commercial relationship with the company or management, whose data we mostly rely on.

1. Introduction

The tokenization of real-world assets (RWAs) on the blockchain is transforming finance by bridging traditional markets with the digital economy. Established structures like securitization have long enhanced public market efficiency by enabling fractional ownership, investor accessibility, and improving liquidity, yet these benefits have been largely limited to large, homogeneous assets within public markets. Tokenization extends these advantages to private markets, unlocking trillions of dollars in RWAs, including real estate, private equity, private debt, and other alternative investments. These assets are often illiquid, characterized by limited tradability, valuation opacity, high transaction and search costs, and barriers to accessibility. Tokenization has the potential to fundamentally reshape tradability, transparency, and price formation in these traditionally illiquid markets. The introduction of observable pricing mechanisms on-chain can increase economic efficiency by enabling transparent valuations and more frequent trading, thereby improving capital allocation. Similar market benefits have long been acknowledged in equity and real asset markets (O'Hara, 2003; Case and Shiller, 1989; Williams, 1995).

Theoretically, tokenization of RWAs increases market divisibility and lowers unit prices, characteristics typically associated with greater liquidity (Muscarella and Vetsuypens, 1996; Benedetti and Rodríguez-Garnica, 2023). On-chain liquidity further enables functionalities such as collateralization, borrowing, and continuous trading in decentralized finance (DeFi) (Xin Li et al., 2024). However, adoption remains constrained by challenges in secondary market design and price discovery. Existing research focuses mainly on the rapidly growing primary issuance of tokens (Kreppmeier et al., 2023)[1], leaving trading dynamics and liquidity formation of these tokens insufficiently explored. Yet, viable secondary markets are essential, as liquidity is a core promise of RWA tokenization. Theoretical models suggest that market fragmentation can both enhance efficiency through competition and increase execution complexity when cross-platform coordination is lacking (Chen, 2021), and empirical evidence from DeFi indicates that fragmentation in cryptocurrency markets creates arbitrage opportunities through price

[1]The total value of tokenized RWAs increased from \$160.7 million in January 2022 to \$11.1 billion in April 2025, according to DefiLlama, an analytics platform for decentralized finance (`https://defillama.com/protocols/RWA`).

discrepancies across venues (Makarov and Schoar, 2020).

As the future projection of blockchain enthusiasts and the financial industry is to own assets individually on the blockchain, the secondary market of heterogeneous (and relatively small or illiquid) assets is hugely important.[2] But despite the widespread optimism regarding RWA tokenization and its liquidity benefits, little empirical evidence exists on the efficiency of secondary markets for these assets. To bridge the gap between conceptual claims and practical realities, we analyze three different liquidity mechanisms around one of the largest and earliest platforms for tokenized RWAs, *RealT*. Based on the three coexisting market mechanisms observed, namely the centralized buyback (Buyback), decentralized peer-to-peer (P2P) marketplaces, and decentralized automated market makers (AMMs), we aim to develop a stylized framework that formalizes the cost-efficiency trade-offs faced by liquidity demanders across the three liquidity mechanisms. Thereby, we focus on three key parameters in the framework: price signal quality, transaction costs, and execution certainty, each shaped by the mechanisms' inherent design and liquidity constraints. We calibrate the framework with a unique set of high-frequency data comprising 444,535 secondary market transactions of RWAs over four and a half years. This allows us to understand how investors adapt their selling behavior in response to the mechanism's liquidity constraints, providing a blueprint for how multi-market systems for RWAs in DeFi can function. Alongside the framework, we analyze the data to empirically assess price discovery efficiency and arbitrage interactions across the three different market mechanisms. To the best of our knowledge, this is the first study to both formalize and empirically analyze the microstructure of secondary markets for tokenized RWAs.

While our empirical data focuses on real estate tokens, we view this setting as a fully transparent laboratory for studying thin, fragmented secondary markets. Many RWA platforms implement at least one of the mechanisms, but to our knowledge, this is the only setting where all three mechanisms coexist and are simultaneously observable through publicly accessible on-chain data (see Table A.1 and Appendix A.1). This special structure enables direct empirical comparisons across mechanism types and al-

[2]Larry Fink, CEO of BlackRock, stated in his 2025 Annual Chairman's Letter to Investors that 'Every stock, every bond, every fund—every asset—can be tokenized. If they are, it will revolutionize investing.' (`https://www.blackrock.com/corporate/investor-relations/larry-fink-annual-chairmans-letter`).

lows the disentanglement of their structural interactions under consistent token design and market conditions. A special and very rare empirical feature of our approach is that we can directly observe arbitrage activities. The secondary market dynamics we document—such as fragmentation, price discovery and arbitrage—may apply to other appraisal-anchored assets traded on-chain, although generalizability remains an open empirical question. In addition, our findings on market liquidity empirically complement the key literature on token market design, which often assumes fully liquid markets (see, e.g., Cong et al., 2021; Cong et al., 2022).

Our findings indicate that while multiple market mechanisms coexist because they fulfill distinct and complementary roles in liquidity provision, the secondary market for RWAs remains fragmented in terms of arbitrage flows, price discovery, and overall liquidity. In particular, we document that the current application of AMMs to RWAs, although revolutionary due to continuous and automatic market making in cryptocurrency markets, remains limited to small transactions, due to the complexity of pricing heterogeneous assets and the risk of inefficient pricing combined with increased arbitrage activity. Centralized buybacks contribute to price stability and support guaranteed but limited and costly liquidity, used in particular for larger transactions and as a reliable exit option. We document that decentralized P2P marketplaces have emerged as the dominant mechanism for RWAs, which we attribute to their enhanced price discovery, low costs, and reduced exposure to liquidity-draining arbitrage activity, even though their peer-specific offer structure can imply a lower execution certainty. Using a diff-in-diff research design around an exogenous DeFi market shock, we find that AMM pricing structures are more susceptible to arbitrage exploitation during periods of market instability than P2P marketplaces, highlighting a structural vulnerability in fragmented decentralized markets.

Consequently, our study highlights the need for carefully structured hybrid liquidity designs that integrate traditional price discovery with advancements of blockchain-based DeFi. Such hybrid systems must accommodate both centralized and decentralized trading venues to effectively manage heterogeneous assets. Understanding the dynamics of these integrated markets is crucial for informing future developments in DeFi and guiding regulatory frameworks that can foster innovation while ensuring market stability. Our research contributes to the broader discourse on tokenization to enhance the efficiency and accessibility of financial markets, laying the groundwork for future studies on the integration of RWAs into the digital asset ecosystem. By positioning our findings at the intersection of traditional finance and the DeFi ecosystem, we pave the way for a more inclusive and accessible financial market driven by blockchain technology. If these challenges remain unresolved, tokenization risks replicating traditional inefficiencies in digital form—raising a critical question: *Can RWAs be liquid in fragmented markets?*

2. Related literature and theory development

2.1. Related literature and research gap

Distributed Ledger Technology (DLT) and blockchain technology enable a decentralized and transparent infrastructure for asset representation, digital ownership transfer, automated execution of contracts, and real-time settlement (Buterin, 2013; Cong and He, 2019; Benedetti and Rodríguez-Garnica, 2023).[3] These innovations underpin the expansion of DeFi (Schär, 2021), yet the effectiveness of blockchain-based trading venues in fostering liquidity and price discovery remains uncertain. Centralized exchanges (CEXs) aggregate liquidity through limit order books (Kyle, 1985; O'Hara, 2003)[4], while decentralized exchanges (DEXs) rely on algorithmic pricing via AMMs (Park, 2023). AMMs improve accessibility and continuous liquidity, although they introduce inefficiencies such as deterministic pricing, susceptibility to arbitrage, and exposure to sandwich attacks (Park, 2023; Barbon and Ranaldo, 2024). These inefficiencies are well-documented in cryptocurrency markets, yet their impact on the liquidity and price discovery of tokenized RWAs remains largely unexplored. The inherent characteristics of RWAs further complicate liquidity formation. Unlike cryptocurrencies, which are native to the blockchain, fungible and actively traded across global markets, RWAs are heterogeneous, exhibit lower turnover, and depend on the integration of off-chain data such as valuations, legal records, and income flows, introducing additional frictions through price oracles (Cong et al., 2025; Harvey and Rabetti, 2024). Theoretical models suggest that decentralized trading venues could enhance liquidity of blockchain-based assets by reducing intermediation costs and enabling broader market access (Malinova and Park,

[3]The terms DLT and blockchain are used interchangeably in this paper, although blockchain is a specific type of DLT. For a comprehensive discussion, see Liu et al. (2020).

[4]While most centralized exchanges worldwide use a central limit order book (CLOB), also alternative trading methods such as request-for-quote (RFQ) systems or over-the-counter (OTC) trading are employed, especially for less liquid markets, complex products, or large transactions.

2017). However, first empirical evidence from tokenized real estate markets indicates that these markets struggle with thin trading volumes, but also show signs of increasing maturation and integration of traditional real estate and modern financial market features (Swinkels, 2023; Bergkamp et al., 2025). Although prior studies have examined liquidity determinants in cryptocurrency markets—both on centralized (Brauneis et al., 2022; Brauneis et al., 2021) and decentralized (Zhu et al., 2025) exchanges—little research has explored liquidity mechanisms in RWA token markets, where price discovery and execution certainty may be significantly impaired by market fragmentation. Beyond AMMs, the coexistence of centralized and decentralized liquidity mechanisms adds further complexity. While some research suggests that centralized and decentralized markets can complement each other through liquidity spillovers (Aoyagi and Ito, 2024), this remains untested in RWA markets. Unlike cryptocurrencies, which benefit from deep global trading pools, RWAs are often traded across fragmented venues with varying degrees of liquidity. Traditional financial market theory suggests that liquidity typically concentrates in a dominant trading venue (Pagano, 1989), yet blockchain-based RWA markets may not exhibit the same network effects. Instead, fragmented liquidity pools may exacerbate price inefficiencies, increase search costs, and limit execution certainty (Makarov and Schoar, 2020). These challenges also raise concerns about price discovery across competing trading mechanisms. While price formation in traditional CEXs has been extensively studied (Kyle, 1985; Hasbrouck, 1995; O'Hara, 2003), and emerging research has examined AMM-driven price discovery (Capponi et al., 2024), tokenized RWAs introduce additional complexities. Given their illiquid nature, valuation dependencies on external appraisals, and potential exposure to cross-market liquidity fragmentation, it remains unclear whether AMMs, P2P networks, or centralized buybacks provide the most efficient trading environment. Previous studies primarily focus on primary issuance mechanisms, such as Security Token Offerings (STOs), and their role in lowering investment barriers through fractional ownership (Kreppmeier et al., 2023). However, these studies do not address secondary market inefficiencies, leaving critical gaps in understanding liquidity formation, price efficiency, and execution dynamics. As blockchain-based RWA trading expands, the need to analyze liquidity provision across multiple market structures—centralized buybacks, decentralized P2P trading, and AMMs—becomes increasingly urgent. This study seeks to fill this empirical void by systematically examining liquidity formation and price discovery in tokenized RWA markets, contributing to the broader discourse on financial market microstructure and the long-term viability of DeFi-based asset markets.

2.2. Liquidity mechanism and market design of RWA markets

While tokenization expands market access through fractional ownership, its ability to enhance secondary market efficiency depends on how liquidity is structured. Each mechanism—whether centralized or decentralized—introduces distinct trade-offs in execution certainty, price efficiency, and transaction costs, ultimately shaping market depth and stability. While traditional asset markets rely on centralized intermediaries to facilitate liquidity, tokenized RWAs operate within a fragmented ecosystem where liquidity can be sourced through multiple competing mechanisms. Understanding how these mechanisms interact is essential for assessing whether tokenization enhances market efficiency or simply replicates existing financial frictions in digital form. Generally, RWA marketplaces contain some combination of the following liquidity mechanisms[5], often integrating multiple mechanisms simultaneously to accommodate different trading preferences and conditions:

Buyback mechanism: The buyback mechanism (Figure 1) provides a centralized liquidity outlet, where investors sell tokens back to the issuer at a price fixed to an appraisal-based valuation of the underlying asset rather than a quote-driven market rate. Buybacks offer appraisal-based stable pricing but limit price discovery and flexibility.

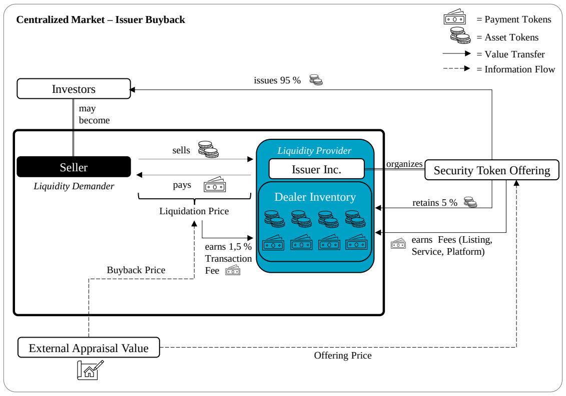
P2P mechanism: The P2P model (Figure 2) supports direct trading on decentralized platforms like AirSwap, Swapcat, and YAM, each allowing different trade volumes and trade sizes, offering flexibility in price-setting but lower execution certainty compared to the buyback. The P2P structure mirrors over-the-counter (OTC) trading, linking buyers and sellers directly and enabling trades based on transparent asset appraisals without intermediaries or order books. Bypassing fees and enabling real-time pricing updates make P2P markets effective for trades prioritizing market price alignment over execution speed. Transactions settle on-chain using smart contracts, reducing intermediary costs to zero compared to traditional OTC models. For larger, less time-sensitive trades, the P2P model is advantageous, allowing market participants

[5] For further details regarding RealT, see Appendix A.8.

to set prices based on market demand, creating efficient price signals. However, due to lacking automated order matching, execution certainty can be limited, making P2P less ideal for highly time-sensitive transactions.

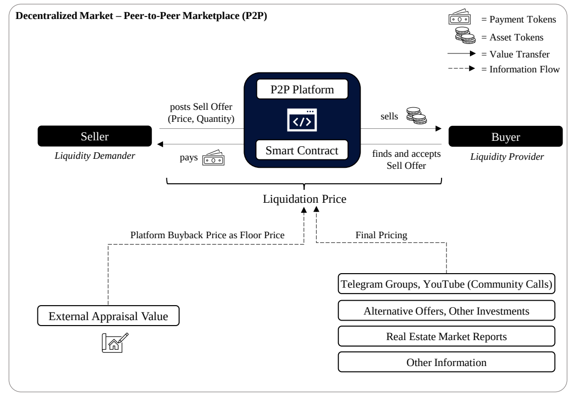
AMM mechanism: Figure 3 illustrates AMMs, effective for high-frequency trades and suitable for traders prioritizing immediate execution over precise pricing. AMMs, like Uniswap on Ethereum, eliminate continuous order matching by using liquidity pools and algorithmic pricing formulas, optimizing costs and latency for blockchain-based transactions. Originating in the cryptocurrency markets, AMMs can theoretically handle high-volume trades efficiently by dynamically adjusting prices based on pooled asset ratios through the Constant Product Market Making (CPMM) formula, which forces the product of the quantities of both tokens (the RWA token and the currency token) in the pool to be constant. For a more detailed conceptualization of CPMM, see Figure A.10 in Appendix A.9. AMMs present high execution certainty and comparably low fees, particularly suitable for trades where immediacy is prioritized over price precision, while arbitrageurs continuously adjust pool prices to market levels (Angeris et al., 2019).

Figure 1: Centralized Buyback



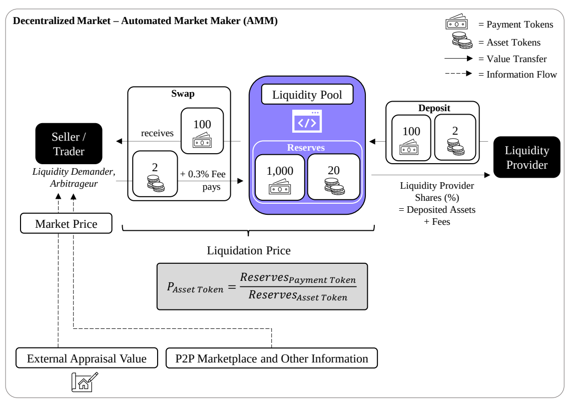
Note: This figure illustrates the buyback process as a centralized market design.

Figure 2: Peer-to-Peer Market (P2P)



Note: This figure illustrates the transaction process on a decentralized P2P market design.

Figure 3: Automated Market Maker (AMM)



Note: This figure illustrates the transaction process on a decentralized automated market maker (AMM) exchange.

Each mechanism offers distinct (dis)advantages. However, it remains unclear how the mechanisms perform in practice, particularly in fragmented secondary markets. To understand the interplay between these liquidity mechanisms, we introduce a framework in the next section that captures their key characteristics.

2.3. Stylized execution cost framework

In RWA markets, liquidity is simultaneously sourced from multiple competing mechanisms, each characterized by distinct trade-offs in execution certainty, price efficiency, and transaction fees. As traders allocate their transactions across decentralized AMMs and P2P marketplaces and centralized buyback mechanisms according to their specific preferences and market conditions, an aggregate market-level allocation emerges. This observed market allocation reflects a balance among the different liquidity characteristics provided by each mechanism. To formally analyze this aggregate market allocation, we introduce a stylized theoretical framework capturing various execution parameters, including costs, speed, slippage, liquidity depth, and arbitrage-driven liquidity reallocation dynamics across these competing venues. Our framework, rooted in traditional market microstructure literature (Kyle, 1985; Glosten and Milgrom, 1985), thus enables a deeper understanding of how trader preferences and liquidity constraints jointly determine the overall liquidity structure in tokenized RWA markets.

The total execution cost is modeled as the sum of mechanism-specific execution costs, each normalized by its corresponding execution efficiency. The model incorporates several key parameters. The total trade size, q, represents the total volume to be traded and is allocated to the liquidity mechanisms: q_{AMM} for AMM, q_{P2P} for P2P, and q_{B} for the centralized company buyback (B). Liquidity constraints are critical, particularly for AMMs, where available liquidity (L_{AMM}, measured in dollars) determines slippage and execution costs.[6] In constant-product AMMs, the proportional liquidity pool value (L_{AMM}) perfectly reflects the market depth as as execution prices are directly determined by the reserve size of the token being sold (Zhu et al., 2025). Transaction fees, denoted as F_{AMM}, F_{P2P}, and F_{B}, which represent the percentage values, vary across platforms and significantly affect execution costs. Sensitivity to transaction fees is incorporated via β. Price signal quality ($\eta \in [0,1]$) reflects how closely each platform's price matches the true market value, with $\eta = 1$ representing the perfect price signal.[7] Sensitivity to execution time is incorporated via γ, which captures the trade-off between time-sensitive execution and other cost components, as execution time (t) varies significantly across mechanisms.

The execution efficiency (E) reflects the combined impact of price signal quality, and execution time (t). The execution cost (C_{exec}) accounts for slippage and transaction

[6] Slippage occurs as trades shift the pool's token ratio, causing a gap between expected and executed prices. This mechanic—visualized as a movement along the token reserve curve—is illustrated in Figure A.10.

[7] Buyback prices are fixed via appraisals rather than market signals, but we assign η_{B} to reflect their relative price informativeness and to ensure consistency across mechanisms.

fees specific to each market mechanism.

For AMMs, the efficiency is defined as:

$$E_{\text{AMM}} = \eta_{\text{AMM}} \cdot L_{\text{AMM}} \cdot \left(\frac{1}{\bar{t}_{\text{AMM}}}\right)^{\gamma}, \tag{1}$$

where the liquidity pool reserves L_{AMM} reflect the market depth of the AMM. Execution time for AMMs is technologically fixed and typically near-instant, implying $\bar{t}_{\text{AMM}} \approx 1$. Since execution costs in AMMs increase nonlinearly with trade size, we adopt a quadratic slippage approximation inspired by Park (2023), resulting in a total execution cost for AMMs:

$$C_{\text{exec, AMM}} = \beta \cdot F_{\text{AMM}} \cdot q_{\text{AMM}} + \frac{q_{\text{AMM}}^2}{L_{\text{AMM}}}. \tag{2}$$

For P2P marketplaces, the efficiency is given by:

$$E_{\text{P2P}} = \eta_{\text{P2P}} \cdot L_{\text{P2P}} \cdot \left(\frac{1}{t_{\text{P2P}}(\eta_{\text{P2P}})}\right)^{\gamma}, \tag{3}$$

where L_{P2P} represents the available liquidity or market depth, measured as the contemporary dollar volume of active offers for the token, and t_{P2P} denotes execution time, which varies and further depends on η_{P2P}.[8]

The execution cost for P2P is:

$$C_{\text{exec, P2P}} = \beta \cdot F_{\text{P2P}} \cdot q_{\text{P2P}} + \frac{q_{\text{P2P}}^{\delta}}{L_{\text{P2P}}}, \tag{4}$$

where $\delta \in (1, 2)$ ensures that execution costs increase nonlinearly with trade size relative to the offer volume (liquidity), reflecting the cost of consuming increasingly less favorable offers.[9]

Execution time for P2P, denoted t_{P2P}, varies depending on market conditions and the speed of matching buyers and sellers.

[8] We model P2P execution time as inversely related to price informativeness: $t_{\text{P2P}} = \frac{t_{\text{baseline}}}{\eta_{\text{P2P}}}$, with t_{baseline} based on empirical time on market (e.g. 25 days). This reflects the idea that better pricing quality facilitates faster matching and shorter execution times.

[9] This follows standard microstructure models, where execution costs rise nonlinearly with trade size due to limited depth (e.g., Kyle, 1985; Almgren and Chriss, 2001). We assume $1 < \delta < 2$ to ensure convexity while capturing the more moderate price impact in P2P markets compared to the quadratic curve in AMMs.

For centralized buybacks, the efficiency is:

$$E_{\mathrm{B}} = \eta_{\mathrm{B}} \cdot \overline{L}_{\mathrm{B}} \cdot \left(\frac{1}{t_{\mathrm{B}}(q_{\mathrm{B}})} \right)^{\gamma}, \tag{5}$$

where $\overline{L}_{\mathrm{B}}$ is a fixed buyback limit per trade per token, imposed by the centralized buyback mechanism and reset periodically (e.g. weekly) and $t_{\mathrm{B}}(q_{\mathrm{B}})$ is a decreasing function of trade size q_{B}.[10]

The execution cost is:

$$C_{\text{exec, B}} = \beta \cdot F_{\mathrm{B}} \cdot q_{\mathrm{B}}. \tag{6}$$

The total execution cost aggregates the efficiency-adjusted execution costs of each mechanism:

$$C_{\text{total}} = \frac{C_{\text{exec, AMM}}}{E_{\text{AMM}}} + \frac{C_{\text{exec, P2P}}}{E_{\text{P2P}}} + \frac{C_{\text{exec, B}}}{E_{\mathrm{B}}}. \tag{7}$$

Note that this amount depends on market conditions as well as the preference parameters β and γ. In our framework, it is the representative investor's decision quantity.

The total trade size is distributed across mechanisms, so that we have

$$q = q_{\text{AMM}} + q_{\text{P2P}} + q_{\mathrm{B}}. \tag{8}$$

As the allocation to each market mechanism is constrained by its respective liquidity, we impose

$$q_{\text{AMM}} \leq L_{\text{AMM}}, \quad q_{\text{P2P}} \leq L_{\text{P2P}}, \quad q_{\mathrm{B}} \leq \overline{L}_{\mathrm{B}}. \tag{9}$$

[10]While platforms often state a maximum payout period (e.g., 10 business days), on-chain data suggest that execution timing depends on both a fixed schedule and the volume of pending buyback requests. Larger trades may accelerate batch execution, shortening actual payout times. We model this with: $t_{\mathrm{B}}(q_{\mathrm{B}}) = t_{\min} + (t_{\max} - t_{\min}) \cdot \left(1 - \frac{q_{\mathrm{B}}}{\overline{L}_{\mathrm{B}}}\right)^{\kappa}$, where $t_{\min}$ and $t_{\max}$ are lower and upper bounds (e.g., 7 and 10 days), and $\kappa \geq 1$ controls the slope.

The optimization problem to be solved minimizes the total execution cost:

$$\begin{aligned}\min_{q_{\text{AMM}},\ q_{\text{P2P}},\ q_{\text{B}}} \quad C_{\text{total}} = \frac{C_{\text{exec, AMM}}}{E_{\text{AMM}}} \\ + \frac{C_{\text{exec, P2P}}}{E_{\text{P2P}}} \\ + \frac{C_{\text{exec, B}}}{E_{\text{B}}}\end{aligned} \tag{10}$$

subject to the market clearing condition (8) and liquidity constraints (9).

The optimal allocation $(q^*_{\text{AMM}},\ q^*_{\text{P2P}},\ q^*_{\text{B}})$ is obtained as the solution to the constrained optimization problem (10), subject to the market clearing condition (8) and the liquidity constraints (9).

The solution is given by the first-order condition (12), which equates the marginal execution cost per unit of efficiency across all mechanisms. This condition allows us to determine how trade volume is optimally distributed among the three available mechanisms, given trader preferences and prevailing market conditions. Since the objective function in (10) is additively separable and each component depends only on its respective allocation variable, the optimization problem decomposes into marginal comparisons across mechanisms.

In cases where none of the liquidity constraints in (9) are binding, and the necessary conditions for an interior solution hold, that is,

$$q^*_{\text{AMM}} < L_{\text{AMM}}, \quad q^*_{\text{P2P}} < L_{\text{P2P}}, \quad q^*_{\text{B}} < \overline{L}_{\text{B}}, \tag{11}$$

the solution is an interior optimum and satisfies the condition that marginal execution cost per efficiency unit is equalized across all mechanisms:

$$\begin{aligned}\frac{\partial}{\partial q_{\text{AMM}}}\left(\frac{C_{\text{exec, AMM}}}{E_{\text{AMM}}}\right) \\ = \frac{\partial}{\partial q_{\text{P2P}}}\left(\frac{C_{\text{exec, P2P}}}{E_{\text{P2P}}}\right) \\ = \frac{\partial}{\partial q_{\text{B}}}\left(\frac{C_{\text{exec, B}}}{E_{\text{B}}}\right)\end{aligned} \tag{12}$$

By numerically solving the constrained optimization problem across varying preference parameters, liquidity constraints, and mechanism-specific execution characteristics, we assess how optimal trade allocations adjust in response to changing market environments and investor behavior, as detailed in Section 4.1.

This framework allows us to analyze how each mechanism contributes to liquidity provision in the current RWA market, how they interact, and what structural challenges emerge in such fragmented environments. It further illustrates how investors adapt their behavior in response to evolving frictions and preferences within the DeFi landscape. Although our empirical focus lies on one platform, both the theoretical framework and the simulation components capture general structural features of decentralized markets. Importantly, the framework captures the core trade-off logic between execution cost and execution efficiency, shaped by the distinct characteristics of each liquidity mechanism, which is broadly representative in fragmented tokenized asset markets. Next, we examine how the market allocates liquidity across mechanisms given the trade-offs in execution certainty, price informativeness, and transaction costs. We then analyze how arbitrage flows and trader sophistication shape and respond to these allocations, testing the empirical relevance of the model's structure.

3. Data and methodology

3.1. Transaction data

The specific RWA tokenization platform that we analyze is *RealT*, which started in 2019. It is one of the earliest and largest tokenization platforms in terms of tokenized value. As of April 2025, the platform's total tokenized value stands at $140 million, with new tokenized properties added on a weekly to monthly basis.[11] Built on public blockchain and smart contract infrastructure, it enables full transparency of data and represents one of the most advanced implementations of a tokenized market for RWAs currently observable in DeFi. To conduct our analysis, we analyze the secondary market transactions of 511 unique and active RWAs representing heterogeneous assets in the form of tokenized properties traded on the secondary market.[12]

[11] According to DefiLlama, an analytics platform for decentralized finance (`https://defillama.com/protocol/realt-tokens`)

[12] For more details on the the real estate tokens used in our sample, refer to Appendix A.6.

We collected all blockchain transactions associated with wallets linked to these tokenized properties from the Ethereum and Gnosis blockchains during the period from September 3, 2019, to May 31, 2024, amounting to a total of 2,409,303 transactions. Our analysis of investor and trading behavior is conducted at the wallet level; however, we acknowledge the possibility of wash trading, as multiple wallets could belong to the same individual, potentially inflating trade volume and transaction frequency (Cong et al., 2023). The data was retrieved using freely accessible APIs from blockchain explorers, namely *Blockscout* and *Etherscan*.

To refine the data and ensure valid and relevant secondary market transactions, in the first step we exclude all non-secondary market transactions, which included primary market activities such as token mints, STOs, liquidity pool interactions (e.g., adding or withdrawing liquidity), internal transfers (e.g., cross-chain transfers between the Ethereum and Gnosis blockchains for technical or operational purposes), and non-value transfers (e.g., administrative token movements) by checking the `method` of the blockchain transactions. This step reduced the dataset by 978,018 transactions. Next, we removed 203,503 transactions involving non-relevant tokens, such as RealT governance token.[13] Since each secondary market transaction involves both a real estate token and at least one payment token, we consolidated the associated transactions, reducing the dataset by approximately 60% or 781,184 entries.[14] Furthermore, we excluded transactions of inactive or removed tokens. Finally, we retain a high-frequency dataset of 444,535 unique secondary market transactions spanning a 4.5-year period. Figure 4 shows all transaction prices analyzed, segmented by market mechanism.

3.2. Metadata

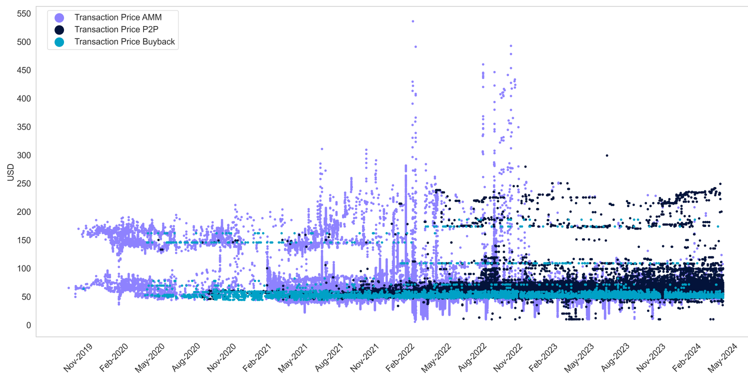
To account for the distinct market mechanisms, we enrich the transaction data with additional blockchain data (offer details for P2P markets, liquidity pool information for AMMs) and non-blockchain data (appraisal values for Buybacks).

Offer data (P2P): We analyze P2P marketplaces (Airswap, Swapcat, YAM) by retrieving offer creation timestamps and fulfillment details using marketplace-specific methods. Offer creation data are recorded on-chain for Swapcat and YAM; Airswap

[13]For a full overview of the payment tokens and their distribution, please refer to Appendix A.7.

[14]In AMMs, *multihop swaps*, which exchange assets through intermediate tokens, can generate multiple transactions requiring consolidation.

Figure 4: All transaction prices by market mechanism



Note: This figure shows all transaction prices segmented by market mechanisms ($N = 444{,}535$).

processes offers off-chain, but its minimal transaction volume makes its exclusion negligible. *Time on Market* is calculated as the interval between offer creation and fulfillment. Prices are fixed by offer creators, thus we exclusively use final transaction prices.

Liquidity pool data (AMM): We extract liquidity pool reserves and token exchange amounts before and after each swap from Uniswap v1/v2 (Ethereum) and Levinswap (Gnosis). Real estate tokens each have distinct liquidity pools, typically paired with payment tokens (e.g., USDC, ETH). Reserve data are retrieved using blockchain-specific APIs, and token prices are calculated using the constant product formula $P = \frac{y}{x}$, where x and y represent the quantities of RWA and payment tokens in the pool, respectively.

Slippage, defined as the difference between the execution price and the pre-swap price, is calculated as:

$$\text{Slippage} = \frac{P_{\text{Execution}} - P_{\text{Before}}}{P_{\text{Before}}}, \tag{13}$$

where $P_{\text{Execution}}$ is the actual price at which the swap is executed, and P_{Before} is the price based on the pool reserves before the swap. Detailed methodological descriptions of the metadata can be found in Appendix A.11.

3.3. Price Signals

Each mechanism generates distinct publicly available price signals essential for traders and price discovery (Section 4.3). While transaction prices reflect executed trades, price signals indicate market prices at any time, even without transactions. These signals vary by mechanism and guide trading decisions. Our dataset comprises 1,301,828 price signals across all tokens, visualized in aggregate in Figure A.12 and described in greater detail in Appendix A.10. Below, we briefly outline how each type of price signal is derived.

Buyback price signals: The Buyback price signals are continuously set by the centralized token issuer based on external property appraisals commissioned by the company. All historical buyback prices are available on the issuer's website (RealT).

P2P price signals: The *Time on Market*, described in Section 3.2, reflects how long an offer remains active and serves as a publicly available price signal, with each offer specifying a fixed price and quantity. Since multiple offers from different participants often exist simultaneously, the P2P price signal for token i at time t is defined as the quantity-weighted average of all active offer prices, computed by summing the product of each offer's price and its corresponding quantity, and dividing by the total quantity across all active offers for that token and time.

AMM price signals: The AMM continuously generates price signals based on liquidity pool reserves and the constant product market-making mechanism.

3.4. Descriptive statistics

Table 1 presents descriptive statistics on real estate token trades at both the intraday (transaction-level) and daily intervals, as used in our regression analyses in Section 4. Our dataset covers 511 unique tokens.[15] Intraday, the average token amount per trade is 0.79 (SD = 4.63), with a median of 0.05 and a maximum of 965.03 tokens, reflecting substantial trade size variability. AMMs account for 76% of intraday trades, mainly in smaller transactions, while P2P and Buyback mechanisms account for 21% and 3%, respectively. The majority (76%) of secondary market activity involves the sale of real estate tokens, with the remaining 24% comprising token purchases. Mechanism usage percentages at the daily interval are computed by aggregating all intraday trades per token by mechanism and calculating each mechanism's share of the total daily traded volume in dollars for that token. This volume-based weighting approach accurately captures the relative economic significance of each mechanism at the token level.

[15] The descriptive variables for the real estate tokens are presented in Table A.6 in the Appendix.

While the average and median price signals are similar across mechanisms, the Buyback mechanism consistently shows the lowest price signals, whereas P2P mechanisms display the highest. AMM shows the highest variability in price signals.[16] Notably, only 1% of all transactions (8% of all transaction volume) occur on the Ethereum blockchain, which has been largely replaced by the more cost-efficient Gnosis chain, an Ethereum sidechain. Daily, the average volume traded per token is \$180.22 (SD = 765.50), with a median of \$26.67 and a maximum of \$54,498. The average trade count per token per day is 4.11 (median = 2), suggesting generally low trading frequency but with spikes up to 576 trades. Slippage is only defined on days with at least one AMM transaction. Because imputing zeros would bias the interpretation of this control variable, we restrict the sample accordingly in the regression analysis, which reduces the number of usable token-day observations for AMM relative to P2P and Buyback. In summary, the daily data further reveals substantial heterogeneity in trading activity, liquidity, and mechanism choice, with a generally clear preference for P2P and AMM mechanisms.

Arbitrage opportunities emerge from structural price differences both within and across decentralized liquidity mechanisms. To empirically identify such behavior, we analyze transaction-level blockchain data using wallet-level identifiers (wallet addresses) alongside transaction directionality—specifically, the recipient (`to`) and sender (`from`) addresses. We classify as *arbitrage* any sequence in which the same wallet buys and sells (or sells and buys) the same token within a predefined time window—1 hour in the baseline analysis and 5 minutes in robustness checks (see Section 5.1). While these patterns resemble classical arbitrage, they are more accurately described as *quasi-arbitrage* due to real-world execution constraints in decentralized environments. Imperfect price discovery, liquidity fragmentation, and timing delays introduce risk and frictions that prevent arbitrage from being truly simultaneous or risk-free. Nevertheless, our identification strategy offers a consistent proxy for detecting arbitrage-like behavior. We identify 111,686 arbitrage transactions, representing approximately 25% of all observed trades.

To classify arbitrage into *within-mechanism* and *into-mechanism* categories, we focus on the mechanism used in the sell leg of each arbitrage sequence—where tokens are

[16]The extremely high maximum price signal (\$7,134) in AMMs stems from a de facto empty liquidity pool, causing a significant distortion in the reserve ratios.

offloaded and liquidity is demanded. Since each arbitrage trade consists of two legs, this sell-side classification avoids double-counting and more accurately captures where price pressure and liquidity usage occur. For example, if a wallet acquires tokens through a P2P trade and subsequently sells them into an AMM pool within the predefined time window, the volume is labeled *Arbitrage into AMM*, with AMM identified as the exit venue. We analyze the daily, per-token volume of arbitrage both within and into each liquidity mechanism, allowing us to assess arbitrage activity and mechanism usage. Naturally, given the fragmented structure of these markets—particularly in the early stages of secondary trading—and the strict wallet-, address-, and time-based criteria for identification, certain token-day combinations show no detectable arbitrage activity.

Additionally, we classify traders according to their market sophistication using transaction frequency and volume on both the buy (`to`) and sell (`from`) sides. Our classification is based on wallets engaged in trading a given token on a given day. Wallets consistently engaging in high-frequency and high-volume transactions (90th percentile) on the sell side (*high frequency/volume sellers*) are classified as sophisticated sellers (*high frequency seller* × *high volume seller*), whereas wallets with low-frequency and low-volume transactions (10th percentile) on the sell side are classified as unsophisticated sellers (*low frequency seller* × *low volume seller*). We specifically define arbitrageurs as wallets exhibiting exceptionally high-frequency and high-volume transaction patterns simultaneously on both the buy and sell sides (*high frequency/volume buyer* × *high frequency/volume seller*), indicative of short-term profit-seeking behavior rather than long-term investment motives. Such short-term buying-and-selling patterns would typically not be economically rational for regular investors. This combined classification facilitates a detailed empirical assessment of how different trader types and arbitrage behaviors influence liquidity.[17] To examine the interplay between trading behavior and liquidity across market mechanisms, we compute liquidity measures for each token at a daily level. Given the absence of conventional bid-ask spreads, we rely on transaction-based proxies derived from price data (open, high, low, close), transaction counts, and dollar volumes. We include Amihud illiquidity (Amihud, 2002), high-low spread, the Corwin and Schultz Estimator (Corwin and Schultz, 2012), and turnover

[17]Since DeFi trade volume does not clearly indicate trade direction, we infer behavior at the wallet level. Consequently, deviations from exact 90th or 10th percentile thresholds arise at the daily level due to our volume-based classification.

ratio—using token-level market valuation. Complete variable definitions, formulas, and further details are provided in Table A.2 and A.3.

Table 1: Descriptive statistics

Variable	N	Mean	St. Dev.	Min	25%	Median	75%	Max
Intraday Perspective								
Realtoken Amount	444,535	0.79	4.63	0.00	0.01	0.05	0.18	965.03
Dollar Amount	444,535	43.87	252.17	0.00	0.57	2.61	9.94	54,495
Transaction Price USD	444,535	55.90	15.91	5.56	50.51	53.44	57.64	535.93
Total Transaction Fee USD	444,535	0.29	2.60	0.00	0.002	0.003	0.015	133.54
Realtoken Sell	444,535	0.76	0.43	0.00	1.00	1.00	1.00	1.00
Realtoken Buy	444,535	0.24	0.43	0.00	0.00	0.00	0.00	1.00
AMM Mechanism	444,535	0.76	0.43	0.00	1.00	1.00	1.00	1.00
P2P Mechanism	444,535	0.21	0.41	0.00	0.00	0.00	0.00	1.00
Buyback Mechanism	444,535	0.03	0.16	0.00	0.00	0.00	0.00	1.00
Price Signal AMM USD	443,956	56.22	32.46	2.14	50.51	53.55	58.02	7,134
Price Signal P2P USD	413,337	58.84	13.92	10.00	52.88	56.00	60.99	299.00
Price Signal Buyback USD	444,535	52.87	12.06	41.50	50.23	50.85	52.08	185.80
Gnosis Blockchain	444,535	0.99	0.12	0.00	1.00	1.00	1.00	1.00
Ethereum Blockchain	444,535	0.01	0.11	0.00	0.00	0.00	0.00	1.00
Dependent Variables (Intraday Perspective)								
Arbitrage	444,535	0.251	0.434	0	0	0	1	1
Arbitrage Volume	111,686	10.589	88.777	0.000	0.517	0.998	4.987	9,245.768
Dependent Variables (Daily Perspective)								
AMM Usage (in %)	108,217	0.51	0.48	0.00	0.00	0.51	1.00	1.00
P2P Usage (in %)	108,217	0.40	0.47	0.00	0.00	0.00	1.00	1.00
Buyback Usage (in %)	108,217	0.09	0.28	0.00	0.00	0.00	0.00	1.00
Turnover Ratio Token M'Cap	108,217	0.000884	0.002962	0.00	0.000038	0.000158	0.000711	0.14
Volume per Token USD	108,217	180.22	765.50	0.00	5.53	26.67	106.00	54,498.48
Number of Trades per Token	108,217	4.11	9.41	1.00	1.00	2.00	4.00	576.00
Amihud	59,772	0.003248	0.02	0.00	0.000076	0.000742	0.001745	0.92
CS Estimator	59,321	0.007082	0.03	0.00	0.00	0.00	0.001748	1.32
High Low	59,820	0.06	0.11	0.00	0.008659	0.03	0.06	1.73
Control Variables (Daily Perspective)								
Arbitrage into AMM	108,217	0.98	14.30	0.00	0.00	0.00	0.00	1,574
Arbitrage within AMM	108,217	5.25	149.80	0.00	0.00	0.00	0.00	24,812
Slippage	67,045	-0.001	0.027	-0.574	-0.008	-0.003	0.007	2.537
Liquidity Pool Value (USD)	107,726	2,098.898	5,559.669	0.000	646.478	1,704.525	2,354.962	190,297.600
Arbitrage into P2P	108,217	0.77	65.95	0.00	0.00	0.00	0.00	17,921
Arbitrage within P2P	108,217	1.44	94.44	0.00	0.00	0.00	0.00	22,990
Arbitrage into Buyback	108,217	0.02	4.04	0.00	0.000	0.00	0.00	1,164
Transaction Price/Buyback Δ	108,217	0.071	0.151	-0.828	0.000	0.039	0.108	7.183
High Volume Buyer	108,217	0.850	0.327	0.000	1.000	1.000	1.000	1.000
High Frequency Buyer	108,217	0.007	0.073	0.000	0.000	0.000	0.000	1.000
High Volume Seller	108,217	0.007	0.078	0.000	0.000	0.000	0.000	1.000
High Frequency Seller	108,217	0.803	0.366	0.000	0.833	1.000	1.000	1.000
Low Frequency Seller	108,217	0.006	0.069	0.000	0.000	0.000	0.000	1.000
Low Volume Seller	108,217	0.007	0.078	0.000	0.000	0.000	0.000	1.000
Blockchain Transaction Fee USD	108,217	0.19	1.83	0.000027	0.000415	0.000595	0.001044	114.36
Volatility 7 Days	104,711	0.070	0.073	0.000	0.032	0.051	0.081	1.367
Market to Appraisal Ratio	108,217	1.27	0.27	0.18	1.15	1.22	1.33	9.70
Cumulative Return ETH (One Week before)	108,217	0.009149	0.11	-0.51	-0.05	0.002699	0.07	0.68
Average Ethereum Fee USD	108,217	11.46	12.95	0.07	3.71	6.22	13.93	200.06
One Month Treasury Δ	108,217	0.004667	0.15	-1.39	-0.001800	0.00	0.001803	1.79
Ten Year Treasury Δ	108,217	0.001076	0.02	-0.32	-0.006734	0.00	0.01	0.34
ADS Index Δ	108,217	-0.002247	0.34	-2.69	-0.05	0.002455	0.05	6.17
S&P Case Shiller Index Δ	108,217	0.006692	0.009617	-0.01	-0.002628	0.008109	0.01	0.03

Note: This table reports the number of observations, mean, standard deviation, minimum, 25^{th} percentile, median, 75^{th} percentile, and maximum for the data on the transaction level (intradaily) and aggregated to daily intervals for the relevant dependent and control variables. Mechanism usage (%) is calculated as a weighted average, with weights based on transaction volume (Volume per Token USD). For the full table of intradaily transactions, see Table A.4 in the Appendix.

4. Main results

4.1. Simulation

To simulate optimal trade allocation outcomes in our fragmented market setting, we solve the constrained optimization problem developed in Section 2.3 based on analytically derived first-order conditions (see Appendix A.14), and compute the exact solution numerically across a range of empirically grounded parameter combinations (Table 3). This approach allows us to examine how trade volume is optimally allocated under varying market and trading conditions.

For each scenario, we solve the cost minimization problem in Equation (10), subject to the market clearing condition (8) and the liquidity constraints (9).[18]

We use sequential quadratic programming, an iterative method for constrained nonlinear optimization[19], and initialize the solver with an economically motivated starting point that allocates more volume to mechanisms with lower execution cost per efficiency unit.[20] This initialization approximates the expected direction of the optimum, while the final allocation is obtained by solving the full optimization problem.

We simulate optimal allocations over a grid of parameters, including mechanism-specific liquidity, transaction fees, price signal quality, execution time, and trader sensitivities to time and fees. The scenarios, summarized in Table 3, are based on an empirically calibrated baseline and extended to explore alternative market environments and mechanism configurations.

[18]While the model assumes interior solutions, the simulation enforces liquidity constraints. Corner solutions may occur when the trade size exceeds available liquidity in a mechanism—especially by design as trade size and available liquidity vary independently in the simulation setup—but are handled numerically and do not affect comparative outcomes.

[19]We apply the Sequential Least Squares Programming (SLSQP) algorithm from the `scipy.optimize.minimize` package in Python.

[20]For details on the initial allocation, see Appendix A.14.

To define the key varying parameters—trade size and available liquidity—we use the 10th and 90th percentiles within each mechanism to define range boundaries, and median values for fixed parameters, based on empirical observations (Table A.5). Buyback liquidity is held constant, as determined by the issuing company. Transaction fees and execution times reflect observed mechanism characteristics. P2P execution time is based on the average time on market to better capture long waiting periods, while Buyback execution specifications reflect batch processing and company-reported timelines. AMM execution is near-instant due to its technical design and is approximated as 1. Relative price signal quality is defined on a 0–1 scale, reflecting the structural design of each pricing mechanism.[21]

For each parameter combination, we compute the optimal trade allocation across mechanisms by solving the optimization problem. The results are visualized as a three-dimensional allocation landscape in Figure 5. These simulated allocation patterns serve as a comparative statics tool, illustrating how investors adapt their selling behavior in response to market frictions, liquidity constraints, and varying trade sizes. Additional variations, particularly those involving non-neutral trader sensitivity parameters, are presented in Appendix A.14.

[21]Collective P2P pricing is most precise (0.9), AMMs exhibit some inefficiencies due to deterministic pricing rules (0.8), and Buyback relies on externally appraised values, making them less responsive to market information (0.7). These rankings align with the information share analysis (Figure 8) and are supported by findings on the lower price informativeness of AMM prices (Angeris et al., 2019).

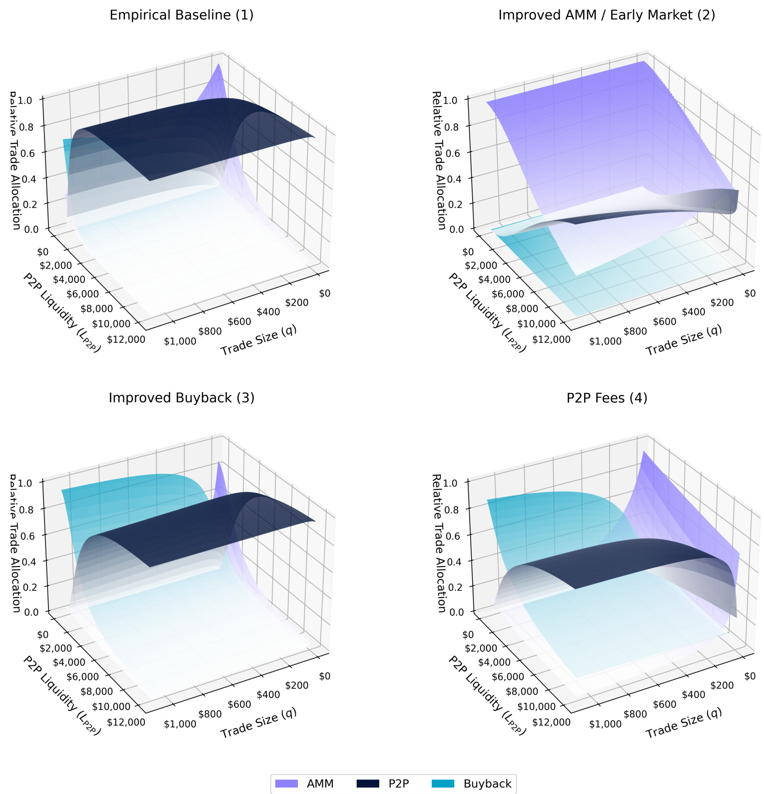
Table 3: Parameter combinations for trade allocation analysis under different market conditions

Parameter		**Empirical Baseline (1)**	**Early Market / Improved AMM (2)**	**Improved Buyback (3)**	**P2P Fees (4)**
Trade Size	q	\$0.5-\$1,100	\$0.5-\$1,100	\$0.5-\$1,100	\$0.5-\$1,100
Available Liquidity (Market Depth)	L_{AMM}	\$955	\$18,685 ↑	\$955	\$955
	L_{P2P}	\$61-\$12,130	\$61-\$12,130	\$61-\$12,130	\$61-\$12,130
	$\overline{L}_{\text{B}}$	\$2,000	\$2,000	\$2,000	\$2,000
Transaction Fees	F_{AMM}	0.3%	0.3%	0.3%	0.3%
	F_{P2P}	≈ 0	≈ 0	≈ 0	0.5% ↑
	F_{B}	3%	3%	1% ↓	3%
Execution Time	t_{AMM}	≈ 1	≈ 1	≈ 1	≈ 1
	t_{P2P}	25	25	25	25
	$\bar{t}_{\text{B, min}}$	7	7	2 ↓	7
	$\bar{t}_{\text{B, max}}$	10	10	4 ↓	10
Price Signal Quality	η_{AMM}	0.8	0.8	0.8	0.8
	η_{P2P}	0.9	0.9	0.9	0.9
	η_{B}	0.7	0.7	0.75 ↑	0.7
Sensitivity	γ (Time)	1	1	1	1
	β (Fees)	1	1	1	1

Note: The table presents various parameter combinations inserted into the optimization framework in Section 2.3 to solve for the optimal trade allocation across AMM, P2P, and Buyback. Arrows (↑, ↓) denote directional changes from the *Empirical Baseline (1)*. Ranges indicate the varying parameters on the axes in Figure 5. To ensure nonlinear P2P execution costs relative to liquidity, we set $\delta = 1.2$, with $1 < \delta < 2$, allowing for a strictly convex but flatter cost curve than the AMM's quadratic specification. Increasing δ amplifies the cost of large P2P trades, thereby shifting allocations accordingly. L_{AMM} refers to the dollar value of the counter-reserve (i.e., the token received), which effectively determines market depth and slippage in a constant-product pool. κ, controlling how execution time responds to buyback size, is fixed at 1 to avoid over-parameterization.

The resulting *Empirical Baseline (1)* scenario in Figure 5 highlights the overall dominating trade volume allocation on P2P, as also illustrated in the empirical breakdown of monthly trading volume in the next section (Figure 6). Yet, particularly when P2P liquidity is low, very small trades tend to shift toward AMMs due to instant settlement and minimal slippage, while larger trades increasingly move to Buybacks once they exceed what AMMs can efficiently absorb. In the *Early Market / Improved AMM (2)* scenario, we statically increase the AMM liquidity pool to \$18,685, reflecting the median payment token pool reserve during the early market phase up to March 17, 2021, the point at which the cost-efficient Gnosis sidechain emerged, overall transaction activity and P2P trading increased (Figure 6 and 7). The higher AMM liquidity, effectively representing an improved AMM, leads to greater AMM allocation due to reduced slippage. This is particularly evident at very low levels of P2P liquidity, mirroring the early market period when P2P trading volume were barely present (Figure 6). During this time of market evolution, cross-mechanism arbitrage was virtually nonexistent (Figure 8). As a result, AMM pools remained stable and largely unexploited, leading to heavier AMM usage. However, when we increase P2P liquidity and trade size along the axis, once again AMM loses allocation due to slippage disadvantages. The *Improved Buyback (3)* scenario shifts trade across all sizes away from P2P and, to some extent, AMM toward Buybacks, as lower fees (1%), faster execution (maximum 4 days), and improved price signal quality (0.75) make Buybacks more competitive. The introduction of a modest 0.5% transaction fee on P2P, for instance as part of potential protocol monetization, in the *P2P Fee (4)* scenario meaningfully reduces P2P allocation, shifting smaller trades toward AMMs and larger trades toward Buybacks. This highlights how sensitive the competitive balance is to fee structures in a multi-mechanism setting. The next section traces the marketplace's evolution over time and empirically validates these framework-derived patterns.

Figure 5: Optimal trade allocation

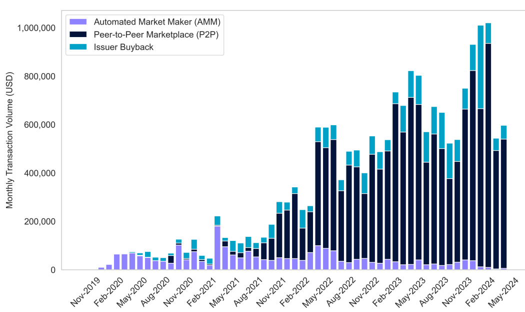


Note: This figure shows the resulting optimal trading allocations when solved the optimization problem in Section 2.3 using the parameters from Table 3.

4.2. Liquidity trends and market evolution

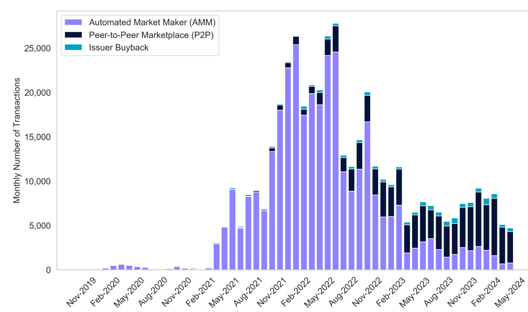
In alignment with the simulated optimal trade allocation outcomes, we observe a clear reallocation of trading activity across liquidity mechanisms. From 2019 to early 2024, tokenized RWA markets shifted from AMM dominance to P2P trading, consistent with our theoretical predictions. AMMs initially dominated due to their instant execution, relatively low-fees, continuous liquidity—and perhaps most crucially—the absence of a developed P2P market. However, increased opportunities for exploitable arbitrage between AMMs and P2P, enabled by lower transaction costs on the Gnosis blockchain, the maturation of P2P platforms, and the collapse of the Levin token in late 2021, triggered a major withdrawal of AMM liquidity. This marked a turning point and led to a sharp and sustained decline in AMM usage (see Figures 6, 7, and 11). Beginning in late 2021, P2P marketplaces gained traction and became the dominant trading mechanism by early 2022. Their flexibility in pricing and accommodation of irregular trade patterns made them better suited to the heterogeneity of RWA tokens, despite higher search costs and lower execution certainty. Centralized buybacks, while infrequent, consistently handled large transactions, acting as a stable but limited liquidity outlet. These dynamics confirm our framework's prediction: traders adjust their venue choice based on execution constraints, liquidity depth, and pricing flexibility. In the following sections, we explore the underlying economic drivers of this evolution in greater depth.

Figure 6: Transaction volume by market mechanism



Note: This figure presents the monthly transaction volume in USD categorized by market mechanisms.

Figure 7: Number of transactions by market mechanism



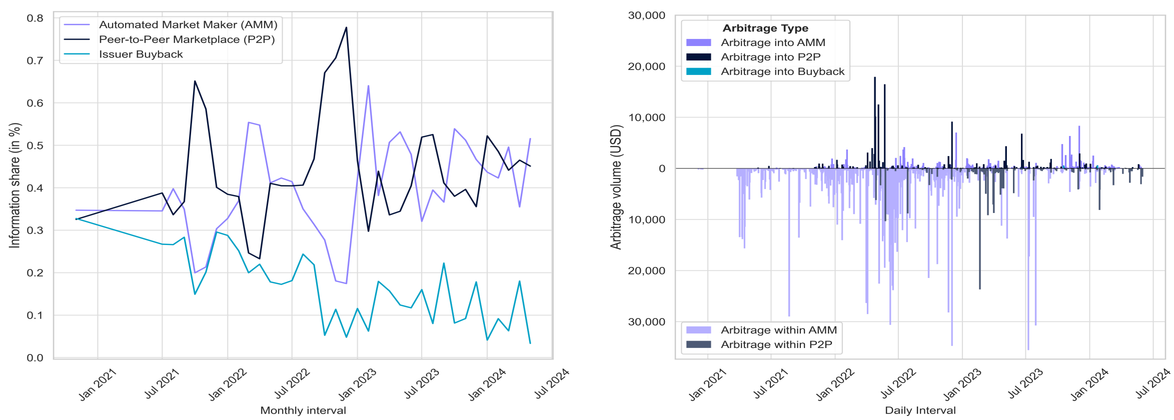
Note: This figure presents the monthly number of transactions categorized by market mechanisms.

4.3. Price discovery and arbitrage within fragmented markets

Building on the fragmented liquidity structures documented above, we now examine how different mechanisms contribute to price discovery—and whether fragmentation creates persistent inefficiencies that arbitrageurs exploit. The different mechanisms generate distinct and often conflicting price signals, complicating valuation and execution. The key question is whether these signals converge to form a consistent market price or instead reflect structural dislocations that facilitate arbitrage across venues.

To quantify each mechanism's role in price formation, we apply the information share metric proposed by Hasbrouck (Hasbrouck, 1991a,b, 1995), a standard approach in market microstructure. This method decomposes the variance of residuals from a cointegrated price system to estimate the relative contribution of each venue to the common efficient price. A higher information share indicates a stronger influence on price discovery, while a lower share suggests limited informational relevance. Although traditional applications adjust for correlated innovations across venues, this adjustment is less informative in our setting due to structural misalignment between Buyback prices and actual trading prices.[22]

Figure 8: Information share analysis and arbitrage volume across market mechanisms



Note: This figure presents the information share analysis (left) and arbitrage volume (right) across market mechanisms. The left panel shows the distribution of information shares across mechanisms for all transactions over monthly intervals, illustrating the evolving contributions of AMM, P2P, and Buyback designs to price discovery. The right panel reports arbitrage volumes over the same period, highlighting liquidity flows and the relative importance of different arbitrage types. For methodological details on information share computation, see Appendix A.4.

The fragmented structure of liquidity mechanisms gives rise to interdependent dynamics between price discovery and arbitrage. Figure 8 illustrates this interaction. The left panel shows the evolution of the information share, capturing each mechanism's contribution to price discovery based on deviations from executed transaction prices. As P2P infrastructure matures, it surpasses AMMs by mid-2022, indicating a shift in where market participants anchor their pricing. By 2023, AMM and P2P contributions converge, suggesting a more competitive price discovery environment. The right panel plots arbitrage volumes, revealing how diverging price signals are exploited. While arbitrage helps align prices, it also exploits persistent inefficiencies across them. Taken together, the two panels highlight how evolving price leadership across mechanisms shapes both arbitrage behavior and liquidity allocation.

To formally evaluate how arbitrage activity influences the perceived efficiency of each mechanism, we estimate the following panel regression model:

[22] For details on the computation and interpretation of information share, see Appendix A.4.

$$\text{Usage}_{i,t}^{m} = \beta_1 \cdot \text{ArbInto}_{i,t}^{m} + \beta_2 \cdot \text{ArbWithin}_{i,t}^{m} + \beta_3 \cdot \text{Controls}_{i,t} + \mathbf{X}_{i,t}'\boldsymbol{\gamma} + \alpha_i + \delta_t + \varepsilon_{i,t} \quad (14)$$

where the dependent variable $\text{Usage}_{i,t}^{m}$ denotes the daily usage share (in %) of mechanism $m \in \{\text{AMM}, \text{P2P}, \text{Buyback}\}$ for token i on day t. The variable $\text{ArbInto}_{i,t}^{m}$ captures arbitrage volume into mechanism m, defined as arbitrage trades that exit via mechanism m. $\text{ArbWithin}_{i,t}^{m}$ measures arbitrage volume occurring entirely within mechanism m, where both legs of the trade are executed in the same venue. Controls include $\text{Slippage}_{i,t}$ (AMM-only), and a vector $\mathbf{X}_{i,t}$ comprising transaction fees, short-term volatility, valuation spreads, ETH returns, and macroeconomic indicators such as Treasury yields, the ADS Index, the Case-Shiller Index, and gas fees. Token-level fixed effects are captured by α_i, while δ_t denotes year-month fixed effects. The error term $\varepsilon_{i,t}$ is clustered at the token level.

Table 4: Arbitrage flow and mechanism efficiency

	Dependent variable:		
	AMM Usage (in %)	P2P Usage (in %)	Buyback Usage (in %)
	(1)	(2)	(3)
Arbitrage into mechanism m	−0.0003***	0.0001***	0.0001
	(0.0001)	(0.00002)	(0.0002)
Arbitrage within mechanism m	0.00002***	−0.00001	/
	(0.00000)	(0.00001)	
Slippage	0.273***	/	/
	(0.081)		
Blockchain Transaction Fee USD	1.210***	−4.737***	4.897***
	(0.254)	(0.332)	(0.718)
Volatility 7 Days	0.042**	−0.191***	0.173***
	(0.019)	(0.032)	(0.022)
Market to Appraisal Ratio	−0.050***	0.276***	−0.232***
	(0.019)	(0.087)	(0.059)
Cumulative Return ETH (One Week)	−0.111***	0.067***	0.043***
	(0.010)	(0.018)	(0.013)
Average Ethereum Fee USD	0.0001**	−0.001***	−0.0001**
	(0.0001)	(0.0001)	(0.0001)
One Month Treasury Δ	−0.005**	0.010***	0.002
	(0.002)	(0.003)	(0.003)
Ten Year Treasury Δ	−0.0001	−0.085**	0.095***
	(0.024)	(0.037)	(0.029)
ADS Index Δ	−0.001	−0.003	−0.007***
	(0.002)	(0.003)	(0.002)
S&P Case Shiller Index Δ	−0.249	−1.886***	1.543***
	(0.481)	(0.689)	(0.360)
Individual Fixed Effects	Yes	Yes	Yes
Year-Month Fixed Effects	Yes	Yes	Yes
Observations	65,140	104,711	104,711
R^2	0.153	0.297	0.068
Adjusted R^2	0.146	0.293	0.063

Note: The table presents results for the panel regression of *mechanism usage (in %)* on a daily basis with respect to arbitrage within and into the mechanism. All models include year-month-fixed effects and token-level individual-fixed effects. Robust standard errors clustered at the token level are shown in parentheses. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in the Appendix.

Table 4 shows first correlative evidence for the relationship between arbitrage activity and mechanism usage. We interpret daily usage shares as proxies for perceived mechanism efficiency and assess whether arbitrage flows increase or reduce a venue's attractiveness. Arbitrage into AMMs significantly reduces their overall usage (coefficient: -0.0003, $p < 0.01$). Since usage is measured in decimal format, where 0.01 equals 1%, this implies that each additional dollar in arbitrage flow into AMMs reduces usage by approximately 0.03%. This negative relationship suggests that arbitrageurs primarily extract rather than contribute liquidity. Their activity depletes pool depth, increases execution costs, and amplifies adverse selection risks (Capponi and Jia, 2021;

Park, 2023). In contrast, arbitrage within AMMs has a small but statistically significant positive effect (coefficient: 0.00002, $p < 0.01$), indicating that each additional dollar in internal arbitrage increases usage by 0.002%, reflecting marginal improvements in pricing stability without materially boosting perceived efficiency. Slippage is positively associated with AMM usage (coefficient: 0.273, $p < 0.01$), which may reflect traders' continued reliance on AMMs for guaranteed execution—even at deteriorating prices. Usage also rises with blockchain transaction fees (coefficient: 1.210, $p < 0.01$), consistent with AMMs being the preferred venue under high-friction conditions due to their immediate liquidity. Arbitrage into P2P mechanisms increases usage slightly (coefficient: 0.0001, $p < 0.01$), corresponding to a 0.01% increase in usage per additional dollar of arbitrage. Arbitrage within P2P has no significant effect (coefficient: -0.00001), implying limited impact of internal flow on user behavior. P2P usage declines with volatility (-0.191, $p < 0.01$) and is highly sensitive to transaction fees (-4.737, $p < 0.01$), consistent with search frictions and delayed execution under uncertainty. Buybacks act as a stabilizing fallback. Arbitrage into buybacks increases usage marginally, although the effect is not statistically significant. Because contemporaneous regressions may suffer from endogeneity, we re-estimate the specification using future usage (at $t + 1$) as the dependent variable and exclude arbitrage within a mechanism to avoid mechanically inflating usage, see Table A.10 in the Appendix. The results remain consistent, albeit with lower explanatory power. We additionally estimate log-ratio regressions to account for the compositional nature of mechanism usage shares, which sum to one; the results in Tables A.11 and A.12 confirm that our main findings remain consistent.

These results highlight the dual role of arbitrage in fragmented markets: it can improve pricing within mechanisms but also erode liquidity across venues—particularly in AMMs. Despite deterministic pricing, AMMs continue to serve as a default for instant execution, while P2P mechanisms grow in importance when search costs are low and volatility is manageable. Buybacks offer predictable exit routes but are structurally disconnected from real-time price signals. While the regression results reveal strong correlations between arbitrage activity and mechanism usage, they leave open whether these patterns reflect causal effects or are driven by trader self-selection into venues with favorable conditions. To address this identification challenge, we next implement a difference-in-differences design around the collapse of the TerraUSD (UST / Terra

Luna) stablecoin—an exogenous shock to market conditions—to assess whether AMMs are systematically more exposed to arbitrage exploitation during periods of stress.

4.4. Difference-in-differences analysis: The UST collapse

The collapse of the TerraUSD (UST) stablecoin on May 7, 2022 constitutes a highly suitable exogenous shock for analyzing the causal impact of systemic stress on arbitrage behavior in fragmented decentralized markets.[23] Importantly, none of the liquidity pools or tokens in our dataset are directly paired with UST or its sister token Luna, which insulates our sample from mechanical price contagion through direct asset linkages or reserve rebalancing. Instead, the shock introduced broad-based market uncertainty across the DeFi ecosystem—triggering volatility, fee spikes, liquidity withdrawals, and, crucially, execution frictions. The depegging of UST and the resulting loss of confidence spilled over into other stablecoins, many of which temporarily traded at discounts or experienced lagged adjustments, thereby creating a wave of cross-stablecoin arbitrage opportunities (Uhlig, 2022; Briola et al., 2023; Lee et al., 2023). These second-order effects, while externally imposed and orthogonal to the fundamentals of the tokenized real estate assets in our sample, altered arbitrage profitability across trading venues in ways unrelated to token characteristics. As such, the UST collapse provides a quasi-experimental setting that enables identification of the causal relationship between market fragmentation and arbitrage behavior—particularly the comparative vulnerability of different liquidity mechanisms to price inefficiencies.

To test whether AMMs are more exposed to arbitrage exploitation in fragmented markets than P2P marketplaces during periods of market instability, we implement a transaction-level difference-in-differences (DiD) design that leverages the UST collapse as an exogenous shock most similar to Makarov and Schoar (2020) or Brogaard et al. (2025). We regress the binary dependent variable, $Arbitrage_{it}$, which equals one if the same wallet executes a profitable trade (buy-sell or sell-buy) in the same token within a 60-minute window—regardless of the underlying trading mechanism—and zero otherwise. The treatment group consists of trades executed through AMMs, while the control group includes trades completed on decentralized P2P marketplaces. We define

[23] At the time, UST was the third-largest stablecoin by market capitalization at $18 billion—after USDT and USDC—and deeply embedded in the DeFi ecosystem. Its collapse triggered widespread contagion across crypto markets (Briola et al., 2023).

the post-event period as trades occurring on or after May 7, 2022, and restrict the analysis to a narrow two-week window (May 1–14) to avoid contamination from longer-term market adjustments. The regression model is specified as:

$$Arbitrage_{it} = \beta_0 + \beta_1 AMM_i + \beta_2 Post_t + \beta_3 (AMM_i \times Post_t) + \mathbf{X}_{it}' \boldsymbol{\gamma} + \alpha_s + \varepsilon_{it} \tag{15}$$

where AMM_i is a dummy variable equal to one if the transaction occurred via an AMM, and $Post_t$ equals one if the transaction occurred on or after May 7. The interaction term $AMM_i \times Post_t$ captures the differential increase in arbitrage probability for AMM-based trades relative to P2P trades in the wake of the shock. The vector $\mathbf{X}_{it}$ includes transaction-level controls: total transaction fees as a percentage of trade size, the token's market-to-appraisal ratio, and the dollar value of liquidity pool reserves (for AMM trades). Fixed effects α_s absorb all time-invariant token-level heterogeneity, and standard errors are clustered at the token level. Across linear probability, logit, and probit specifications, we find a significant post-shock increase in arbitrage probability for AMM transactions in comparison to P2P. These findings demonstrate that deterministic, passive pricing structures—characteristic of AMMs—are more susceptible to arbitrage during periods of instability than their custom-priced P2P counterparts, highlighting a core vulnerability of fragmented decentralized market designs.

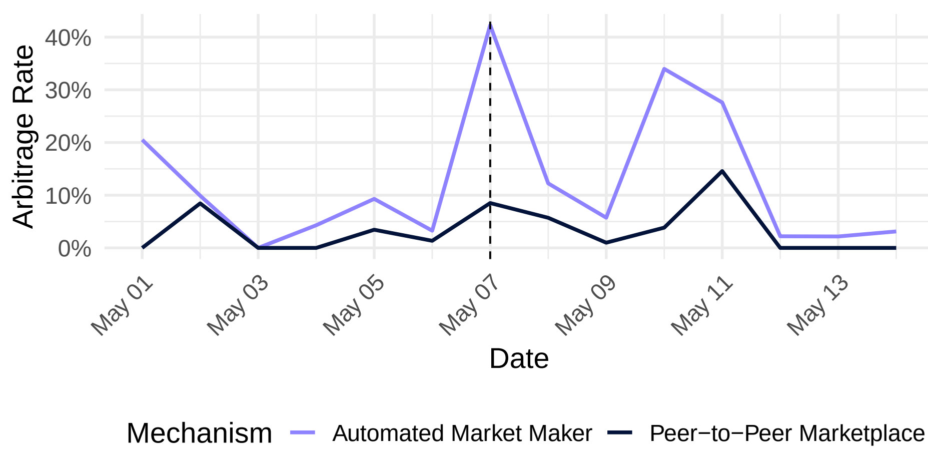
Table 5: Difference-in-differences of arbitrage

	Dependent variable: Arbitrage		
	OLS	Logit	Probit
	(1)	(2)	(3)
AMM	0.073*	1.326***	0.632***
	(0.038)	(0.368)	(0.160)
Post Event	0.012	0.203	0.089
	(0.039)	(0.445)	(0.194)
Total Fee (%)	−4.079***	−24.690***	−12.570***
	(0.521)	(4.729)	(2.387)
Market-to-Appraisal Ratio	−0.735***	−0.497***	−0.248***
	(0.147)	(0.130)	(0.067)
Liquidity Pool Value (USD)	0.00024**	0.000063***	0.000041***
	(0.00009)	(0.00002)	(0.00001)
AMM × Post Event	0.093**	0.773*	0.447**
	(0.032)	(0.453)	(0.199)
Individual-Fixed Effects	Yes	No	No
Clustered SE	Yes	No	No
Observations	10,609	10,609	10,609
Adjusted R^2	0.174	–	–

Note: This table reports regression results for the binary outcome *arbitrage* across three specifications. Model (1) is estimated using OLS with symbol fixed effects and standard errors clustered at the symbol level. Models (2) and (3) are estimated using Logit and Probit specifications, respectively. Coefficient estimates are shown with standard errors in parentheses. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

The regression results in Table 5 provide strong empirical support for the hypothesis that AMMs are more vulnerable to arbitrage exploitation during periods of systemic stress than their P2P counterparts. Across all three model specifications—OLS, Logit, and Probit—the interaction term *AMM* × *Post Event* is positive and statistically significant, indicating that the probability of arbitrage increases disproportionately for AMM-based trades following the UST collapse. In the OLS specification, the post-shock arbitrage probability is 9.3 percentage points higher for AMM trades relative to P2P, holding all else constant. This finding is echoed in the non-linear models, where the marginal effect remains significant, albeit with smaller coefficients due to the scaling of logit and probit transformations. Importantly, the baseline AMM indicator is also significant, suggesting that even prior to the shock, AMMs exhibited a higher arbitrage propensity. Meanwhile, transaction-level controls behave as expected: higher fees reduce arbitrage—an economically modest but statistically significant effect, given that fees are expressed in decimal form (e.g., 0.005 = 0.5%), so a one percentage point increase corresponds to only a 4.1 basis point decline in arbitrage probability. Deeper AMM liquidity and more severe pricing deviations (as captured by market-to-appraisal ratios) influence arbitrage likelihood in predictable directions. To support the parallel trends assumption required for causal interpretation of the DiD estimator, Figure 9 plots the daily arbitrage probability separately for AMM and P2P transactions over the two-week event window. The arbitrage rate is simply calculated as the percentage of trades classified as arbitrage relative to the total number of trades of one day per market mechanism. Prior to the UST collapse on May 7, arbitrage rates for both mechanisms move in parallel and at low levels, indicating comparable baseline trends. Immediately following the shock, we observe a pronounced and persistent increase in AMM-based arbitrage, while P2P arbitrage remains low. The absence of pre-treatment divergence and the clear post-treatment separation suggest that the DiD interaction term captures a genuine mechanism-level shift in arbitrage behavior driven by the shock, rather than underlying trends. In unreported analyses, we also include alternative specifications controlling for daily return volatility, and our results remain robust. Descriptive details and a robustness check using a 5-minute arbitrage window are provided in Appendix A.13.

Figure 9: Parallel Trends



Note: This figure plots the daily arbitrage probability for trades executed via AMMs and P2P marketplaces between May 1 and May 14, 2022. The vertical dashed line marks the collapse of the UST stablecoin on May 7, used as the exogenous shock in our difference-in-differences design. Both mechanisms exhibit parallel trends prior to the shock, followed by a sharp divergence with AMM arbitrage increasing and P2P remaining low.

Collectively, the results underscore the fragility of deterministic pricing mechanisms in fragmented markets under stress, highlighting the relative robustness of custom-priced P2P marketplaces when facing systemic disruptions. To better understand how vulnerabilities emerge from fragmented market design, we now turn to the role of trader behavior across mechanisms.

4.5. Investor sophistication and trading behavior

To analyze who exploits fragmented markets—similar to informed traders in traditional financial settings—we use wallet-level blockchain data to classify participants by trading frequency, volume, and directional activity (i.e., `from` vs. `to` address behavior). As in conventional markets, traders vary in sophistication, speed, and market access. Understanding how these characteristics relate to mechanism usage and liquidity dynamics is central to our analysis. Specifically, we examine how trader sophistication influences engagement with the mechanisms at the token-day level. We estimate the following panel regression to examine how trader sophistication relates to daily usage of different liquidity mechanisms:

$$\text{Usage}_{i,t}^{m} = \beta_1 \cdot \text{Arbitrageur}_{i,t} + \beta_2 \cdot \text{SophSell}_{i,t} + \beta_3 \cdot \text{UnsophSell}_{i,t} + \mathbf{X}_{i,t}' \boldsymbol{\gamma} + \alpha_i + \delta_t + \varepsilon_{i,t} \quad (16)$$

where $\text{Usage}_{i,t}^{m}$ denotes the percentage share of trades routed through mechanism m for token i on day t. The variables $\text{Arbitrageur}_{i,t}$, $\text{SophSell}_{i,t}$, and $\text{UnsophSell}_{i,t}$ are dummy variables indicating whether trading activity for token i on day t is dominated by wallets classified as arbitrageurs, sophisticated sellers, or unsophisticated sellers, respectively. The control vector $\mathbf{X}_{i,t}$ includes , and the model includes token-level fixed effects (α_i) and year-month fixed effects (δ_t). Standard errors are clustered at the token level.

Table 6: Trader sophistication and mechanism usage

	Dependent variable:		
	AMM Usage (in %)	P2P Usage (in %)	Buyback Usage (in %)
	(1)	(2)	(3)
Arbitrageur	0.300***	−0.219***	/
	(0.069)	(0.073)	/
Sophisticated seller	−0.113*	0.125*	0.008
	(0.064)	(0.067)	(0.037)
Unsophisticated seller	−0.242***	0.235***	0.081***
	(0.035)	(0.036)	(0.020)
Controls	Yes	Yes	Yes
Individual-Fixed Effects	Yes	Yes	Yes
Year-Month-Fixed Effects	Yes	Yes	Yes
Observations	104,711	104,711	104,711
R^2	0.405	0.327	0.407
Adjusted R^2	0.402	0.324	0.404

Note: The table presents results for the panel regression of *mechanism usage (in %)* on daily basis as in the previous section with dummy variables for trader classification of *Arbitrageur* (90% quantile in volume and transaction on the buy / to side), sophisticated seller (90% quantile in volume and transaction on the sell / from side) and unsophisticated trader (10% quantile in volume and transaction on the sell / from side). All models include token-level individual-fixed effects, year-month-fixed effects and the control variables *Blockchain Transaction Fee (USD)*, *Volatility (7 Days)*, *Market to Appraisal Ratio*, *Cumulative Return ETH (One Week)*, *Average Ethereum Fee (USD)*, *One Month Treasury* Δ, *Ten Year Treasury* Δ, *ADS Index* Δ, and *S&P Case Shiller Index* Δ. The table includes coefficient estimates and corresponding standard errors, presented in parentheses. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.2.

The results in Table 6 reveal a clear segmentation of trading behavior by trader sophistication. Wallets classified as *arbitrageurs* increase *AMM Usage* by 30 percentage points (coefficient: 0.300, $p < 0.01$) and reduce *P2P Usage* by 21.9 points (coefficient: -0.219, $p < 0.01$), suggesting a systematic strategy of sourcing tokens in P2P markets and selling them into AMMs for immediate execution. While this arbitrage aligns prices across venues, it drains AMM liquidity and increases slippage for other users. *Sophisticated sellers* favor P2P trading, increasing *P2P Usage* by 12.5 points and decreasing *AMM Usage* by 11.3 points (both $p < 0.1$), consistent with a preference for execution quality and strategic counterpart matching. In contrast, *unsophisticated sellers* shift away from AMMs (-24.2 points, $p < 0.01$) and toward both P2P (+23.5 points, $p < 0.01$) and Buybacks (+8.1 points, $p < 0.01$), indicating a reliance on more transparent and predictable mechanisms. Taken together, these patterns highlight how fragmentation interacts with trader heterogeneity: arbitrageurs concentrate in AMMs, experienced traders gravitate toward P2P, and less experienced participants rely on Buybacks.

To complement the analysis of mechanism usage, we next examine how trader sophistication influences overall market liquidity. Specifically, we estimate a panel regression linking wallet-level sophistication to token-level liquidity metrics:

$$\text{Liquidity}_{i,t} = \beta_1 \cdot \text{Arbitrageur}_{i,t} + \beta_2 \cdot \text{SophSell}_{i,t} + \beta_3 \cdot \text{UnsophSell}_{i,t} + \mathbf{X}'_{i,t}\boldsymbol{\gamma} + \alpha_i + \delta_t + \varepsilon_{i,t} \tag{17}$$

where $\text{Liquidity}_{i,t}$ denotes one of six daily token-level liquidity measures: Turnover, Volume, Trades, Amihud, CS Estimator, or High-Low spread. Trader classification follows the same volume- and frequency-based thresholds as before. All regressions include the control variables from previous sections, as well as token fixed effects (α_i) and year-month fixed effects (δ_t). Standard errors are clustered at the token level.

Table 7: Trader sophistication and liquidity

	Dependent variable:					
	Turnover	Volume	Trades	Amihud	CS Estimator	High Low
	(1)	(2)	(3)	(4)	(5)	(6)
Arbitrageur	0.002***	531.632***	6.703***	−0.0004	0.020**	0.070**
	(0.001)	(154.400)	(1.851)	(0.006)	(0.010)	(0.032)
Sophisticated seller	0.002***	81.202	1.632	−0.005	0.017*	0.128***
	(0.001)	(140.162)	(1.680)	(0.006)	(0.009)	(0.031)
Unsophisticated seller	−0.001***	−502.189***	0.318	−0.014	−0.007	−0.065
	(0.0003)	(76.527)	(0.918)	(0.009)	(0.016)	(0.050)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual-Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month-Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	108,217	108,217	108,217	59,772	59,321	59,820
R^2	0.043	0.010	0.060	0.053	0.017	0.056
Adjusted R^2	0.038	0.005	0.055	0.044	0.008	0.047

Note: The table presents the panel regression results for the liquidity analysis on daily and as in the previous section with dummy variables for trader classification of *Arbitrageur* (90% quantile in volume and transaction on the buy / to side), sophisticated seller (90% quantile in volume and transaction on the sell / from side) and unsophisticated trader (10% quantile in volume and transaction on the sell / from side). The dependent variables are *Turnover Ratio*, *Dollar Volume*, *Trades*, *Amihud*, *CS Estimator*, and *High Low* on token-level as further explained in Appendix A.3. All models include year-month-fixed effects and token-level individual-fixed effects and the control variables as in the previous regression. The table includes coefficient estimates and corresponding standard errors, presented in parentheses. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.2.

The results, reported in Table 7, show that *arbitrageurs* increase turnover (0.002, $p < 0.01$), trading volume (531.6, $p < 0.01$), and number of trades (6.70, $p < 0.01$), but also widen spreads (CS Estimator: 0.020, $p < 0.05$; High Low: 0.070, $p < 0.05$), indicating liquidity extraction and fragmentation. *Sophisticated sellers* also raise turnover (0.002, $p < 0.01$) and modestly increase spreads. In contrast, *unsophisticated sellers* reduce turnover (-0.001, $p < 0.01$) and volume (-502.2, $p < 0.01$), with limited effect on spread-based measures, suggesting lower engagement in liquidity-relevant activity.

Overall, these findings show how trader sophistication shapes liquidity by reallocating volume across venues and altering trading costs. Arbitrage exploits price discrepancies between P2P venues and AMMs, draining P2P liquidity and increasing execution costs for bilateral traders, while inflating slippage in AMMs through repeated exit pressure. Although arbitrage contributes to price alignment, it does so at the expense of aggregate liquidity and capital efficiency.

These dynamics highlight the importance of mechanism design in managing heterogeneous trader behavior. AMMs offer immediate execution but are structurally exposed to liquidity depletion through arbitrage, which reduces incentives for liquidity providers—especially under volatile conditions where impermanent loss risk increases (see Figure A.7 in Appendix A.7). Adaptive designs such as dynamic pricing curves and volatility-sensitive trading fees may help address these vulnerabilities (Cao et al., 2025; Makarov and Schoar, 2020).

In contrast, P2P venues provide greater pricing flexibility but remain constrained by fragmentation and low frequency. Enhancing P2P liquidity through incentives or dynamic offer mechanisms could improve execution depth and market resilience. Centralized Buybacks, while limited in scalability, offer predictable execution for unsophisticated traders and help stabilize markets during stress.

Designing effective tokenized markets thus requires balancing AMMs, P2P marketplaces, and Buybacks to accommodate diverse trader needs while ensuring long-term liquidity sustainability across mechanisms.

5. Robustness and broader perspective

5.1. Time for transactions

As outlined in Section 4, we reduce the time window between buy and sell trades from 1 hour to 5 minutes to ensure robustness regarding the arbitrage-like nature of the transactions. Table A.13 and Section A.13 in the Appendix report the results for this adjustment. While the stricter time constraint leads to a reduction in the number of observations, the findings of Section 4.3 and Section 4.4 remain consistent.

5.2. Market development and liquidity pools

To contextualize and reinforce our main findings, we examine market capitalization trends and the evolution of AMM liquidity pools. As shown in Figure 10, the tokenized real estate market grew steadily, reaching a market cap of $119.4 million by May 2024—36% above underlying appraisals—reflecting strong investor demand and market maturity. Cumulative trading volume reached $19.5 million, or 20% of market cap. A key shift in liquidity provisioning occurred following the 2021. As illustrated in Figure 11, RealT and other providers withdrew 80% of AMM liquidity, exposing structural limitations of AMMs in RWA markets characterized by low turnover, appraisal anchoring, and irregular trading. Increased slippage and arbitrage drained pool depth, reducing AMM relevance over time. While the mid-2022 transition to stablecoin pairs helped limit impermanent loss, it also amplified arbitrage between AMMs and P2P venues. By May 2024, AMMs held just $287,179 in reserves—still functioning but significantly diminished. Together, these dynamics support our empirical evidence on trading preferences and underscore the structural misalignment between AMMs and tokenized RWAs, helping explain the rise of P2P marketplaces.

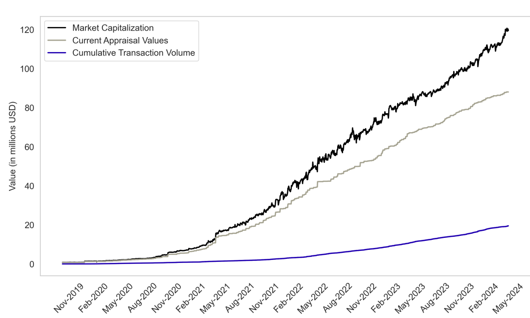


Figure 10: Market cap, book value and trading volume

Note: This figure illustrates the daily value of all real estate tokens based on their last transaction prices (market capitalization), the current appraisal values as provided by an external appraisal company, and the cumulative transaction volume of the real estate tokens on the secondary market. All values are in USD.

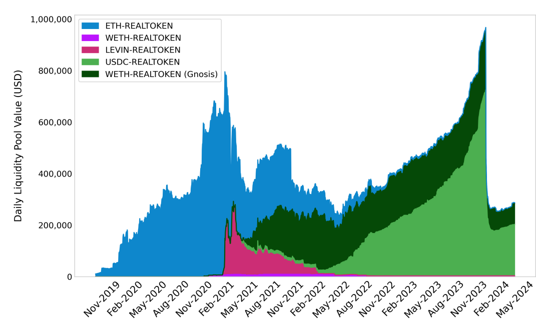


Figure 11: Liquidity-pool value by payment-token pair

Note: This figure illustrates the daily total liquidity pool value across all Automated Market Makers (AMMs) in USD categorized by the payment token involved in the liquidity pool pairs. REALTOKEN serves as a placeholder for specific real estate token pool pairs, with each token having its own dedicated liquidity pool.

6. Conclusion

This study provides an in-depth analysis of liquidity mechanisms for tokenized RWAs using a highly transparent and exceptionally detailed dataset consisting of 444,535 secondary market transactions around RealT—the largest operational issuance platform for tokenized real estate on public blockchain infrastructure. The unique transparency and granularity of our wallet-level data facilitate deep insights into investor behavior, arbitrage dynamics, and the comparative effectiveness of different liquidity provision mechanisms: AMMs, P2P marketplaces, and centralized buybacks.

We develop a stylized framework to formalize the cost-efficiency trade-offs faced by liquidity demanders across three coexisting liquidity mechanisms. This framework guides our empirical analysis, which yields three key findings. First, despite their success and widespread adoption in liquid cryptocurrency markets, AMMs exhibit critical structural vulnerabilities when applied to heterogeneous, infrequently traded RWAs. Their deterministic pricing models lead to persistent arbitrage opportunities, systematically draining liquidity and undermining the sustainability of AMMs in low-frequency trading environments. This is specifically confirmed in our diff-in-diff analysis, which utilizes the UST collapse in 2022 as an exogenous DeFi market shock. Second, centralized buyback mechanisms offer valuable liquidity guarantees, particularly attractive to unsophisticated investors. However, they face constraints related to high transaction costs, limited scalability, and static pricing disconnected from real-time market dynamics. Third, our analysis robustly identifies P2P marketplaces as the dominant trading mechanism, especially advantageous for RWAs due to their flexible and customized pricing structures. P2P platforms facilitate accurate price discovery by directly reflecting true asset values, thereby minimizing susceptibility to arbitrage.

The market phenomena documented—arbitrage-driven liquidity flows, fragmentation across trading venues, and varying investor sophistication—represent fundamental dynamics extensively observed in liquid market contexts (Capponi and Jia, 2021; Park, 2023). Our findings importantly extend these insights to heterogeneous and illiquid RWAs, using the unique setting of real estate tokens, which serve as an example for other tokenized heterogeneous assets like private equity and debt instruments, fund shares, commodities, art, and intellectual property . Although several RWA platforms adopt individual liquidity mechanisms, RealT remains the only platform where all three coexist and are fully transparent via public blockchain data (see Table A.1 in Appendix A.1).

This unique observability provides a rare empirical lens into the structural interactions and trade-offs between mechanism types in tokenized markets. Therefore, the systemic and behavioral insights from our detailed empirical investigation serve as a robust baseline for understanding broader secondary-market microstructures within decentralized finance.

The practical implications of our results are significant, particularly for market design and policy frameworks. Our findings highlight the coexistence of complementary yet fragmented liquidity mechanisms, underscoring the need for a hybrid market setting that more effectively integrates both centralized and decentralized elements. In RWA markets, AMMs alone do not serve as fully reliable decentralized price oracles (Fabi and Prat, 2025), as we find that cross-mechanism arbitrage for price synchronization is limited and price discovery across venues often remains fragmented. To mitigate these inherent limitations of AMMs in RWA markets, a two-layer adaptive pricing mechanism informed by market-driven feedback could be further investigated. Initially, AMM transaction fees should dynamically adjust based on deviations between AMM prices and volume-weighted average prices (VWAP) derived from contemporaneous P2P transactions. Increasing fees during pronounced price divergences discourages arbitrage-driven liquidity depletion and incentivizes liquidity provision. As a result, pool inventory grows and trading costs decline—supporting greater trading volume (Hasbrouck et al., 2022), potentially contributing to overall price stability. Further, AMM baseline pricing should incorporate frequent, real-time P2P market signals or updated centralized buyback valuations, aligning AMM prices more closely with real market conditions. In broader terms, the implementation of robust oracle infrastructures is critical, as reliable and timely off-chain data integration not only informs AMM design but serves as the foundational link between on-chain tokens and the value and legitimacy of the underlying RWAs.

Moreover, a regulatory framework which combines centralized oversight with decentralized innovation, such as Regulated Decentralized Finance (RegDeFi), is essential to ensure investor protection, market stability, and continued technological advancement. Enhancing governance through decentralized autonomous organizations (DAOs) also offers a promising pathway for resolving trust and centralization concerns within tokenized asset markets.

Future research could build on our empirical foundation by estimating structural liquidity costs across trading mechanisms and analyzing governance and incentive structures within DAOs managing tokenized assets. It could also examine operational and theoretical oracle implementations for RWA platforms and compare market evolution under diverse regulatory environments. Investigating these complex issues will be crucial for ensuring tokenization realizes its transformative potential—reshaping rather than merely digitizing existing market structures.

However, the successful realization of the benefits of tokenization depends critically on the resolution of ongoing economic, structural, and regulatory challenges through strategic market design as well as incremental implementation. If left unresolved, these challenges threaten to digitally replicate existing inefficiencies—resulting in fragmented, illiquid markets burdened by significant search costs and persistent price distortions. Rather than fostering a more accessible, efficient, and inclusive financial ecosystem, unaddressed structural frictions could amplify risk premia, exacerbate liquidity constraints, and ultimately reinforce the very inefficiencies that tokenization seeks to eliminate. As a cautious answer to the question raised at the outset, *RWAs can be liquid in fragmented markets*—but only if fragmentation is counterbalanced by thoughtful mechanism and pricing design, which currently remains incomplete.

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Appendix

A.1. RWA marketplaces and liquidity mechanisms

This section positions RealT within the broader landscape of tokenized RWA platforms. While no single platform can capture the full diversity of market designs, RealT's rare combination of AMM, P2P, and centralized buyback mechanisms—alongside one of the earliest and fully transparent, on-chain data—offers a uniquely comprehensive environment to study the structural trade-offs in secondary market liquidity. This makes it particularly well-suited to the stylized modeling and empirical objectives of our analysis. Table A.1 summarizes a selection of active platforms in the tokenized RWA space, spanning real estate, private credit, private equity, art, and securities. All listed platforms implement at least one of the liquidity mechanisms analyzed in this study: AMMs, P2P marketplaces, or centralized buybacks or matching. Centralized trading infrastructures and P2P liquidity provisioning are common design choices across asset classes, yet AMMs are increasingly being explored for offering continuous on-chain liquidity native to the DeFi ecosystem. However, to our knowledge, RealT is the only platform for which all three mechanisms coexist and are observable via publicly available on-chain data. This unique structure enables a rare empirical opportunity to study the trade-offs across mechanism types under uniform trading conditions and consistent token design. As such, while our empirical application is based on a single platform, its structure and frictions are broadly representative of the liquidity challenges across the evolving RWA and DeFi ecosystem.

Table A.1: Overview of tokenized RWA platforms and their liquidity mechanisms

Platform	**Website**	**Asset class**	**Liquidity mechanism**	**Description**
RealT	`https://realt.co`	Real Estate	AMM (Uniswap, Levinswap), P2P (Swapcat, YAM), Centralized Buyback	Tokenized real estate platform using multiple DeFi-native liquidity mechanisms. High transparency, core case study for this paper.
Lofty.ai	`https://www.lofty.ai`	Real Estate	Centralized Marketplace with P2P Listing and Buyout Options	Tokenized real estate platform offering appraisal-based pricing, investor buyout options, and P2P listings for secondary trades.
AssetBlock	`https://www.assetblock.com`	Real Estate	Centralized Matching	Tokenizes commercial real estate; uses centralized onboarding and resale processes.
Maple Finance	`https://maple.finance`	Private Credit	Centralized Matching, DeFi Wrapper	Institutional DeFi credit markets. Secondary liquidity internal and limited.
Centrifuge	`https://centrifuge.io`	Private Credit	P2P Lending Pools (DAI issuance)	Tokenizes real-world invoices and receivables for DeFi lending; decentralized credit pools.
Credix	`https://www.credix.finance`	Private Credit	P2P Lending with Institutional Access	Connects DeFi capital with private credit markets in emerging economies.
Artfi	`https://artfi.world`	Art	Centralized Buyback	Fractionalized art investment platform with token buyback and burn features.
Artory	`https://www.artory.com`	Art	Secondary Trading via Tokeny Integration	Partners with tokenization infrastructure providers to enable compliant secondary trading.
IX Swap	`https://www.ixswap.io`	Private Equity / Security Tokens	AMM	AMM-powered DEX for tokenized private equity and security tokens.
Aktionariat	`https://www.aktionariat.com`	Private Equity / Company Shares	On-chain Order Book + AMM Hybrid	Swiss platform allowing direct trading of tokenized company shares using blockchain infrastructure.
Swarm Markets	`https://swarm.com/`	U.S. Treasuries / Company Shares / Gold	AMM (Balancer) / "dOTC" (decentralized OTC)	German regulated DeFi platform enabling compliant trading via AMM-based DEX and on-chain OTC service.
Securitize	`https://www.securitize.io`	Private Equity / Funds / Securities	Centralized Matching / Secondary Market (ATS)	SEC-registered platform enabling tokenized securities and private equity with secondary trading via regulated Alternative Trading System.
Ondo Finance	`https://ondo.finance`	Bonds / ETFs / Company Shares	AMM / Centralized Buyback	Tokenization platform bringing traditional public securities onchain, with tokens that are usable in DeFi.

A.2. Variable definition

Table A.2: Definition of all variables

Variable	Definition	Calculation
	Secondary market transactions analysis (Intraday Perspective)	
Realtoken Amount	Exact realtoken amount traded (for AMM trades it is the exact token amount swapped in the liquidity pool)	Own calculations
Dollar Amount	Exact payment token amount in USD (for AMM trades it is the exact token amount swapped in the liquidity pool)	Own calculations
Transaction Price USD	Exact transaction price (for AMM it is based on the exact liquidity pool reserves)	Own calculations
Total Transaction Fee USD	Sum of corresponding transaction fees converted to USD involved in the transaction, i.e. blockchain transaction fee, transaction fee by issuance and buyback platform (1.5%), transaction fee by payment processor working for issuance and buyback platform (1.5%), AMM trading fee for uniswap v1, uniswap v2 and levinswap it of 0.3% on the traded value	Own calculations
Realtoken Sell	A dummy variable that indicates initiated sell of realtoken	Own calculations
Realtoken Buy	A dummy variable that indicates initiated buy of realtoken	Own calculations
AMM Mechanism	A dummy variable that shows if the transaction occurred on AMM, 0 otherwise.	Own calculations
P2P Mechanism	A dummy variable that shows if the transaction occurred on P2P, 0 otherwise.	Own calculations
Buyback	A dummy variable that shows if the transaction occurred through buyback (RealT platform), 0 otherwise.	Own calculations
Price Signal AMM USD	Liquidity pool price based on the liquidity pool reserves at the time of transaction for P2P or buyback transactions or right before the time of transaction for AMM transactions	Own calculations
Price Signal P2P USD	Price signal of P2P is approximated for non-P2P transactions using the (average) price of active (concurrent) P2P offers (see Section3.3) or (if not existent) the most recent historic P2P transaction. For P2P transactions itself, the transaction price of the offer itself is the price signal of it.	Own calculations
Price Signal Buyback USD	Current buyback price at time of transaction	RealT website
Gnosis Blockchain	A dummy variable that shows if the transaction occurred on the Gnosis blockchain, 0 otherwise.	Own calculations
Ethereum Blockchain	A dummy variable that shows if the transaction occurred on the Ethereum blockchain, 0 otherwise.	Own calculations
	Dependent Variables (Intraday Perspective)	
Arbitrage	A dummy variable that shows if the same wallet buys and sells (or sells and buys) the same token within a 1-hour window with profit, 0 otherwise. Captures quasi-arbitrage behavior based on transaction sequencing and wallet-level matching.	Own calculations
Arbitrage Volume	Dollar volume (in USD) of token trades identified as arbitrage sequences by the same wallet within a 1-hour window. Reflects intensity of arbitrage behavior.	Own calculations
	Dependent Variables (Daily Perspective)	
AMM Usage (in %)	Share of a token's total daily transaction volume (USD) occurring on AMM marketplaces. Calculated by aggregating all intraday trades per token by mechanism. This volume-based weighting reflects the relative economic significance of each mechanism. If no trade occurs in the mechanism on a given day, the value is set to 0.	Own calculations
P2P Usage (in %)	Share of a token's total daily transaction volume (USD) occurring on P2P marketplaces. Calculated by aggregating all intraday trades per token by mechanism. This volume-based weighting reflects the relative economic significance of each mechanism. If no trade occurs in the mechanism on a given day, the value is set to 0.	Own calculations
Buyback Usage (in %)	Share of a token's total daily transaction volume (USD) occurring on buyback marketplaces. Calculated by aggregating all intraday trades per token by mechanism. This volume-based weighting reflects the relative economic significance of each mechanism. If no trade occurs in the mechanism on a given day, the value is set to 0.	Own calculations
Turnover Ratio Token Market Capitalization	Ratio of *Volume per Token USD* relative to the token market cap based on the last market price and adjusted by the free-floating percentage (95 percent, excluding 5 percent retainment held by RealT)	Own calculations
Volume per Token USD	Transaction volume per property token per period across all marketplaces in USD	Own calculations
Number of Trades per Token	Number of trades per property token per period across all marketplaces	Own calculations
Amihud Illiquidity Ratio per Property Token	Amihud (2002) illiquidity ratio calculated as the absolute return (measured from the opening to the closing price within a given period) in relation to *Volume per Token USD* across all marketplaces	Own calculations
CS Estimator	Corwin and Schultz 2012 bid-ask spread estimator based on the daily high and low prices per token of two adjacent periods across all marketplaces. Negative values of the proxy are set to zero (see e.g. Brauneis et al. (2021).	Own calculations
High Low	High Low Estimator that estimates the bid-ask spread using the daily high and low price per token within a given period across all marketplaces	Own calculations
	Control Variables (Daily Perspective)	
Arbitrage into AMM	Volume of trades (in USD or token units) classified as arbitrage sequences where the sell leg occurs via an AMM pool, aggregated at the token-day level	Own calculations
Arbitrage within AMM	Volume of trades classified as arbitrage sequences where both the buy and sell legs occur within AMM pools, aggregated at the token-day level	Own calculations
Arbitrage into P2P	Volume of trades classified as arbitrage sequences where the sell leg occurs via a P2P mechanism, aggregated at the token-day level	Own calculations
Arbitrage within P2P	Volume of trades classified as arbitrage sequences where both legs occur within P2P mechanisms, aggregated at the token-day level	Own calculations
Arbitrage into Buyback	Volume of trades classified as arbitrage sequences where the sell leg occurs via a protocol buyback mechanism, aggregated at the token-day level	Own calculations

Slippage	Calculated price slippage, which in AMMs refers to the difference between the expected price of a token and the actual price at which the trade is executed using the CPMM. The fee is already included as the blockchain data is already deducted by the trading fee of 0.3% implied as this fee reduces the amounts swapped in the pool charging the liquidity demander for either realtoken or paymenttoken	Own calculations
Δ Buyback	Difference between the price paid by RealT on the current appraisal value and the last transaction price independent of the mechanism	Own calculations
High Frequency Buyer	A dummy variable that shows if the wallet is in the 90th percentile of daily buy-side transaction frequency for a given token, 0 otherwise.	Own calculations
High Volume Seller	A dummy variable that shows if the wallet is in the 90th percentile of daily sell-side transaction volume for a given token, 0 otherwise.	Own calculations
High Frequency Seller	A dummy variable that shows if the wallet is in the 90th percentile of daily sell-side transaction frequency for a given token, 0 otherwise.	Own calculations
Low Frequency Seller	A dummy variable that shows if the wallet is in the 10th percentile of daily sell-side transaction frequency for a given token, 0 otherwise.	Own calculations
Low Volume Seller	A dummy variable that shows if the wallet is in the 10th percentile of daily sell-side transaction volume for a given token, 0 otherwise.	Own calculations
Arbitrageur	Interaction term equal to 1 if the wallet is both a high frequency *and* high volume trader on the buy *and* sell sides for a given token-day Captures short-term profit-seeking behavior consistent with arbitrage	Own calculations
Sophisticated Seller	Interaction term equal to 1 if the wallet is both a high frequency seller *and* a high volume seller	Own calculations
Unsophisticated Seller	Interaction term equal to 1 if the wallet is both a low frequency seller *and* a low volume seller	Own calculations
Volatility 7 Days	Rolling 7-day standard deviation of daily transaction price returns for a given token	Own calculations
Market to Appraisal Ratio	Ratio of the last transaction price of given day independent of the mechanism divided by the current appraisal value	Own calculations
Cumulative Return ETH (One Week)	Cumulative return of Ether over a period of one week before the observation period	Coinmarketcap
Average Ethereum Fee USD	Average transaction costs on the Ethereum blockchain within the observed period, converted to USD	Coinmarketcap
One Month Treasury Δ	Daily log-change of the market yield on U.S. Treasury securities at 1-month constant maturity, quoted on an investment basis.	FRED, Federal Reserve Bank of St. Louis
Ten Year Treasury Δ	Daily log-change of the market yield on U.S. Treasury securities at 10-year constant maturity, quoted on an investment basis.	FRED, Federal Reserve Bank of St. Louis
ADS Index Δ	Daily log-change of the Aruoba-Diebold-Scotti (ADS) Business Condition Index, which measures macroeconomic activity at a daily frequency (Aruoba et al., 2009).	Federal Reserve Bank of Philadelphia
S&P Case-Shiller Index Δ	Monthly log-change of the U.S. S&P Case-Shiller National Home Price Index lagged by one month.	S&P Dow Jones Indices

Note: List and definitions of all variables and the corresponding sources. RealT as a source corresponds to information obtained from RealToken's website.

A.3. Liquidity measures in detail

Table A.3: Measures of liquidity

Name	Formula	Details
Dollar Transaction Volume (*Volume*)	$Volume_{j,t} = \sum_i Volume_{j,t,i}$	The dollar transaction volume is calculated for all intervals t and each token j as the sum of the dollar transaction volume in all subintervals i belonging to interval t.
Number of Transactions (*Trades*)	$Trades_{j,t} = \sum_i Trades_{j,t,i}$	The number of transactions is calculated for all intervals t and each token j as the sum of the number of transactions in all subintervals i belonging to interval t.
Turnover Ratio (*Turnover*)	$\frac{Volume_{j,t}}{TokenMarketCap_{j,t}}$	The turnover ratio is calculated as the ratio between the dollar transaction volume $Volume_{j,t}$ and the dollar market capitalization of the token $TokenMarketCap_{j,t}$ for each interval t and token j.
Amihud Illiquidity Ratio (*Amihud*)	$Amihud_{j,t} = \frac{1}{I} \sum_i \frac{\lvert C_{j,t,i}/O_{j,t,i}-1 \rvert}{Volume_{j,t,i}}$	The illiquidity ratio, following Amihud (2002), is the absolute return divided by the dollar transaction volume within each subinterval i. It is averaged across all subintervals I in t for each token j. Conceptually, the illiquidity ratio serves as a measure of price impact (Amihud, 2002). However, it is frequently employed as a proxy for overall liquidity in empirical studies (see e.g. Brauneis et al., 2021; Brauneis et al., 2022; Wilkoff and Yildiz, 2023).
CS Estimator (*CS Estimator*)	$CS_{j,i,i+1} = \frac{2(\exp(\alpha)-1)}{1+\exp(\alpha)}$	The Corwin and Schultz (2012) estimator is computed from the high and low prices of token j in two adjacent subintervals i and $i+1$. The estimator for period t and token j is the unweighted average across subintervals in t. Furthermore, $\alpha = \frac{\sqrt{2\beta}-\sqrt{\beta}}{3-2\sqrt{2}} - \sqrt{\frac{\gamma}{3-2\sqrt{2}}}$, $\beta = \left[\ln\left(\frac{H_{j,i}}{L_{j,i}}\right)\right]^2 + \left[\ln\left(\frac{H_{j,i+1}}{L_{j,i+1}}\right)\right]^2$, $\gamma = \left[\ln\left(\frac{H_{j,i,i+1}}{L_{j,i,i+1}}\right)\right]^2$. No adjustment is made for trading halts, as the blockchain operates continuously.
High-Low Spread Estimator (*High Low*)	$High - Low_{j,i} = \frac{2(H_{j,i}-L_{j,i})}{H_{j,i}+L_{j,i}}$	The High-Low spread estimator uses the highest and lowest transaction prices within each subinterval to approximate the bid-ask spread. The $High - Low_{j,t}$ estimator is the unweighted average of all High-Low estimators across subintervals within t.

Note: This table presents the summary of liquidity and market metrics with formulas and details. Although the blockchain operates 24/7, we use the UTC time scale, as adopted by Ethereum and Gnosis blockchains, to define the time intervals for the liquidity measures.

A.4. Hasbrouck Information Share calculation

Consider a financial asset traded simultaneously in N distinct markets. Denote the price vector at time t by p_t, following a Vector Error Correction Model (VECM):

$$\Delta p_t = \Pi p_{t-1} + \sum_{k=1}^{K} \Gamma_k \Delta p_{t-k} + \varepsilon_t, \quad \varepsilon_t \sim (0, \Omega), \tag{D.1}$$

where:

- Δp_t is the $N \times 1$ vector of price changes for N markets at time t.
- Ω is the covariance matrix of residuals ε_t.

The prices across markets share a common stochastic trend, implying cointegration and the presence of one common efficient price factor. To quantify each market's relative contribution to the price discovery process, Hasbrouck (1995) introduces the Information Share (IS) measure:

$$IS_i = \frac{(\psi F)_i^2}{\psi \Omega \psi'}, \tag{D.2}$$

where:

- IS_i is the Information Share of market i.
- ψ is the $1 \times N$ vector of long-run impacts (obtained from the VECM), capturing the long-run effect of shocks on the efficient price.
- Ω is the covariance matrix of residuals ($N \times N$) from the VECM.
- F is obtained via the Cholesky decomposition of Ω:

  $$\Omega = FF^{\top}$$

  where F is lower-triangular.
- $(\psi F)_i$ is the i^{th} component of the vector ψF, indicating the price innovation attributable to market i.

The total variance of the common efficient price innovation is given by:

$$\text{Total Variance} = \psi \Omega \psi'. \tag{D.3}$$

Therefore, the IS measure reflects market i's relative contribution to the overall variance of the efficient price innovations.

In practice, due to the sensitivity of the IS measure to the ordering of the Cholesky decomposition, it is common to calculate upper and lower bounds for each market's IS. Specifically, one typically computes:

$$IS_i^{upper}, \quad IS_i^{lower}, \tag{D.4}$$

by varying the order of markets in the decomposition.

Steps for Empirical Implementation:

1. Estimate a VECM model for the prices from multiple market mechanisms.
2. Obtain residual covariance matrix Ω.
3. Compute the long-run impact vector ψ from cointegration relationships.
4. Perform Cholesky decomposition on Ω to obtain F.
5. Calculate the Information Share (IS) for each market mechanism according to the above equation.
6. Provide robustness by varying Cholesky decomposition ordering to obtain upper and lower bounds.

For further details see Hasbrouck (1995).

A.5. Further descriptive statistics - Transactions

Table A.4: Descriptive Variables - Intradaily Transactions (extended)

Statistic	N	Mean	St. Dev.	Min	10%	25%	Median	75%	90%	Max
Intradaily Perspective										
Realtoken Amount	444,535	0.79	4.63	0.00	0.01	0.01	0.05	0.19	1.00	965.03
Dollar Amount	444,535	43.87	252.17	0.00	0.50	0.57	2.61	9.94	65.51	54,495
Transaction Price USD	444,535	55.90	15.91	5.56	48.00	50.51	53.44	57.64	63.00	535.93
Total Transaction Fee USD	444,535	0.29	2.60	0.00	0.00	0.00	0.00	0.02	0.03	133.54
Realtoken Sell	444,535	0.76	0.43	0.00	0.00	1.00	1.00	1.00	1.00	1.00
Realtoken Buy	444,535	0.24	0.43	0.00	0.00	0.00	0.00	0.00	1.00	1.00
AMM Mechanism	444,535	0.76	0.43	0.00	0.00	1.00	1.00	1.00	1.00	1.00
P2P Mechanism	444,535	0.21	0.41	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Buyback Mechanism	444,535	0.03	0.16	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Price Signal AMM USD	443,956	56.22	32.46	2.14	47.85	50.51	53.55	58.02	63.64	7,134
Price Signal P2P USD	413,337	58.84	13.92	10.00	50.72	52.88	56.00	60.99	66.00	299.00
Price Signal Buyback USD	444,535	52.87	12.06	41.50	49.44	50.23	50.85	52.08	54.49	185.80
Transaction Price/Buyback Price Δ	444,535	0.06	0.17	-0.89	-0.06	-0.00	0.04	0.11	0.18	9.05
Number of Active Offers	341,988	22.13	28.86	1.00	2.00	5.00	12.00	28.00	56.00	351.00
Realtoken Amount Active Offers	341,988	85.04	195.77	0.00	1.00	4.69	16.67	65.81	209.66	2,247
Dollar Amount Active Offers	341,988	4,636	10,380	0.00	64.90	275.20	973.35	3,749	11,520	112,787
Liquidity Pool Value USD	443,980	2,401	5,600	0.00	202.59	1,121	1,909	2,437	3,108	190,298
Private Deal	444,535	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Public Deal	444,535	1.00	0.04	0.00	1.00	1.00	1.00	1.00	1.00	1.00
Gnosis Blockchain	444,535	0.99	0.12	0.00	1.00	1.00	1.00	1.00	1.00	1.00
Ethereum Blockchain	444,535	0.01	0.12	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Blockchain Transaction Fee USD	444,535	0.06	1.01	0.00	0.00	0.00	0.00	0.00	0.00	129.61
Total Number of Trades per Trader	444,535	39,236	68,079	1.00	171.00	846.00	2,845	21,529	170,291	170,291
Total Volume per Trader USD	444,535	125,020	295,990	0.05	2,953	7,511	25,413	143,957	209,851	2,006,872
Average Volume per Trader USD	444,535	45.62	104.73	0.05	0.85	2.30	4.90	33.88	138.22	4,632
USD//C on xDai (USDC)	444,535	0.32	0.47	0.00	0.00	0.00	0.00	1.00	1.00	1.00
Wrapped Ether on xDai (WETH)	444,535	0.44	0.50	0.00	0.00	0.00	0.00	1.00	1.00	1.00
USD Coin (USDC)	444,535	0.01	0.07	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Wrapped XDAI (WXDAI)	444,535	0.03	0.16	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Tether USD (USDT)	444,535	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Tether USD on xDai (USDT)	444,535	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Dai Stablecoin (DAI)	444,535	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Mai Stablecoin (MAI)	444,535	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Wrapped Ether (WETH)	444,535	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Monday	444,535	0.16	0.37	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Tuesday	444,535	0.15	0.36	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Wednesday	444,535	0.15	0.36	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Thursday	444,535	0.14	0.35	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Friday	444,535	0.15	0.36	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Saturday	444,535	0.13	0.34	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Sunday	444,535	0.11	0.31	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Single Family	444,535	0.37	0.48	0.00	0.00	0.00	0.00	1.00	1.00	1.00
Duplex	444,535	0.12	0.33	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Multi Family	444,535	0.50	0.50	0.00	0.00	0.00	1.00	1.00	1.00	1.00
Holding Token	444,535	0.02	0.13	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Detroit	444,535	0.73	0.45	0.00	0.00	0.00	1.00	1.00	1.00	1.00

Note: This table is an extended version of Table 1 and reports the number of observations, mean, standard deviation, minimum, 10^{th} percentile, 25^{th} percentile, median, 75^{th} percentile, 90^{th} percentile, and maximum for the data on the transaction level (intradaily).

Table A.5: Descriptive Variables - Intradaily Transactions by Mechanisms

Statistic	N	Mean	St. Dev.	Min	10%	25%	Median	75%	90%	Max
					Intradaily Perspective					
					AMM					
Realtoken Amount	337,255	0.11	0.52	0.00	0.01	0.02	0.10	0.15	0.15	50.00
Dollar Amount	337,255	7.16	43.55	0.00	0.49	0.51	0.99	5.00	8.84	3,807
Transaction Price USD	337,255	55.49	15.41	5.56	47.27	50.36	53.56	57.43	62.20	535.93
Price Signal AMM USD	337,255	55.67	15.92	2.14	47.05	50.34	53.71	57.81	62.73	721.94
Realtoken Sell	337,255	0.68	0.46	0.00	0.00	0.00	1.00	1.00	1.00	1.00
Realtoken Buy	337,255	0.32	0.46	0.00	0.00	0.00	0.00	1.00	1.00	1.00
Blockchain Transaction Fee USD	337,255	0.031210	0.736065	0.00	0.00	0.000471	0.000673	0.000968	0.001619	129.61
Transaction Fee AMM USD	337,255	0.021472	0.130661	0.00	0.001484	0.001551	0.002991	0.015011	0.026522	11.42
Total Transaction Fee USD	337,255	0.052682	0.818738	0.000245	0.002220	0.002522	0.004092	0.015657	0.029903	133.54
Time on Market (days)	337,255	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Price Slippage	337,255	-0.001609	0.036272	-0.829629	-0.013146	-0.005693	-0.003538	0.005462	0.011653	5.55
Liquidity Pool Value USD	337,255	2,591	6,263	5.16	307.45	1,287	1,902	2,420	3,162	190,298
Wrapped Ether on xDai Liq Pool	337,255	0.58	0.49	0.00	0.00	0.00	1.00	1.00	1.00	1.00
Levin Liquidity Pool	337,255	0.26	0.43	0.00	0.00	0.00	0.00	1.00	1.00	1.00
USDC on xDai Liquidity Pool	337,255	0.15	0.35	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Ether Liquidity Pool	337,255	0.01	0.10	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Wrapped Ether Liquidity Pool	337,255	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Dollar Amount Active Offers	237,337	4,816	10,861	0.00	60.86	262.71	949.25	3,768	12,130	102,924
Ethereum Blockchain	337,255	0.01	0.10	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Gnosis Blockchain	337,255	0.98	0.10	0.00	1.00	1.00	1.00	1.00	1.00	1.00
					P2P					
Realtoken Amount	95,213	2.66	9.25	0.00	0.04	0.15	1.00	2.00	5.50	965.03
Dollar Amount	95,213	146.91	501.47	0.00	2.00	8.39	50.90	107.90	309.60	54,495
Transaction Price USD	95,213	57.63	17.67	10.00	50.00	50.90	53.50	59.00	65.10	299.00
Price Signal P2P USD	95,213	57.63	17.67	10.00	50.00	50.90	53.50	59.00	65.10	299.00
Realtoken Sell	95,213	0.99	0.07	0.00	1.00	1.00	1.00	1.00	1.00	1.00
Realtoken Buy	95,213	0.01	0.07	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Blockchain Transaction Fee USD	95,213	0.028032	0.491718	0.000026	0.000382	0.000427	0.000555	0.001058	0.002907	38.69
Total Transaction Fee USD	95,213	0.028032	0.491718	0.000026	0.000382	0.000427	0.000555	0.001058	0.002907	38.69
Time on Market (days)	95,191	25.43	54.45	0.00	0.01	0.22	3.24	21.82	80.31	812.23
Number of Active Offers	95,191	22.79	30.60	1.00	3.00	6.00	13.00	27.00	56.00	351.00
Realtoken Amount Active Offers	95,191	80.24	178.80	0.00	1.00	5.35	18.20	67.33	209.66	2,246
Dollar Amount Active Offers	95,191	4,353	9,378	0.000002	64.90	315.09	1,049	3,840	11,519	112,787
Liquidity Pool Value USD	95,109	1,737	1,336	0.000002	37.35	720.41	1,957	2,459	2,995	120,709
Private Deal	95,213	0.01	0.08	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Public Deal	95,213	0.99	0.08	0.00	1.00	1.00	1.00	1.00	1.00	1.00
USD//C on xDai (USDC)	95,213	0.87	0.32	0.00	0.00	1.00	1.00	1.00	1.00	1.00
USD Coin (USDC)	95,213	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Wrapped XDAI (WXDAI)	95,213	0.12	0.32	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Tether USD (USDT)	95,213	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Tether USD on xDai (USDT)	95,213	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Dai Stablecoin (DAI)	95,213	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Mai Stablecoin (MAI)	95,213	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Ethereum Blockchain	95,213	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Gnosis Blockchain	95,213	0.99	0.03	0.00	1.00	1.00	1.00	1.00	1.00	1.00
					Buyback					
Realtoken Amount	12,067	4.81	6.96	0.01	1.00	2.00	5.00	8.00	15.00	40.00
Dollar Amount	12,067	257.06	372.31	0.49	50.76	101.88	259.85	500.00	1,099	1,999
Transaction Price USD	12,067	53.67	13.94	44.19	50.25	50.84	52.13	53.50	54.95	185.80
Price Signal Buyback USD	12,067	53.68	13.94	44.19	50.25	50.84	52.16	53.50	54.95	185.80
Realtoken Sell	12,067	1.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Realtoken Buy	12,067	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Blockchain Transaction Fee USD	12,067	1.23	4.38	0.000087	0.000275	0.000366	0.002004	0.50	5.00	110.79
Platform Transaction Fee USD	12,067	7.71	11.17	0.014702	1.52	3.06	7.80	15.00	25.00	60.00
Total Transaction Fee USD	12,067	8.94	12.28	0.014977	1.53	3.40	11.01	17.00	28.00	117.78
Time on Market (days)	12,067	10.00	0.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00
Dollar Amount Active Offers	9,460	2,948	6,830	0.00	54.99	197.68	730.90	2,310	6,648	88,401
Liquidity Pool Value USD	11,616	2,327	6,353	0.00	34.69	708.39	1,798	2,450	3,033	159,086
USD Coin (USDC)	12,067	0.19	0.38	0.00	0.00	0.00	0.00	0.00	1.00	1.00
USD//C on xDai (USDC)	12,067	0.81	0.38	0.00	0.00	1.00	1.00	1.00	1.00	1.00
Ethereum Blockchain	12,067	0.19	0.38	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Gnosis Blockchain	12,067	0.81	0.38	0.00	1.00	1.00	1.00	1.00	1.00	1.00

Note: This table reports the descriptive statistics (number of observations, mean, standard deviation, minimum, 10^{th} percentile, 25^{th} percentile, median, 75^{th} percentile, 90^{th} percentile, and maximum) for the transaction data segmented by the market mechanisms AMM, P2P and Buyback.

A.6. Further descriptive statistics - Real estate tokens

Table A.7: Descriptive Variables - Real Estate Tokens

Statistic	N	Mean	St. Dev.	Min	25%	Median	75%	Max	$\sum$
Volume USD	511	38,166.81	67,653.13	50.27	4,734.88	15,688.62	34,521.37	573,563	19,503,242
Volume Realtoken	511	685.48	1,171.00	1.00	94.01	290.24	621.64	9,553.64	350,278
Number of Trades	511	869.93	1,168.18	1.00	62.00	349.00	1,295.50	7,560.00	444,535
Total Turnover Ratio (Traded Token)	511	0.19	0.17	0.000566	0.06	0.16	0.28	1.47	
Total Turnover Ratio (Traded Volume)	511	0.20	0.18	0.000573	0.06	0.16	0.29	1.50	
Average Liq Pool Value USD	511	1,687	1,876	0.000002	512.76	1,750	2,183	24,136	862,328
Average Days on Market (P2P)	510	21.01	13.89	0.012847	11.46	19.07	27.93	99.63	
STO Price	511	51.33	6.85	44.19	50.16	50.56	51.13	161.84	
Token Valuation (Asset)	511	41.49	7.37	15.33	39.29	41.35	43.33	144.74	
Token Revaluation (Asset)	161	55.68	15.22	44.74	51.54	53.00	55.42	185.66	
Token Revaluation (Buyback Price)	161	56.51	15.15	41.50	52.58	53.87	56.12	185.80	
US	511	0.99	0.06	0.00	1.00	1.00	1.00	1.00	509
Panama	511	0.003914	0.06	0.00	0.00	0.00	0.00	1.00	2
Michigan (MI)	511	0.82	0.37	0.00	1.00	1.00	1.00	1.00	424
Florida (FL)	511	0.005871	0.07	0.00	0.00	0.00	0.00	1.00	3
Ohio (OH)	511	0.08	0.27	0.00	0.00	0.00	0.00	1.00	42
New York (NY)	511	0.001957	0.04	0.00	0.00	0.00	0.00	1.00	1
Illinois (IL)	511	0.03	0.17	0.00	0.00	0.00	0.00	1.00	17
Georgia (GA)	511	0.003914	0.06	0.00	0.00	0.00	0.00	1.00	2
Alabama (AL)	511	0.007828	0.08	0.00	0.00	0.00	0.00	1.00	4
Louisiana (LS)	511	0.001957	0.04	0.00	0.00	0.00	0.00	1.00	1
Missouri (MO)	511	0.03	0.17	0.00	0.00	0.00	0.00	1.00	16
Province of Chiriquí (CP)	511	0.001957	0.04	0.00	0.00	0.00	0.00	1.00	1
Detroit (MI)	511	0.80	0.39	0.00	1.00	1.00	1.00	1.00	413
Dearborn Heights (MI)	511	0.001957	0.04	0.00	0.00	0.00	0.00	1.00	1
Deerfield Beach (FL)	511	0.001957	0.04	0.00	0.00	0.00	0.00	1.00	1
Akron (OH)	511	0.001957	0.044	0.00	0.00	0.00	0.00	1.00	1
Cleveland (OH)	511	0.04	0.20	0.00	0.00	0.00	0.00	1.00	22
Rochester (NY)	511	0.001957	0.04	0.00	0.00	0.00	0.00	1.00	1
Chicago (IL)	511	0.03	0.17	0.00	0.00	0.00	0.00	1.00	17
Highland Park (MI)	511	0.01	0.10	0.00	0.00	0.00	0.00	1.00	6
Toledo (OH)	511	0.01	0.13	0.00	0.00	0.00	0.00	1.00	9
Kissimmee (FL)	511	0.003914	0.06	0.00	0.00	0.00	0.00	1.00	2
Jackson (MI)	511	0.003914	0.06	0.00	0.00	0.00	0.00	1.00	2
Birmingham (MI)	511	0.001957	0.04	0.00	0.00	0.00	0.00	1.00	1
East Cleveland (OH)	511	0.003914	0.06	0.00	0.00	0.00	0.00	1.00	2
Covington (GA)	511	0.001957	0.04	0.00	0.00	0.00	0.00	1.00	1
Montgomery (AL)	511	0.007828	0.08	0.00	0.00	0.00	0.00	1.00	4
Playa Venao (CP)	511	0.001957	0.04	0.00	0.00	0.00	0.00	1.00	1
Griffin	511	0.001957	0.04	0.00	0.00	0.00	0.00	1.00	1
St. Louis (MO)	511	0.02	0.16	0.00	0.00	0.00	0.00	1.00	14
Jennings (MO)	511	0.001957	0.04	0.00	0.00	0.00	0.00	1.00	1
Boquete (CP)	511	0.001957	0.04	0.00	0.00	0.00	0.00	1.00	1
Maple Heights (OH)	511	0.003914	0.06	0.00	0.00	0.00	0.00	1.00	2
Euclid (OH)	511	0.003914	0.06	0.00	0.00	0.00	0.00	1.00	2
Garfield Heights (OH)	511	0.007828	0.08	0.00	0.00	0.00	0.00	1.00	4
Saint Ann (MO)	511	0.001957	0.04	0.00	0.00	0.00	0.00	1.00	1
Ecorse (MI)	511	0.001957	0.04	0.00	0.00	0.00	0.00	1.00	1
Maintenance Amount	511	5,131	7,745	0.00	1,600	1,946	3,615	52,600	2,622,034
Renovation Amount	511	9,123	23,419	0.00	0.00	3,000	10,000	420,000	4,662,350
Issued Token	511	3,984	5,469	750.00	1,300	1,480	3,050	37,000	2,035,695
Initial Investment Amount	511	203,911	278,138	48,080	65,345	75,315	164,657	1,881,450	104,198,433
Initial Asset Valuation (Appraisal)	511	166,826	233,902	26,000	53,000	60,000	135,000	1,610,000	85,247,850
Current Investment Amount	511	205,655	278,098	50,250	67,269	76,146	168,937	1,881,450	105,089,833
Current Asset Valuation (Appraisal)	511	172,244	234,222	26,000	56,000	68,500	146,100	1,610,000	88,016,825
Average Token Market Cap USD	511	211,694	284,217	52,867	68,061	78,967	175,212	1,911,193	108,175,535
Asset Value Change (%)	511	0.07	0.12	-0.009324	0.00	0.00	0.18	1.10	
Investment Value Change (%)	511	0.02	0.05	-0.29	0.00	0.00	0.04	0.87	
Interior Size (SQM)	511	294.73	392.90	0.00	96.00	130.00	239.00	2,816	150,605
Lot Size (SQM)	511	691.53	835.89	0.00	385.50	445.00	579.00	7,870	353,372
Price/ SQM (Current Asset Valuation)	511	619.05	375.96	0.00	449.50	554.00	704.00	4,609	
Door Price	511	63,951	64,798	13,529	49,000	55,000	65,000	915,000	
Rented Units	511	3.39	5.36	0.00	1.00	1.00	2.00	36.00	1,734
Rented Units (%)	511	0.98	0.09	0.00	1.00	1.00	1.00	1.00	
Annual Gross Rent	511	32,688	45,881	0.00	10,920	12,000	24,420	315,600	16,703,792
Annual Net Rent	511	20,717	28,065	0.00	6,858	8,106	17,338	193,698	10,586,382
Net Rent on Current Inv. Amount (%)	511	0.10	0.01	0.00	0.09	0.10	0.11	0.17	
Building Age	511	79.14	25.66	3.00	73.00	83.00	97.00	137.00	
Number of Units	511	3.50	5.49	1.00	1.00	1.00	2.00	36.00	1,786
Single Family	511	0.64	0.47	0.00	0.00	1.00	1.00	1.00	329.00
Duplex	511	0.12	0.32	0.00	0.00	0.00	0.00	1.00	63.00
Multi Family	511	0.23	0.42	0.00	0.00	0.00	0.00	1.00	119.00
Holding Token	511	0.05	0.22	0.00	0.00	0.00	0.00	1.00	28.00

Note: This table reports the descriptive statistics (number of observations, mean, standard deviation, minimum, 25^{th} percentile, median, 75^{th} percentile, maximum, and sum) for the real estate token in our transaction data sample. Note, that our initial dataset consisted of 548 real estate tokens. However, 18 tokens were duplicates representing the same properties due to a transition from the Ethereum to the Gnosis blockchain. Additionally, 19 properties were initially tokenized under both Regulation D (for U.S.-accredited investors) and Regulation S (for non-U.S. investors); these have since been consolidated into Regulation S tokens only and are no longer tradable. With the removal of Regulation D tokens, U.S. investors can no longer invest in any RealT real estate token. Of the 511 unique tokens, 28 are classified as "holding tokens," each representing multiple properties and covering a total of 178 properties. These properties contain between 1 and 36 units, resulting in 661 unique tokenized properties. Tokens with 1 unit represent single-family properties, those with 2 units represent duplexes, and tokens with 3 or more units represent multifamily properties. Holding tokens represent either duplexes or multifamily properties, depending on the number of units they include. Each property can contain one or more units, resulting in a total of 1,786 unique tokenized units.

A.7. Further analysis on liquidity trends and market evolution

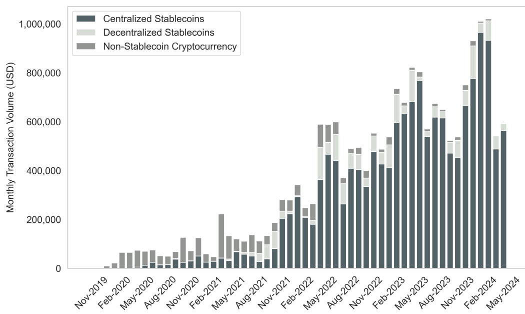


Figure A.1: Transaction volume by payment token

Note: This figure presents the monthly transaction volume in USD categorized by payment token classification.

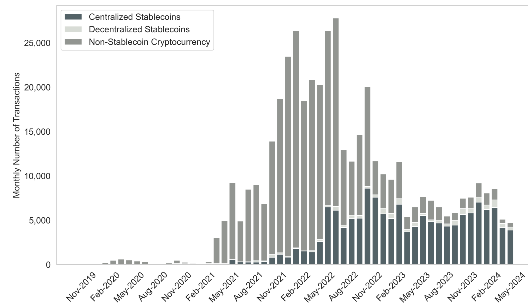


Figure A.2: Number of transactions by payment token

Note: This figure presents the monthly number of transactions categorized by payment token classification.

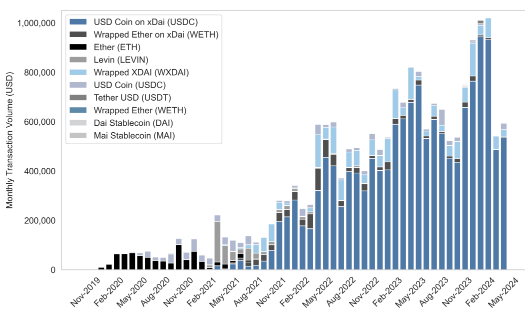


Figure A.3: Transaction volume by payment token (detailed)

Note: This figure presents the monthly transaction volume in USD categorized by payment token.

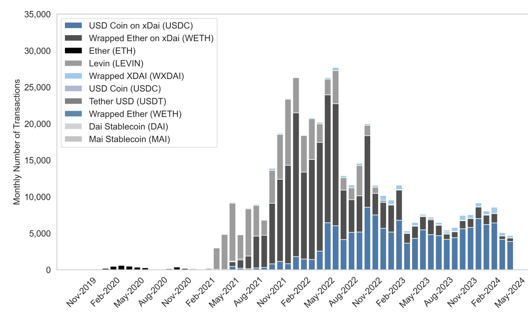


Figure A.4: Number of transactions by payment token (detailed)

Note: This figure presents the monthly number of transactions categorized by payment token.

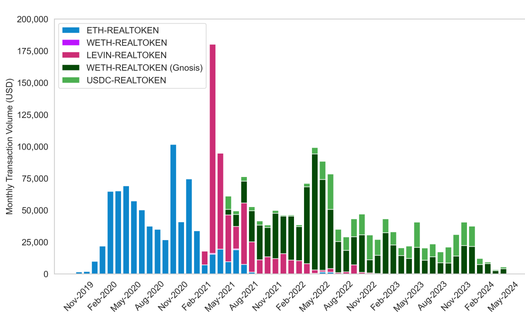


Figure A.5: Transaction volume AMM by liquidity pool pair token

Note: This figure presents the monthly transaction volume within AMMs in USD categorized by liquidity pool pair token. REALTOKEN serves as a placeholder for specific real estate token pool pairs, with each token having its own dedicated liquidity pool.

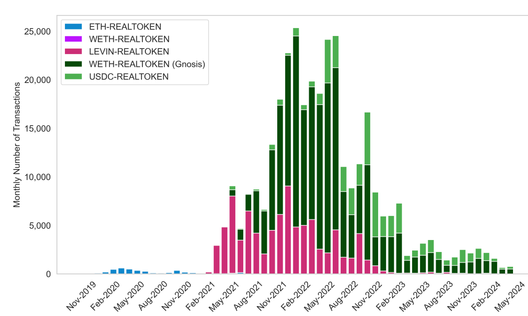
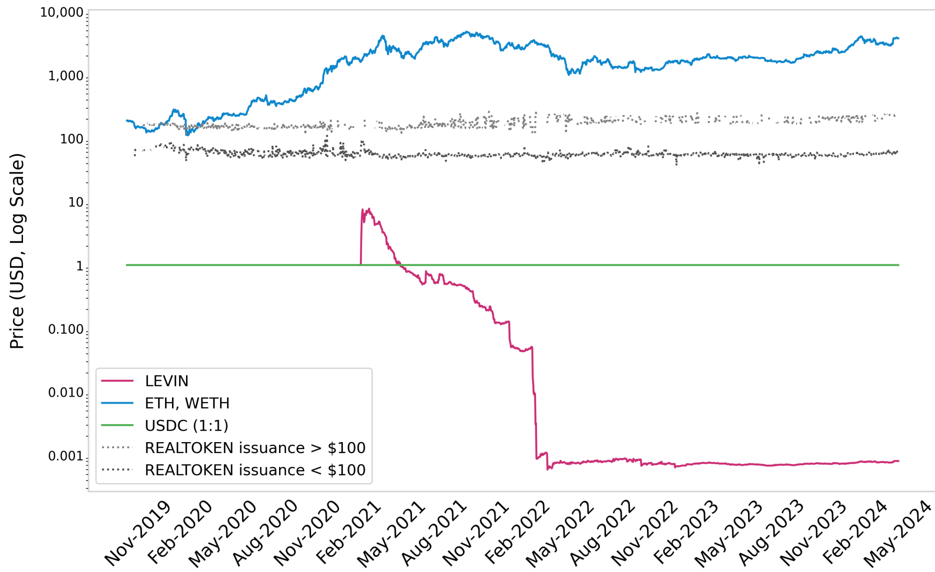


Figure A.6: Number of transactions AMM by liquidity pool pair token

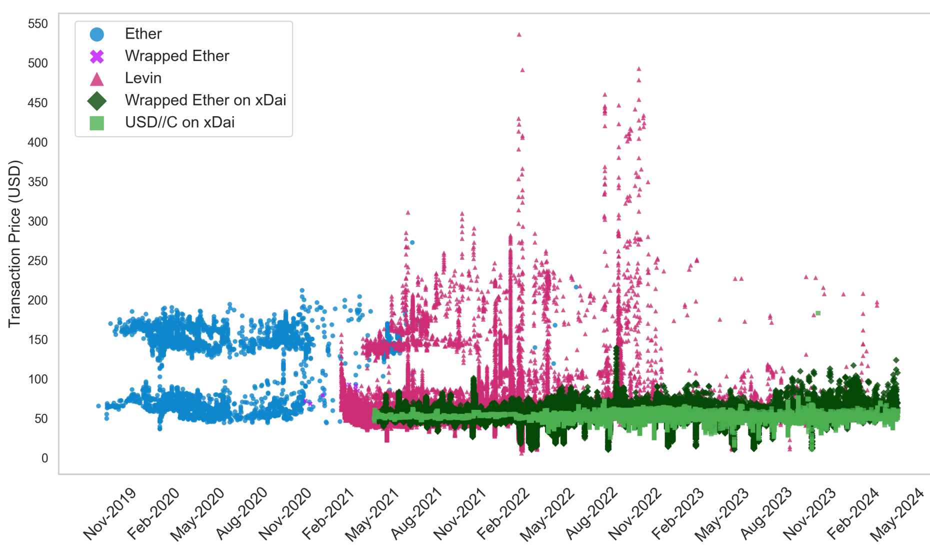
Note: This figure presents the monthly number of transactions within AMMs in USD categorized by liquidity pool pair token. REALTOKEN serves as a placeholder for specific real estate token pool pairs, with each token having its own dedicated liquidity pool.

Figure A.7: Liquidity pool token prices



Note: This figure presents liquidity pool pair token prices in USD on a logarithmic scale. WETH prices follow ETH, while USDC is assumed to maintain a 1:1 USD peg. REALTOKEN prices are based on average transaction prices, segmented into those issued below and above $100. The visualization highlights price stability across pool tokens in the context of impermanent loss risk.

Figure A.8: Transaction prices on AMM by liquidity pool payment token



Note: This figure presents the transaction prices on AMMs categorized by the liquidity pool payment token pair prices in USD (N=337,255).

A.8. STO process and the secondary market

Our dataset consists of real estate tokens issued by RealToken LLC (RealT), a prominent platform for tokenizing real estate assets in the USA. Based on the application of the *Howey test*, digital assets such as these tokens are classified as investment contracts and therefore considered securities. As a result, real estate tokens must comply with U.S. securities laws, and RealT operates its token offerings under specific regulatory exemptions. These offerings are conducted as private placements under Regulation D 506(c) for U.S.-accredited investors and Regulation S for non-U.S. investors, as defined by the Securities Act. As of May 31, 2024, there have been 18 real estate token offerings under Regulation D, which have since been inactivated and converted to Regulation S tokens. Since then, U.S. investors can no longer invest in any RealT real estate token. The company has stated that it is working on solutions to include U.S. investors.[24] Figure A.9 illustrates the process of real estate tokenization and security token offerings (STOs) in the case of RealT.[25]

Each tokenized property is owned by a RealToken Series LLC, created specifically for each property by RealToken LLC, as real estate cannot be directly digitized. These special purpose vehicles (SPVs) hold the property deed and function as standalone legal entities.[26] Once established, the SPVs are tokenized using the Ethereum ERC-20 technical standard. The properties themselves are primarily residential rental buildings, with property management outsourced to local professionals.

Investors acquire tokens during the STO, and upon completing payment and digitally signing the offering memorandum, the tokens are automatically transferred to their wallets through a smart contract. Transactions on the Ethereum blockchain incur an additional *gas fee*, which users must pay to execute operations. Ownership of these tokens gives investors a stake in the associated RealToken Series LLC. Net rental income, after deducting operating costs, insurance, and taxes, is distributed weekly to token holders through a smart contract linked to the property, which automatically transfers payments to the investors' wallets.

The token's value is derived from the assessed property value (after accounting for a reserve for maintenance and repairs) divided by the total number of tokens issued. RealT charges a 10% fee for this service, and in return, investors receive governance tokens from RealT, granting them certain voting rights. While still in its early stages, RealT is exploring the integration of DAOs to enable RealToken holders to participate in decision-making processes related to property management, maintenance, and financial allocations through on-chain voting mechanisms.

After the STO, investors can trade on the secondary market. Importantly, those entering the secondary market without prior participation in the STO must complete a free whitelisting process, managed by the token issuance company RealT, to comply with KYC/AML regulations. Whitelisting is available for up to fourteen properties per day. Investors have three primary options to exit their token holdings on the secondary market:

- Selling tokens back to RealT through a company buyback program (Buyback).
- Trading peer-to-peer (P2P) with other investors.
- Utilizing automated market makers (AMMs) on decentralized exchanges (DEXs) as part of the decentralized finance (DeFi) ecosystem.[27]

[24]For more information, please see `https://faq.realt.co/en/article/what-is-realt-who-can-invest-how-do-i-invest-1yyc5h5/`.

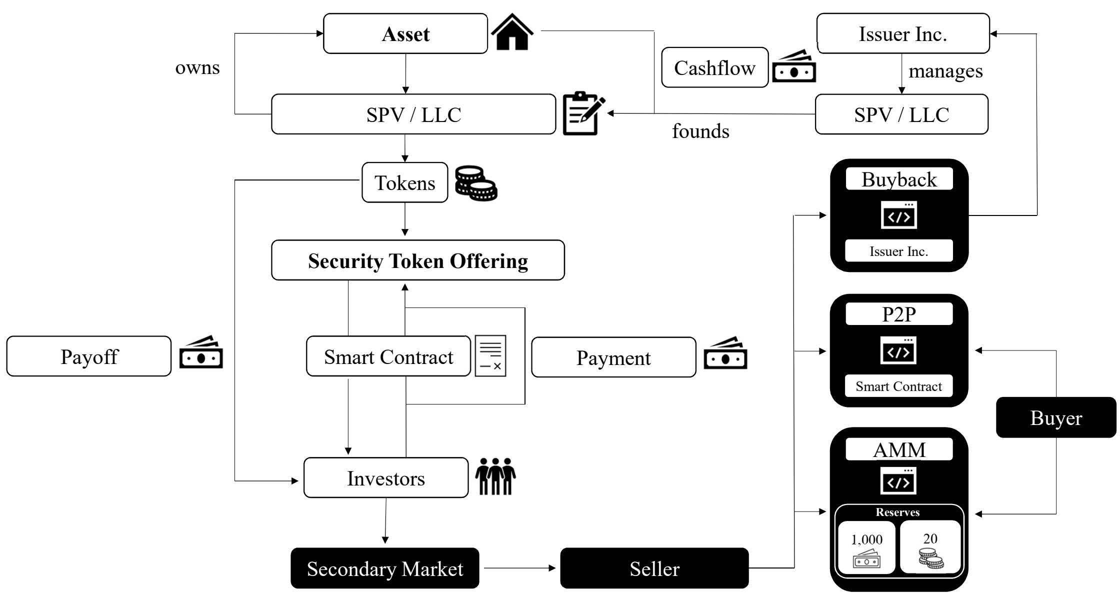
[25]For further discussion on the ICO or STO processes, see Momtaz (2020) and Lambert et al. (2022).

[26]While Non-Fungible Tokens (NFTs) or Decentralized Autonomous Organizations (DAOs) are alternative forms of digitizing ownership, these are more theoretical and less commonly applied to real estate markets, and thus are outside the scope of this paper.

[27]For more detail, see Aspris et al. (2021).

The value of tokens fluctuates annually based on property reappraisals, which may result in appreciation or depreciation. In early 2021, due to rising transaction costs and longer execution times on the Ethereum blockchain, RealT introduced the option to conduct transactions on the Gnosis blockchain.[28] This alternative is particularly beneficial for smaller transactions, such as the relatively low weekly rental payments, as it significantly reduces transaction fees compared to Ethereum.
This detailed description of RealT's real estate tokenization process, including primary and secondary market mechanisms, sets the stage for our analysis of tokenized real estate and its liquidity across these different trading venues.

Figure A.9: Process Map



Note: This figure illustrates the process of from the Security Token Offering to the secondary market and the mechanisms to choose from based on the illustration of Kreppmeier et al. (2023).

Marketplace specifics regarding liquidity mechanisms:
RealT offers capped liquidity to investors under set conditions, with the buyback price directly linked to a periodically updated external appraisal, which is transparently published. RealT retains 5% of tokens to ensure available liquidity and demonstrate risk retention, while appraisals by third-party evaluators may be infrequent, leading buyback prices to sometimes reflect older valuations.
Eligibility for buybacks requires that 95% of tokens be sold to investors. The buyback process,

[28]Gnosis (formerly xDai) is a second-layer protocol designed to facilitate more cost-effective transactions for digital assets on Ethereum.

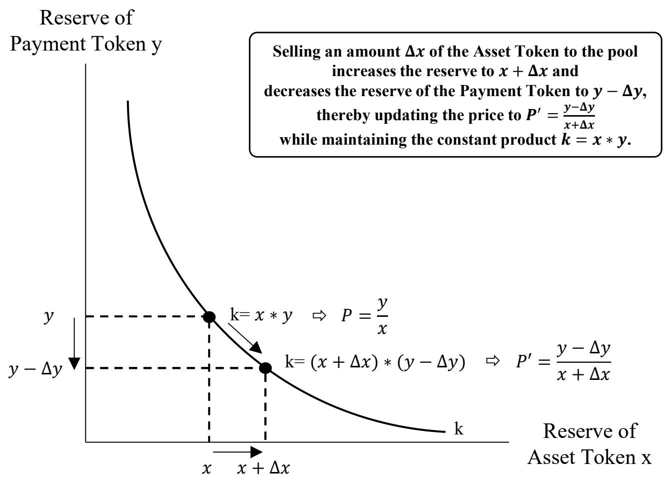
capped at \$2,000 USD per week and including fractions of tokens, is suitable for trades seeking execution certainty with minimal price fluctuations. However, trade execution is not immediate and can take up to 10 business days. Transactions occur on-chain, using either Ethereum or Gnosis, and are settled in USDC. Fees include a blockchain gas fee, a 1.5% RealT platform fee, and an additional 1.5% external processing fee based on the trading volume.

RealT incentivizes liquidity providers in AMMs through rental income distributions alongside trading fees, contrasting with centralized market makers who directly profit from bid-ask spreads. Although large trades in AMMs may incur slippage due to limited pool depth, AMMs facilitate lower overall fees and instant execution without intermediary constraints.

Regulatory compliance requires KYC verification and address whitelisting for each asset and investor, which RealT facilitates by offering free whitelisting for up to fourteen properties every day. Furthermore, the DeFi ecosystem around RealT has enabled a broad range of community-run applications, including on-chain analytic platforms and integrations with decentralized lending and borrowing protocols, such as RealT's RMM network.

A.9. Token reserve curve - Constant product market making

Figure A.10: Token reserve curve in the case of a shift in the liquidity pool ratio

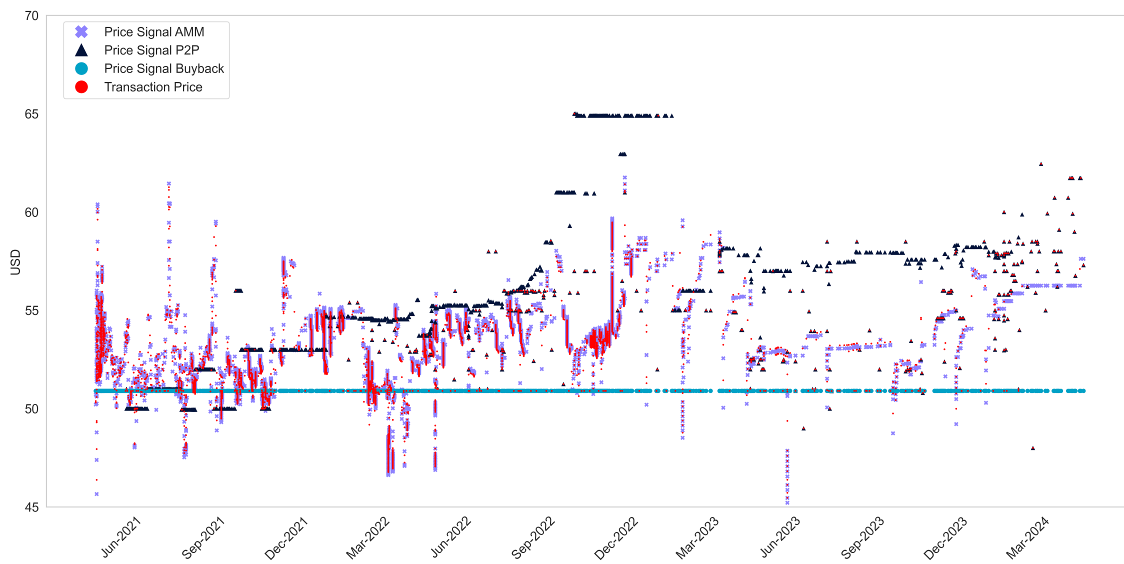


Note: This figure illustrates the movement along the token reserve curve of an Automated Market Maker (AMM) exchange using a Constant Product Market Making (CPMM) formula during an asset token sale. The effect of transaction fees has been excluded in this illustration.

A.10. Details on price signals

Figure A.11 shows the price signals and transaction prices of one RWA and therefore the result of these different mechanisms in the data. Naturally, with a linked asset the market prices fluctuate around the issuance price, but show distinct variances across the mechanisms (Kreppmeier et al., 2023; Swinkels, 2023). Buyback transactions maintain stable, since the prices are fixed based on appraisal values, offering predictability.[29] AMMs show significant price dispersion due to deterministic pricing. Unlike P2P markets, where prices adjust to bids and offers, AMMs rely on liquidity pool ratios, making them prone to slippage and arbitrage exploitation. This results in lower realized prices for sellers and liquidity depletion over time. In contrast, P2P transactions achieve higher consecutive prices and narrower spreads, reflecting efficient, market-driven price discovery. P2P platforms show growing activity indicated by transactions (red dots) overlapping the price signals (black triangles), while AMM activity declines.

Figure A.11: Price signals and transaction prices for an exemplary RWA



Note: This figure shows all concurrent price signals by mechanism and the transaction prices for all 7,560 transactions of an exemplary real estate token (REALTOKEN-S-4852-4854-W.CORTEZ-ST-CHICAGO-IL). Note that the red dots do not always overlap with the purple crosses for AMM, as the price signal deviates from the final transaction price due to slippage.

AMM price signals

To construct AMM price signals, we retrieve liquidity pool reserves using smart contract functions and blockchain logs. For Uniswap v2 and Levinswap pools, we use the `getReserves()` function at the precise `block.timestamp` of each transaction, i.e. AMM, P2P, and Buyback transactions. For Uniswap v1 pools, we apply the `ethReserve` and `tokenReserve` functions via the Alchemy RPC. In

[29]Although the website claims all properties receive annual appraisals, our data shows much longer intervals without reappraisal for most properties. This explains the lack of price signal variation for years in Figure A.11.

cases where post-swap reserve values are available, pre-swap reserves are inferred using the token amounts exchanged. In rare instances where no AMM liquidity pool existed at the time of a non-AMM transaction, price signals are missing. However, this only affects 579 out of 107,280 non-AMM transactions, as liquidity pools are typically created shortly after a token's primary issuance (STO).

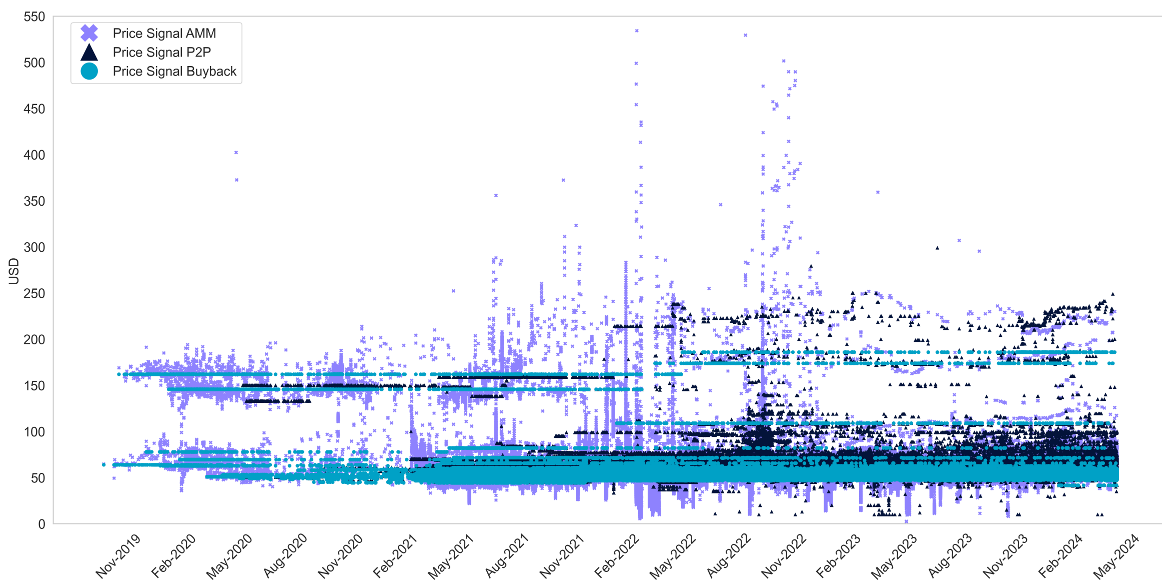
P2P price signals

When no active P2P offer is available at the timestamp of a transaction, we use the most recent historical P2P transaction for the respective token to approximate the price signal. This method is applied to 71,349 of the 444,535 transactions in the dataset. Additionally, since P2P mechanisms were only introduced in October 2020, no P2P price signals are available for 31,198 earlier transactions.

Buyback price signals

Buyback price signals are based on appraisals set by the centralized token issuer and are publicly accessible through the RealT API at `https://api.realtoken.community/`. Using the full history of buyback prices and their associated revaluation dates, we assign a corresponding buyback price signal to every non-buyback transaction. As the buyback mechanism was the first form of secondary trading available for these tokens, buyback price signals are available without gaps across the entire non-buyback transaction dataset.

Figure A.12: All price signals by market mechanism



Note: This figure shows all price signals segmented by market mechanisms (N=1,301,828).

A.11. Details on metadata

To account for the distinct market mechanisms observed, we enrich the initial transaction data by incorporating additional blockchain data, such as offer details for P2P markets and liquidity pool information for AMMs, associated with each transaction hash. Additionally, we add non-blockchain data, such as appraisal values to enrich the Buyback mechanism data. Since the term "transaction" is often used differently in the blockchain context compared to finance, we clarify that *financial transactions* refer specifically to those involving the exchange of tokens tied to payments.

Offer data (P2P)

We analyze three P2P marketplaces: Airswap, Swapcat, and YAM.[30] Each marketplace can be explicitly identified by its smart contract address, which is involved in the financial transactions as the interaction contract address. To calculate the *Time on Market* as the distance between offer creation and offer fulfillment, we enrich the financial transaction data including the offer fulfillments with the datetime of offer creation, retrieved using marketplace-specific methodologies. Swapcat and YAM record offer creation on-chain. For Swapcat, we match the `offerId` from offer creation transactions (`makeoffer`) with fulfillment transactions (`buy`). Since `offerId` is not publicly stored on-chain, we rely on additional sources such as the Blockscout REST API and The Graph subgraphs to retrieve indexing data.[31] YAM simplifies this process by explicitly storing `offerId` in the logs for both offer creation (`OfferCreated`) and fulfillment (`OfferAccepted`). Airswap processes offers off-chain, making the datetime of offer creation unavailable (Oved and Mosites, 2017). However, with only 22 transactions observed on Airswap, its exclusion has minimal impact.
The enriched data from this process enables the classification of tokens as either real estate tokens or payment tokens, allowing us to identify transactions as initiated sales or purchases of real estate tokens.[32] Furthermore, P2P marketplaces do not support bargaining or negotiation on offers, as prices are fixed by the offer creator. While prices can be updated by the creator, our analysis focuses exclusively on the final transaction prices to reduce complexity.[33]

Liquidity pool data (AMM)

To enhance our financial transaction data on AMMs, we retrieve liquidity pool reserves and token exchange amounts before and after each swap. Each real estate token (REALTOKEN) has a unique liquidity pool, typically paired with payment or quote tokens such as USDC. The distribution of these pools across the observed platforms is summarized in Table A.8.
To retrieve the reserve data from the observed AMMs, we apply different logics based on their smart contract design. For Levinswap and Uniswap v2, we use the Gnosis and Ethereum Blockscout REST API transaction logs to extract `Sync` and `Swap` events, which provide post-swap reserves (`reserve0`, `reserve1`) and token amounts exchanged (`amount0In`, `amount1In`, `amount0Out`, `amount1Out`).

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[30] `https://www.airswap.xyz/`, `https://swap.cat/`, `https://yam.realtoken.network/`

[31] The Graph enables the creation of community-driven, custom open APIs (subgraphs) that index and organize blockchain data for specific decentralized applications (dApps). We use the following subgraphs for Swapcat: `BC5uHuHf4YybNfQECjvHJyZmEfLrPSUu8fLNMZsQ38jx` for Gnosis and`4zYp9FYpdepxqgMCwDTawDvfFbS9VsXmocyiSFLwEvi7` for Ethereum.

[32] Additionally, 620 private deals, that are enabled on YAM and likely prearranged through Telegram groups associated with RealT, can be identified by analyzing the buyer address in the offer creation data. Private deals refer to offers directed at specific buyer wallet addresses, i.e. the buyer address of the contract call is not a zero address (`0x00...`), making them unavailable to the general market.

[33] Our data review confirms that deviations between offer prices and transaction prices are negligible.

Table A.8: Number of liquidity pools analyzed

	Ethereum		Gnosis
Token Pair	Uniswap v1	Uniswap v2	Levinswap
ETH-REALTOKEN	11		
WETH-REALTOKEN		2	
LEVIN-REALTOKEN			97
WETH-REALTOKEN			96
USDC-REALTOKEN			318

Note: The table summarizes the number of liquidity pools analyzed, including their token reserves and swapped token amounts. *Levinswap* (Gnosis), is a fork of *Uniswap v2* (Ethereum) and its functionality and structure is identical. REALTOKEN serves as a placeholder for specific real estate token pool pairs, with each token having its own dedicated liquidity pool. Additionally, the Ethereum pools were later migrated to the Gnosis chain (formerly xDai), contributing to a total of 511 real estate token pools.

Pre-swap reserves are calculated by adjusting post-swap reserves with the token amounts exchanged. Unlike v2-based AMMs, Uniswap v1 reserves must be retrieved using the Ethereum Blockscout REST API state changes endpoint and the quote token for Uniswap v1 is always ETH.[34]
Finally, reserve amounts of quote tokens (e.g., Wrapped Ether on xDai, Wrapped Ether, and Ether) are converted using pricing data from *CoinMarketCap*. The price trends are illustrated in Figure A.7 in Appendix A.7.[35] Using the constant product formula ($x \cdot y = k$), where x (y) is the number of RWA (payment) tokens in the pool, we can calculate the token prices for every liquidity pool reserves state as $P = \frac{y}{x}$. Furthermore, exact price slippage, which in AMMs refers to the difference between the swap execution price and the price before the swap, caused by the swap impacting the pool's reserves and shifting the price, can be calculated as follows:

$$\text{Slippage} = \frac{P_{\text{Execution}} - P_{\text{Before}}}{P_{\text{Before}}}$$

where $P_{\text{Execution}}$ is the actual price at which the swap is executed (swap price) and P_{Before} is the price based on the liquidity pool reserves before the swap occurs (pre-swap price).

[34] Where REST APIs fail, reserves are reconstructed via Alchemy RPC or manually looked up using Gnosisscan.

[35] For Levin, not constantly listed on centralized exchanges, its price is calculated manually using reserves from the LEVIN-WXDAI pool. The stable peg of USDC to USD allows direct use of its value without conversion.

A.12. Robustness and time for transactions

Table A.9: Arbitrage flow and mechanism efficiency

	Dependent variable:		
	AMM Usage (in %)	P2P Usage (in %)	Buyback Usage (in %)
	(1)	(2)	(3)
Arbitrage into AMM	−0.0003***		
	(0.0001)		
Arbitrage within AMM	0.00002***		
	(0.00000)		
Slippage	0.273***		
	(0.081)		
Arbitrage into P2P		0.0001***	
		(0.00002)	
Arbitrage within P2P		−0.00001	
		(0.00001)	
Arbitrage into Buyback			0.0001
			(0.0002)
Blockchain Transaction Fee USD	1.210***	−4.737***	4.897***
	(0.254)	(0.332)	(0.718)
Volatility 7 Days	0.042**	−0.191***	0.173***
	(0.019)	(0.032)	(0.022)
Market to Appraisal Ratio	−0.050***	0.276***	−0.232***
	(0.019)	(0.087)	(0.059)
Cumulative Return ETH (One Week)	−0.111***	0.067***	0.043***
	(0.010)	(0.018)	(0.013)
Average Ethereum Fee USD	0.0001**	−0.001***	−0.0001**
	(0.0001)	(0.0001)	(0.0001)
One Month Treasury Δ	−0.005**	0.010***	0.002
	(0.002)	(0.003)	(0.003)
Ten Year Treasury Δ	−0.0001	−0.085**	0.095***
	(0.024)	(0.037)	(0.029)
ADS Index Δ	−0.001	−0.003	−0.007***
	(0.002)	(0.003)	(0.002)
S&P Case Shiller Index Δ	−0.249	−1.886***	1.543***
	(0.481)	(0.689)	(0.360)
Individual Fixed Effects	Yes	Yes	Yes
Year-Month Fixed Effects	Yes	Yes	Yes
Observations	65,140	104,711	104,711
R^2	0.153	0.297	0.068
Adjusted R^2	0.146	0.293	0.063

Note: The table presents results for the panel regression of *mechanism usage (in %)* on a daily basis with respect to arbitrage within and into the mechanism. All models include year-month-fixed effects and token-level individual-fixed effects. Robust standard errors clustered at the token level are shown in parentheses. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.2.

Table A.10: Arbitrage flow and future mechanism efficiency

	Dependent variable:		
	AMM Usage (in %) $t+1$	P2P Usage (in %) $t+1$	Buyback Usage (in %) $t+1$
	(1)	(2)	(3)
Arbitrage into AMM	-0.0001^{*}		
	(0.0001)		
Slippage	-0.126^{**}		
	(0.054)		
Arbitrage into P2P		0.00000	
		(0.00001)	
Arbitrage into Buyback			0.00004
			(0.0002)
Blockchain Transaction Fee USD	-2.719^{***}	-0.212	0.821^{***}
	(0.333)	(0.207)	(0.188)
Volatility 7 Days	-0.004	-0.103^{***}	0.039^{**}
	(0.033)	(0.031)	(0.019)
Market to Appraisal Ratio	-0.035^{*}	0.010	0.003
	(0.020)	(0.016)	(0.005)
Cumulative Return ETH (One Week)	-0.032^{***}	0.032^{***}	-0.005
	(0.011)	(0.011)	(0.007)
Average Ethereum Fee USD	0.0001	-0.0002	-0.0001
	(0.0002)	(0.0001)	(0.0001)
One Month Treasury Δ	-0.007^{*}	0.010^{***}	-0.0003
	(0.004)	(0.003)	(0.003)
Ten Year Treasury Δ	0.005	-0.021	-0.055^{**}
	(0.045)	(0.041)	(0.027)
ADS Index Δ	-0.002	-0.002	0.004^{**}
	(0.003)	(0.003)	(0.002)
S&P Case Shiller Index Δ	-0.489	0.247	-0.958^{**}
	(0.844)	(0.679)	(0.470)
Individual Fixed Effects	Yes	Yes	Yes
Year-Month Fixed Effects	Yes	Yes	Yes
Observations	65,075	104,224	104,224
R^2	0.203	0.279	0.030
Adjusted R^2	0.197	0.275	0.025

Note: The table presents results for the panel regression of *mechanism usage (in %)* on a daily basis on the following day $t+1$ with respect to arbitrage within and into the mechanism. All models include year-month-fixed effects and token-level individual-fixed effects. Robust standard errors clustered at the token level are shown in parentheses. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.2.

To verify the consistency of our main findings, we estimate log-ratio regressions comparing mechanism usage shares relative to a baseline venue. Specifically, Table A.11 presents results using P2P usage as the reference category (log(AMM/P2P) and log(Buyback/P2P)), while Table A.12 uses AMM usage as the reference (log(P2P/AMM) and log(Buyback/AMM)). Using log-ratios allows us to express relative changes in usage shares symmetrically and interpret coefficients as elasticities, facilitating clearer comparisons across mechanisms while preserving the proportional nature of the data. Across both specifications, the results broadly confirm our baseline panel regressions (Table 4): arbitrage into AMMs reduces their relative usage, as indicated by a significantly negative coefficient on arbitrage inflows in log(AMM/P2P). Conversely, arbitrage into P2P modestly increases its relative usage, reflected by positive coefficients on arbitrage into and within P2P in log(P2P/AMM). Arbitrage into Buybacks is consistently associated with higher Buyback usage relative to both P2P and AMM, with positive and significant coefficients across both specifications. Slippage and blockchain fees also exert strong directional effects: they increase AMM usage relative to P2P (positive in log(AMM/P2P)) and decrease P2P usage relative to AMM (negative in log(P2P/AMM)), consistent with the view that AMMs serve as a high-friction fallback under execution pressure. Moreover, market-to-appraisal spreads and cumulative ETH returns load negatively on AMM usage in both sets of regressions—appearing as negative coefficients in log(AMM/P2P) and positive coefficients in log(P2P/AMM)—reinforcing the link between pricing inefficiencies and exit behavior. These robustness checks validate the directional relationships found in the main regression model and support the interpretation that arbitrage activity reallocates liquidity across mechanisms in predictable, mechanism-dependent ways.

Table A.11: Log-Ratio Regressions: AMM and Buyback Usage Relative to P2P

	Dependent variable:	
	log(AMM / P2P)	log(Buyback / P2P)
	(1)	(2)
Arbitrage into AMM	−0.010**	
	(0.004)	
Arbitrage within AMM	−0.0001	
	(0.00005)	
Arbitrage into Buyback		0.012***
		(0.002)
Slippage	5.515***	5.012***
	(1.796)	(1.771)
Blockchain Transaction Fee USD	46.010***	65.715***
	(5.039)	(6.246)
Volatility (7 Days)	1.451***	1.660***
	(0.505)	(0.566)
Market-to-Appraisal Ratio	−1.782**	−2.168**
	(0.722)	(0.912)
Cumulative ETH Return (1W)	−2.443***	−2.174***
	(0.282)	(0.300)
Ethereum Transaction Fee USD	0.002	0.002
	(0.002)	(0.002)
One-Month Treasury Δ	−0.239***	−0.287***
	(0.069)	(0.083)
Ten-Year Treasury Δ	0.534	1.157
	(0.593)	(0.722)
ADS Index Δ	−0.050	−0.116**
	(0.047)	(0.055)
S&P Case-Shiller Index Δ	−2.403	1.515
	(12.113)	(12.578)
Individual Fixed Effects	Yes	Yes
Year-Month Fixed Effects	Yes	Yes
Observations	65,140	65,140
R^2	0.132	0.104
Adjusted R^2	0.125	0.097

Note: This table presents additive log-ratio regressions with P2P as the reference category. Coefficients reflect how AMM and Buyback usage respond relative to P2P under varying arbitrage and market conditions. The table includes coefficient estimates and corresponding standard errors, presented in parentheses. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.2.

Table A.12: Log-Ratio Regressions: P2P and Buyback Usage Relative to AMM

	Dependent variable:	
	log(P2P / AMM)	log(Buyback / AMM)
	(1)	(2)
Arbitrage into P2P	0.001***	
	(0.0003)	
Arbitrage within P2P	0.001***	
	(0.0003)	
Arbitrage into Buyback		0.014***
		(0.002)
Slippage	−5.730***	−0.731**
	(1.836)	(0.359)
Blockchain Transaction Fee USD	−47.263***	18.436***
	(5.044)	(4.596)
Volatility (7 Days)	−1.398***	0.253
	(0.505)	(0.193)
Market-to-Appraisal Ratio	1.806**	−0.365*
	(0.734)	(0.198)
Cumulative ETH Return (1W)	2.542***	0.375***
	(0.287)	(0.092)
Ethereum Transaction Fee USD	−0.002	0.001
	(0.002)	(0.001)
One-Month Treasury Δ	0.249***	−0.042
	(0.070)	(0.054)
Ten-Year Treasury Δ	−0.447	0.671
	(0.595)	(0.463)
ADS Index Δ	0.047	−0.070**
	(0.047)	(0.028)
S&P Case-Shiller Index Δ	1.348	2.808
	(12.129)	(5.666)
Individual Fixed Effects	Yes	Yes
Year-Month Fixed Effects	Yes	Yes
Observations	65,140	65,140
R^2	0.127	0.010
Adjusted R^2	0.120	0.002

Note: This table presents additive log-ratio regressions with AMM as the reference category. Coefficients reflect how P2P and Buyback usage respond relative to AMM under varying arbitrage and market conditions. All models include year-month-fixed effects and token-level individual-fixed effects. The table includes coefficient estimates and corresponding standard errors, presented in parentheses. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.2.

Table A.13: Reduced time frame for the blockchain analysis

	Dependent variable:		
	AMM Usage (in %)	P2P Usage (in %)	Buyback Usage (in %)
	(1)	(2)	(3)
Arbitrage into AMM	−0.001***	/	/
	(0.00004)		
Arbitrage within AMM	0.00003***	/	/
	(0.00000)		
Slippage	0.255***	/	/
	(0.027)		
Arbitrage within P2P	/	0.00005***	/
		(0.00001)	
Arbitrage into P2P	/	−0.00002	/
		(0.00002)	
Arbitrage into Buyback	/	/	0.0004**
			(0.0002)
Transaction Price/Buyback Δ	/	/	−0.192***
			(0.012)
Blockchain Transaction Fee USD	1.149***	−4.736***	4.896***
	(0.155)	(0.193)	(0.131)
Volatility 7 Days	0.044***	−0.191***	0.190***
	(0.012)	(0.017)	(0.011)
Market to Appraisal Ratio	−0.048***	0.276***	−0.095***
	(0.005)	(0.007)	(0.009)
Cumulative Return ETH (One Week)	−0.105***	0.067***	0.052***
	(0.007)	(0.011)	(0.008)
Average Ethereum Fee USD	0.0001	−0.001***	−0.0002
	(0.0001)	(0.0001)	(0.0001)
One Month Treasury Δ	−0.005	0.010	0.002
	(0.004)	(0.007)	(0.005)
Ten Year Treasury Δ	0.004	−0.086*	0.089***
	(0.030)	(0.050)	(0.034)
ADS Index Δ	−0.001	−0.003	−0.007***
	(0.002)	(0.003)	(0.002)
S&P Case Shiller Index Δ	−0.280	−1.886***	1.475***
	(0.422)	(0.647)	(0.440)
Individual-Fixed Effects	Yes	Yes	Yes
Year-Month-Fixed Effects	Yes	Yes	Yes
Observations	65,140	104,711	104,711
R^2	0.161	0.297	0.070
Adjusted R^2	0.154	0.293	0.065

Note: The table presents results for the panel regression of *mechanism usage (in %)* on a daily basis with respect to arbitrage within and into the mechanism and a significantly reduced time windows of 5 minutes. All models include year-month-fixed effects and token-level individual-fixed effects. The table includes coefficient estimates and corresponding standard errors, presented in parentheses. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.2.

A.13. Details on difference-in-differences analysis

This appendix presents a robustness check using a stricter arbitrage definition based on a 5-minute round-trip window. The findings remain consistent with the main analysis and support the conclusion that AMMs are more susceptible to arbitrage during periods of market stress.

Table A.14: Descriptive Statistics: DiD Sample (60-Minute Window)

Variable	N	Mean	St. Dev.	Min	25%	Median	75%	Max
Arbitrage	10,609	0.200	0.400	0	0	0	0	1
AMM	10,609	0.934	0.249	0	1	1	1	1
Post Event	10,609	0.814	0.389	0	1	1	1	1
Total Fee (%)	10,609	0.005	0.007	0.000	0.003	0.003	0.004	0.053
Market-to-Appraisal Ratio	10,609	1.206	0.252	0.396	1.108	1.162	1.234	3.991
Liquidity Pool Value (USD)	10,609	1,782.827	1,215.098	8.210	1,629.301	1,897.569	2,164.522	14,045.740

Note: This table reports summary statistics for the sample used in the difference-in-differences analysis (60-minute arbitrage window). The dependent variable *Arbitrage* indicates whether a trade was part of an arbitrage sequence. *AMM* and *Post Event* are binary indicators for mechanism and post-shock status, respectively. *Total Fee (%)* denotes total transaction fees as a percentage of trade value. *Market-to-Appraisal Ratio* is the ratio of the transaction price to the appraised token value. *Liquidity Pool Value* refers to the dollar value of reserves in the AMM pool at the time of trade.

Table A.15: Descriptive Statistics: Robustness Sample (5-Minute Window)

Variable	N	Mean	St. Dev.	Min	25%	Median	75%	Max
Arbitrage (5-Min)	10,609	0.054	0.226	0	0	0	0	1
AMM	10,609	0.934	0.249	0	1	1	1	1
Post Event	10,609	0.814	0.389	0	1	1	1	1
Total Fee (%)	10,609	0.005	0.007	0.000	0.003	0.003	0.004	0.053
Market-to-Appraisal Ratio	10,609	1.206	0.252	0.396	1.108	1.162	1.234	3.991
Liquidity Pool Value (USD)	10,609	1,782.827	1,215.098	8.210	1,629.301	1,897.569	2,164.522	14,045.740

Note: This table reports summary statistics for the sample used in the robustness check of the difference-in-differences analysis based on a 5-minute arbitrage window. The dependent variable *Arbitrage (5-Min)* indicates whether a trade was part of an arbitrage sequence completed within 5 minutes. *AMM* and *Post Event* are binary indicators for mechanism type and post-shock status, respectively. *Total Fee (%)* denotes total transaction fees as a percentage of trade value. *Market-to-Appraisal Ratio* is the ratio of the transaction price to the appraised token value. *Liquidity Pool Value* reflects the dollar value of reserves in the AMM pool at the time of trade.

Table A.16: Difference-in-differences of arbitrage (5-minute window)

	Dependent variable: Arbitrage (5-Minute Window)
	OLS
	(1)
AMM	0.0067
	(0.0152)
Post Event	−0.0161
	(0.0150)
Total Fee (%)	−1.730***
	(0.5513)
Market-to-Appraisal Ratio	−0.195***
	(0.0583)
Liquidity Pool Value (USD)	0.000042*
	(0.000023)
AMM × Post Event	0.0501***
	(0.0154)
Individual-Fixed Effects	Yes
Clustered SE	Yes
Observations	10,609
Adjusted R^2	0.0885

Note: This table reports regression results for the binary outcome *Arbitrage (5-Minute Window)* using the same transaction-level DiD model as in the main specification. The dependent variable equals one if a wallet executes a profitable round-trip trade in the same token within 5 minutes. Model is estimated using OLS with symbol fixed effects and standard errors clustered at the token level. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

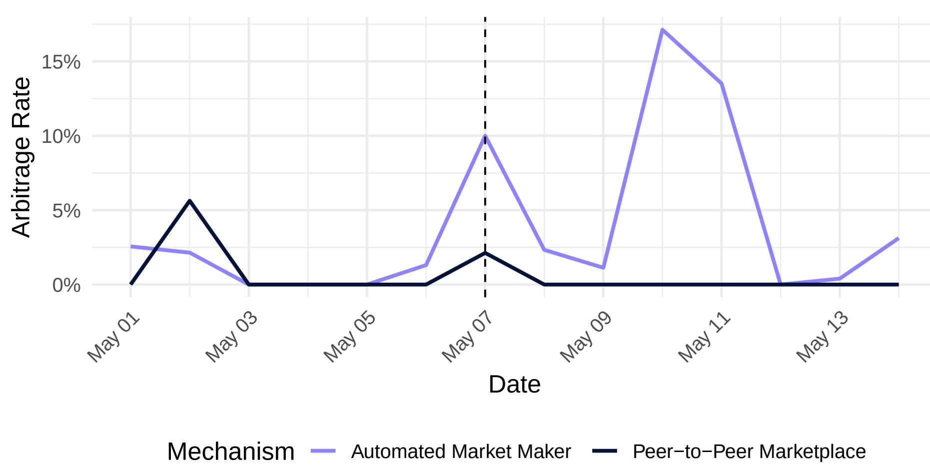

Figure A.13: This figure plots the daily arbitrage probability based on a 5-minute window for trades executed via AMMs and P2P marketplaces between May 1 and May 14, 2022 The vertical dashed line marks the UST collapse on May 7. Trends are parallel pre-shock and diverge sharply post-shock, supporting the identification strategy of the DiD model.

A.14. Details on optimization problem

Partial derivatives

In the interior solution case—where none of the liquidity constraints bind—the optimal allocation $(q^*_{\text{AMM}}, q^*_{\text{P2P}}, q^*_B)$ satisfies the condition that the marginal execution cost per unit of efficiency is equalized across all mechanisms. This corresponds to the first-order condition derived from the Lagrangian of the cost minimization problem.
The total execution cost to minimize is:

$$C_{\text{total}} = \frac{C_{\text{exec, AMM}}}{E_{\text{AMM}}} + \frac{C_{\text{exec, P2P}}}{E_{\text{P2P}}} + \frac{C_{\text{exec, B}}}{E_{\text{B}}}, \tag{N.1}$$

where each component is a function of the respective trade size q_i, and all quantities are subject to the market-clearing condition:

$$q = q_{\text{AMM}} + q_{\text{P2P}} + q_B. \tag{N.2}$$

The partial derivatives for each mechanism express the marginal increase in total execution cost per additional unit traded via mechanism i, holding the others fixed:

For AMMs:

$$C_{\text{exec, AMM}} = \beta \cdot F_{\text{AMM}} \cdot q_{\text{AMM}} + \frac{q^2_{\text{AMM}}}{L_{\text{AMM}}}, \tag{N.3}$$

$$E_{\text{AMM}} = \eta_{\text{AMM}} \cdot L_{\text{AMM}} \cdot \left(\frac{1}{t_{\text{AMM}}}\right)^{\gamma}, \tag{N.4}$$

$$\frac{\partial}{\partial q_{\text{AMM}}}\left(\frac{C_{\text{exec, AMM}}}{E_{\text{AMM}}}\right) = \frac{1}{E_{\text{AMM}}} \cdot \frac{\partial C_{\text{exec, AMM}}}{\partial q_{\text{AMM}}}, \tag{N.5}$$

$$\frac{\partial C_{\text{exec, AMM}}}{\partial q_{\text{AMM}}} = \beta \cdot F_{\text{AMM}} + \frac{2q_{\text{AMM}}}{L_{\text{AMM}}}, \tag{N.6}$$

$$\frac{\partial}{\partial q_{\text{AMM}}}\left(\frac{C_{\text{exec, AMM}}}{E_{\text{AMM}}}\right) = \frac{\beta \cdot F_{\text{AMM}} + \frac{2q_{\text{AMM}}}{L_{\text{AMM}}}}{\eta_{\text{AMM}} \cdot L_{\text{AMM}} \cdot \left(\frac{1}{t_{\text{AMM}}}\right)^{\gamma}}. \tag{N.7}$$

For P2P marketplaces:

$$C_{\text{exec, P2P}} = \beta \cdot F_{\text{P2P}} \cdot q_{\text{P2P}} + \frac{q^{\delta}_{\text{P2P}}}{L_{\text{P2P}}}, \tag{N.8}$$

$$E_{\text{P2P}} = \eta_{\text{P2P}} \cdot L_{\text{P2P}} \cdot \left(\frac{1}{t_{\text{P2P}}}\right)^{\gamma}, \tag{N.9}$$

$$\frac{\partial}{\partial q_{\text{P2P}}}\left(\frac{C_{\text{exec, P2P}}}{E_{\text{P2P}}}\right) = \frac{1}{E_{\text{P2P}}} \cdot \frac{\partial C_{\text{exec, P2P}}}{\partial q_{\text{P2P}}}, \tag{N.10}$$

$$\frac{\partial C_{\text{exec, P2P}}}{\partial q_{\text{P2P}}} = \beta \cdot F_{\text{P2P}} + \frac{\delta \cdot q^{\delta-1}_{\text{P2P}}}{L_{\text{P2P}}}, \tag{N.11}$$

$$\frac{\partial}{\partial q_{\text{P2P}}}\left(\frac{C_{\text{exec, P2P}}}{E_{\text{P2P}}}\right) = \frac{\beta \cdot F_{\text{P2P}} + \frac{\delta \cdot q^{\delta-1}_{\text{P2P}}}{L_{\text{P2P}}}}{\eta_{\text{P2P}} \cdot L_{\text{P2P}} \cdot \left(\frac{1}{t_{\text{P2P}}}\right)^{\gamma}}. \tag{N.12}$$

For Buybacks:

$$C_{\text{exec, B}} = \beta \cdot F_{\text{B}} \cdot q_{\text{B}}, \tag{N.13}$$

$$t_{\text{B}}(q_{\text{B}}) = t_{\min} + (t_{\max} - t_{\min}) \cdot \left(1 - \frac{q_{\text{B}}}{\overline{L}_{\text{B}}}\right)^{\kappa}, \tag{N.14}$$

$$E_{\text{B}} = \eta_{\text{B}} \cdot \overline{L}_{\text{B}} \cdot \left(\frac{1}{t_{\text{B}}(q_{\text{B}})}\right)^{\gamma}. \tag{N.15}$$

Since the efficiency function E_{B} depends on q_{B}, we need to differentiate it as well. The marginal execution cost per efficiency unit for buybacks is:

$$\frac{\partial}{\partial q_{\text{B}}}\left(\frac{C_{\text{exec,B}}}{E_{\text{B}}}\right) = \frac{1}{E_{\text{B}}} \cdot \frac{\partial C_{\text{exec,B}}}{\partial q_{\text{B}}} - \frac{C_{\text{exec,B}}}{E_{\text{B}}^2} \cdot \frac{dE_{\text{B}}}{dq_{\text{B}}}, \tag{N.16}$$

$$\frac{\partial C_{\text{exec,B}}}{\partial q_{\text{B}}} = \beta \cdot F_{\text{B}}, \tag{N.17}$$

$$\frac{dt_{\text{B}}(q_{\text{B}})}{dq_{\text{B}}} = -(t_{\max} - t_{\min}) \cdot \frac{\kappa}{\overline{L}_{\text{B}}} \cdot \left(1 - \frac{q_{\text{B}}}{\overline{L}_{\text{B}}}\right)^{\kappa-1}, \tag{N.18}$$

$$\frac{dE_{\text{B}}}{dq_{\text{B}}} = -\eta_{\text{B}} \cdot \overline{L}_{\text{B}} \cdot \gamma \cdot \left(\frac{1}{t_{\text{B}}(q_{\text{B}})}\right)^{\gamma+1} \cdot \frac{dt_{\text{B}}(q_{\text{B}})}{dq_{\text{B}}}, \tag{N.19}$$

$$\begin{aligned}\frac{\partial}{\partial q_{\text{B}}}\left(\frac{C_{\text{exec,B}}}{E_{\text{B}}}\right) &= \frac{\beta \cdot F_{\text{B}}}{\eta_{\text{B}} \cdot \overline{L}_{\text{B}} \cdot \left(\frac{1}{t_{\text{B}}(q_{\text{B}})}\right)^{\gamma}} \\ &\quad + \frac{\beta \cdot F_{\text{B}} \cdot q_{\text{B}} \cdot \gamma \cdot (t_{\max} - t_{\min}) \cdot \kappa}{\eta_{\text{B}} \cdot \overline{L}_{\text{B}}^2} \\ &\quad \cdot \left(\frac{1}{t_{\text{B}}(q_{\text{B}})}\right)^{\gamma-1} \cdot \left(1 - \frac{q_{\text{B}}}{\overline{L}_{\text{B}}}\right)^{\kappa-1}.\end{aligned} \tag{N.20}$$

Together, these marginal expressions provide the analytical foundation for comparing mechanisms at the margin. The optimal allocation satisfies:

$$\frac{\partial}{\partial q_{\text{AMM}}}\left(\frac{C_{\text{exec, AMM}}}{E_{\text{AMM}}}\right) = \frac{\partial}{\partial q_{\text{P2P}}}\left(\frac{C_{\text{exec, P2P}}}{E_{\text{P2P}}}\right) = \frac{\partial}{\partial q_{\text{B}}}\left(\frac{C_{\text{exec, B}}}{E_{\text{B}}}\right). \tag{N.21}$$

Starting allocation

To improve numerical stability and accelerate convergence in the numerical optimization routine implemented in 4.1, we initialize the iterative solver with a heuristically meaningful starting allocation, denoted as q_i^0. This initial guess reflects the core economic intuition of the framework that traders allocate more volume to mechanisms that offer greater execution efficiency per unit of cost. This logic can be implemented through an inverse-cost-per-efficiency weighting rule, assigning larger volume shares to mechanisms with lower average execution cost per efficiency unit. The share allocated to mechanism i is then given by:

$$q_i^0 = \frac{\frac{1}{C_{\text{total},i}}}{\sum_j \frac{1}{C_{\text{total},j}}} \cdot q, \quad i \in \{\text{AMM}, \text{P2P}, \text{B}\}, \tag{N.22}$$

with total cost per unit of execution efficiency defined as:

$$C_{\text{total},i} = \frac{C_{\text{exec},i}}{E_i}. \tag{N.23}$$

This inverse-cost allocation rule approximates the marginal condition of the full optimization problem, which equalizes execution cost per efficiency unit across mechanisms. In cases where none of the liquidity constraints are binding (i.e., interior solutions), this heuristic allocation closely mirrors the true optimizer, as the first-order condition of the Lagrangian yields a comparable structure. This is because the marginal condition involves the derivative of the same ratio $C_{\text{exec},i}/E_i$, and for near-linear or mildly convex cost and efficiency functions, the average and marginal values of this ratio are nearly identical. Furthermore, since the implemented execution cost and efficiency functions are nearly linear or exhibit only mild curvature over the relevant trade size range, the average cost per efficiency unit serves as a close proxy for the marginal cost in these cases. While the full numerical solution is necessary to accommodate binding constraints and corner cases, the starting guess captures the economically meaningful direction of the optimum and significantly improves convergence stability. In additional robustness checks (unreported), we tested various solver initializations (for example a neutral starting point with equal weights across mechanisms) extensively. These checks consistently confirmed that trade allocations remain stable across all economically relevant initializations.

Further simulations

The following simulations show additional optimal trade allocations under varying model parameters, as described in the figure notes—particularly changes in trader preferences. These results complement the model simulations presented in Section 4.1.

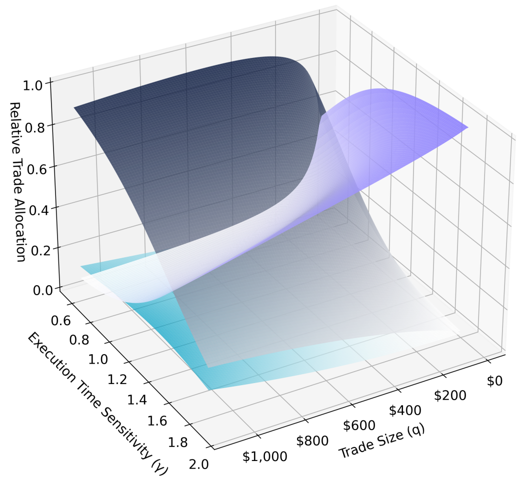

Figure A.14: Time Sensitivity (γ) and Trade Size (q)

Note: Shows the optimal trade allocation using parameters from the Empirical Baseline (1) in Section 4.1, with $L_{P2P} = 973$ (empirical median). Varying the execution time sensitivity γ highlights the preference for the faster AMMs as γ increases.

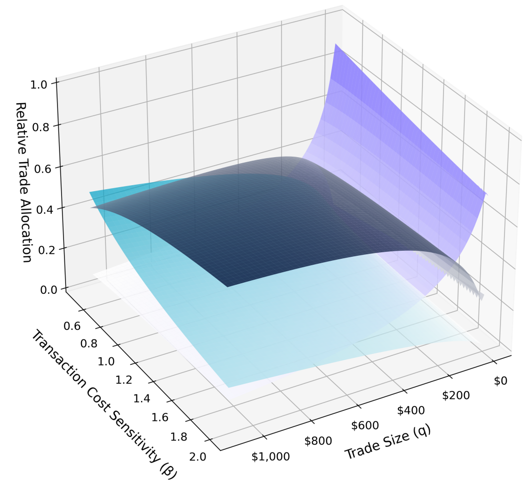

Figure A.15: Transaction Fee Sensitivity (β) and Trade Size (q)

Note: Displays the optimal trade allocation from the Empirical Baseline (1) in Section 4.1, with $L_{P2P} = 973$ (empirical median). As transaction fee sensitivity β increases, allocation shifts toward lower-fee venues such as P2P and AMM.

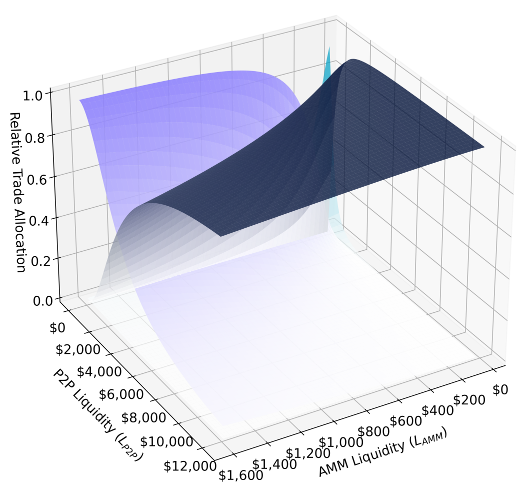

Figure A.16: AMM and P2P Liquidity with fixed Trade Size ($q = \$10$)

Note: Illustrates optimal trade allocation for a fixed trade size of $q = \$10$, using parameters from the Empirical Baseline (1) in Section 4.1. Liquidity levels span the empirical 10$^{\text{th}}$ and 90$^{\text{th}}$ quantiles: $L_{AMM} \in [\$37, \$1{,}600]$ and $L_{P2P} \in [\$61, \$12{,}130]$. The results highlight how small trades tend to reallocate based on the relative liquidity of available execution mechanisms.

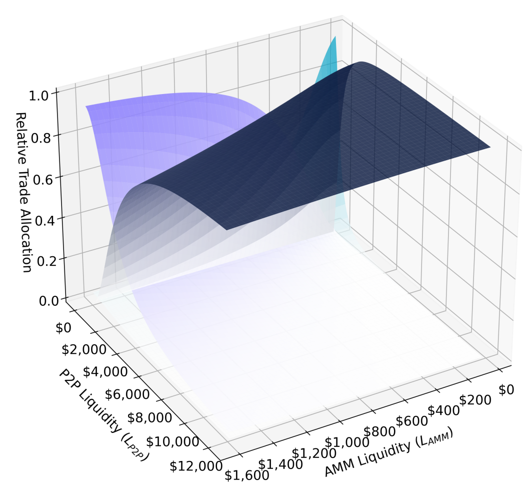

Figure A.17: AMM and P2P Liquidity with fixed Trade Size ($q = \$50$)

Note: Visualizes optimal trade allocation for a fixed trade size of $q = \$50$, using parameters from the Empirical Baseline (1) in Section 4.1. Liquidity levels span the empirical 10$^{\text{th}}$ and 90$^{\text{th}}$ quantiles: $L_{AMM} \in [\$37, \$1{,}600]$ and $L_{P2P} \in [\$61, \$12{,}130]$. The trade size approximates the average token price at STO, serving as a representative benchmark for full-token transactions.