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SUMMARY: This study examines the use of tokenized real estate properties in decentralized finance (DeFi) platforms, focusing on how secondary markets aggregate information about these assets and whether this information is used by borrowers and lenders. The authors analyze data from RealT's ecosystem, which tokenizes rental properties and allows them to be traded on decentralized exchanges (DEXs) and an over-the-counter (OTC) marketplace. The study finds that secondary markets aggregate information about the underlying properties, but token prices also reflect collateral use value once tokens become integrated into DeFi lending. Borrowers use secondary market information to manage credit risk, while lenders appear to respond more to expected returns than to potential run risk. Despite active borrowing and trading, the study does not find evidence of self-reinforcing credit-price cycles.

METHOD: The study uses data from RealT's ecosystem, which tokenizes over 700 rental properties from 2021 to 2025. The authors examine the valuation of underlying properties, including the impact of secondary market prices and collateral valuations used by the lending platform. The analysis includes both decentralized secondary market prices and OTC prices, with secondary market prices containing information about the underlying properties, while collateral valuations used by the lending platform influence borrower and lender behavior.

KEY FINDINGS:

- Secondary markets aggregate information about the underlying properties.
- Token prices reflect collateral use value once tokens become integrated into DeFi lending.
- Borrowers use secondary market information to manage credit risk.
- Lenders respond more to expected returns than to potential run risk.
- No evidence of self-reinforcing credit-price cycles.

IMPLICATION FOR TRADING: The findings suggest that decentralized secondary markets can aggregate information about tokenized real estate properties, and this information is used by borrowers to manage credit risk. However, lenders do not appear to be disciplined by this information, as they respond more to expected returns than potential run risk. These insights can inform the development of DeFi platforms for tokenized real estate, as well as the design of collateral mechanisms and risk management strategies. The lack of self-reinforcing credit-price cycles suggests that the integration of real estate into DeFi may not lead to significant price volatility or instability, which could be beneficial for market participants.

Finance beyond Traditional Intermediaries: Trading and Lending in Tokenized Real Estate*

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ABSTRACT

Decentralized finance (DeFi) outsources services traditionally performed by financial intermediaries to code. We study whether intermediary functions that support financial stability can similarly be disintermediated. Using over 700 tokenized properties, we examine a setting in which the same assets trade in secondary markets and serve as collateral. We find that secondary markets aggregate information about tokenized properties and discipline credit markets through borrowers, but not lenders. Despite credit-driven demand, we find no evidence that buying, borrowing against, and reinvesting in tokenized real estate generates aggregate price-credit cycles.

JEL classification: G12, G14, G23, R31, O33

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1 Introduction

Technological innovation is increasingly transferring financial service functions from intermediaries to automated code. In decentralized finance (DeFi), smart contracts automate trading, lending, and settlement on public blockchains ([Harvey et al., 2021](#); [John et al., 2023](#)). This architecture can reduce intermediation frictions and broaden access to financial services. Yet traditional intermediaries also perform important economic functions, including information production, screening and monitoring ([Stiglitz and Weiss, 1981](#); [Diamond, 1984](#)). Whether disintermediated markets can perform these functions becomes particularly important for financial stability when real world assets enter blockchains and become integrated into DeFi.

We study this question using RealT’s ecosystem of more than 700 tokenized rental properties from 2021 to 2025. RealT converts individual US rental properties into digital tokens that can be traded on decentralized exchanges (DEXs) and an over-the-counter (OTC) marketplace on the Gnosis blockchain. The same tokens can also be pledged as collateral for borrowing. This unique setting allows us to study whether secondary markets produce information about individual physical assets, whether borrowers and lenders use this information in their credit decisions, and whether collateralized borrowing feeds back into token prices

We obtain three main findings. First, decentralized secondary markets aggregate information about the underlying properties, but token prices also reflect collateral use value once tokens become integrated into DeFi lending. Second, borrowers use secondary market information to manage credit risk, whereas lenders appear to respond more to expected returns than to potential run risk. Third, despite active borrowing and trading, we find no evidence of self-reinforcing credit-price cycles.

Our empirical analysis begins by examining the valuation of the underlying properties. RealT’s deed-confirmed acquisition prices are not statistically different from those of comparable non-tokenized properties in Detroit (RealT’s largest market). At issuance,

however, RealT lists properties at an average premium of 43%, reflecting acquisition-related costs as well as maintenance and renovation reserves. After issuance, primary market prices generally adjust with housing fundamentals and do not mechanically increase with buying pressure during initial token offerings, in contrast to the demand-driven pricing effects documented in [Fahlenbrach and Frattaroli \(2021\)](#); [Gan et al. \(2021\)](#).

Against this benchmark, we find that decentralized secondary market prices contain information about the underlying properties. Before tokens become eligible as collateral, a 10% DEX premium predicts a 0.29% increase in RealT’s primary market valuation after six months. OTC prices are substantially less informative, consistent with search and trading frictions slowing price discovery ([Duffie et al., 2005](#); [Hendershott and Madhavan, 2015](#)). Once tokens become usable as collateral, however, the predictive content of DEX prices largely disappears, and prices also impound the utility generated by collateral use.

The second part of the analysis examines whether borrowers and lenders respond to differences between secondary market prices and the collateral valuations used by the lending platform.¹ When the lending platform values collateral above its secondary market price, borrowers receive more borrowing capacity than the market value of the collateral would imply, while lenders face greater potential losses if the collateral must be liquidated at the lower market price. Conversely, when the platform values collateral below its secondary market price, borrowers receive less borrowing capacity than the market value of their collateral would justify and therefore reduce their borrowing. If secondary markets discipline credit markets, we therefore expect lenders to reduce liquidity provision when collateral is overvalued and increase it when collateral is undervalued.

Interestingly, we find little evidence that aggregate liquidity supply tightens when secondary market prices indicate that collateral is overvalued. Instead, lenders withdraw more liquidity when the platform undervalues collateral and retain more liquidity when it

¹On the lending platform, collateral is valued using RealT’s appraisal-based primary market price (property price). This setting differs from most DeFi lending platforms, which typically rely on exchange-based price feeds aggregated across trading venues (see [Schwenkler et al., 2026](#) for an empirical analysis).

overvalues collateral. These patterns run counter to credit risk monitoring and are more consistent with aggregate liquidity responding to the profitability of supplying stablecoins.

Borrower, on the other hand, react strongly to secondary market-implied risks. When the DEX price exceeds the collateral valuation by 10%, borrowers reduce their debt positions by 4% after one week and 17.5% after one month. The adjustment becomes stronger when borrowing constraints are tighter and is more pronounced for DEX prices than for OTC prices. Furthermore, borrowers respond less strongly for properties with high rental yields and tend to retain these assets as collateral despite the market undervaluation. We interpret this finding as consistent with high-yield properties being perceived as higher quality and therefore less likely to experience a downward revision in the primary market valuation that would increase credit risk.

Despite the close technological integration of trading and lending, we find little evidence of an aggregate credit-price cycle. Higher DEX premiums predict lower leverage, but changes in leverage do not predict subsequent DEX prices, and we find no significant dynamic relationship in the OTC market.

The absence of these feedback effects does not imply that borrowers do not use credit to buy tokenized real estate. We show that new loans strongly predict real estate token purchases, but these purchases are concentrated in the primary market. Wallet-level transaction data further show substantial heterogeneity in credit use. The majority of investors seem to actively manage their debt and collateral to reduce leverage, while others engage in stablecoin looping, real estate token looping, or combinations of both to increase leverage. After 30 days, 35.2% of new loans are associated with active debt management, 8.6% with stablecoin looping, 23.2% with real estate-token looping, and 14.6% with both forms of looping. We interpret this as evidence that credit can substantially increase individual leverage without (yet) generating sufficient buying pressure to systematically move prices in decentralized secondary markets.

Finally, we study how DeFi markets respond to a negative real economy information

shock. In July 2025, the City of Detroit filed a lawsuit against RealT identifying properties with serious physical deficiencies. Relative to matched unaffected properties, lawsuit-affected tokens trade at a 3.8% larger discount to their primary market valuations within one week and approximately a 5% larger discount after 30 days. Debt, collateral, and leverage also decline, but the changes are not statistically significant under randomization inference. The shock therefore produces a modest secondary market price reaction, while credit positions respond only weakly.

We make three contributions. First, we contribute to the literature on the pricing and price discovery of cryptoassets. Existing work studies how network effects and other crypto-specific risk factors determine token returns ([Cong et al., 2021](#); [Liu and Tsyvinski, 2021](#); [Sockin and Xiong, 2023](#); [Cong et al., 2025](#)), how the convenience yield generated by token use enters token pricing ([Prat et al., 2026](#)), how market segmentation and limits to arbitrage generate price differences across centralized exchanges ([Makarov and Schoar, 2019, 2020](#)), and how automated market making design, liquidity provision, and arbitrage determine market quality and price discovery on decentralized exchanges ([Hasbrouck et al., 2025](#); [Lehar and Parlour, 2025](#); [Barbon and Ranaldo, 2026](#); [Capponi et al., 2026](#); [Harvey et al., 2026](#)). We extend this literature to tokens backed by individual physical assets and show that token prices reflect both the value of the underlying real estate and, when integrated into a DeFi lending platform, their utility as collateral. The comparison between DEX and OTC marketplace trading further shows how market architecture affects the pricing of tokenized real world assets.

Second, we contribute to the literature on credit supply and asset prices. Canonical models show how collateral constraints can create mutually reinforcing feedback between credit and asset prices ([Kiyotaki and Moore, 1997](#); [Brunnermeier and Pedersen, 2009](#); [Geanakoplos, 2010](#)), contributing to financial crises ([Schularick and Taylor, 2012](#)). Similarly, in housing markets, greater credit supply raises housing demand and prices, while higher property values support additional borrowing ([Mian and Sufi, 2011](#); [Favara and](#)

Imbs, 2015). Our setting allows us to observe each step of this mechanism for the same individual assets. We show that tokenization makes recursive collateralized borrowing and investment technologically possible, but this possibility alone is insufficient to generate aggregate price-credit cycles.

Our third contribution is to the literature on DeFi. Existing work argue that DeFi liquidations can move prices and trigger further liquidations across markets (Lehar and Parlour, 2022). Chiu et al. (2023) show theoretically that rigid smart contracts can generate a price-liquidity feedback effects. Heimbach and Huang (2023) document that high borrower leverage weakens lending resilience by increasing the share of debt close to liquidation. Cornelli et al. (2025) show that borrowing is motivated mainly by speculation and, to a lesser extent, by attempts to increase influence on DeFi platform decisions. Park and Stinner (2023) identify users who deposit and reborrow the same stablecoin specifically to capture extra token rewards. We contribute by showing that DeFi reallocates traditional intermediary functions across different market participants. Secondary market traders aggregate information, while borrowers use secondary market prices to infer implied credit risk. Contrary to expectations, lenders do not respond to secondary market price signals and instead tend to reach for yield.

The remainder of the paper is structured as follows. Section 2 describes the institutional setting and data. Section 3 studies primary market prices and property valuation, Section 4 examines borrower and lender responses to secondary market prices, and Section 5 tests the credit-price feedback mechanism. Section 6 concludes.

2 Tokenized Real Estate and Data

Real estate tokenization is a mechanism through which cash-flow rights on physical properties are represented by cryptocurrencies or tokens.² In our setting, property acquisitions

²Each tokenized property has its own smart contract, identified by the property’s address, which creates the corresponding real estate-backed tokens.

are typically financed with equity raised through a crowdfunding sale of real estate-backed tokens. In a typical structure, an asset management company acquires a property and places it in a limited liability company (LLC) or special purpose vehicle (SPV). Investors buy shares in the LLC/SPV, which represent rental income claims on the property. However, instead of being securitized and traded through real estate investment trusts (REITs) on traditional exchanges, these claims are now tokenized (i.e., converted one-to-one into a fixed number of *permissioned* digital tokens) and held in wallets on public blockchains.

Real estate-backed tokens are generally treated as securities under US law, meaning that investors must pass KYC/whitelisting requirements and that transfers are restricted to approved wallets. Issuers can rely on Regulation S to avoid the disclosure and compliance costs of SEC registration, however, sales are then restricted to non-US investors. Under Regulation D of the Securities Act, issuers can offer securities without SEC registration only to accredited US investors.

Similar to REIT shareholders, real estate-backed tokenholders receive economic rights, including rental income distributions and exposure to property price appreciation. They do not receive direct ownership of the property, occupancy rights, or operational control. This feature distinguishes tokenized real estate from traditional fractional ownership or shared-equity mortgages, where the occupant purchases a fraction of the home while retaining partial ownership and/or occupancy rights ([Benetton et al., 2022](#)). In the appendix, [Table A.1](#) compares shared-equity mortgages, REITs, and tokenized real estate across economic costs and benefits, investor rights, and risk.

One key distinction is that tokenized real estate preserves exposure to individual properties rather than diversified property portfolios. More importantly for our analysis, tokenized real estate can be integrated into DeFi markets, either as a tradable asset or as collateral. This integration creates a direct channel through which local real estate shocks can affect blockchain activity. To study this channel and examine whether asset tokenization and DeFi markets can replicate intermediaries' information production and

monitoring functions—the primary aim of this paper—we first describe the institutional features of RealT’s ecosystem and the construction of our data.

2.1 RealToken Technologies Inc.

The tokenized real estate market is highly concentrated and dominated by RealToken Technologies Inc. (RealT), headquartered in Boca Raton, Florida, which primarily tokenizes individual residential properties in the US. In [Table A.2](#), we provide an overview of the real estate tokenization market by issuing company, number of tokenized properties, and total tokenized value. Other applications of tokenized real estate remain extremely limited and include the tokenization of commercial properties for collateralized short-term lending, as well as fundraising for hotels, luxury apartments, and similar development projects, mostly in Asia. Because these platforms are still at an early stage and typically list only a small number of trial properties, our empirical analysis focuses on RealT.

We create a large, unique data set of tokenized real estate and their characteristics. Data are hand-collected from the [RealT API](#), deed records, Zillow, and the full on-chain market activity on the Gnosis blockchain. As shown in [Table 1](#), we summarize all available characteristics for all RealT-issued tokens.

[\[Table 1 about here\]](#)

We begin with 823 smart contracts corresponding to RealT’s token offerings and retain 780 rental property tokens for the empirical analyses.³ Initially, RealT started tokenizing properties on Ethereum in 2019, but in 2021 it migrated (copied) all smart contracts to the Gnosis blockchain to avoid high transaction costs (gas fees). Because transactions on Ethereum are very limited, we focus on tokens and market activity on the

³We exclude equity, loan income, and factoring profit share tokens. We also exclude deprecated smart contracts. We further exclude tokenized properties issued under Regulation D or without an explicit Regulation S/D classification because we do not observe these tokens trading on secondary markets. Finally, we exclude tokens related to properties in Panama, Mexico, and Colombia, which mostly refer to pre-construction loans for development projects.

Gnosis blockchain. Our on-chain data sample therefore starts in March 2021 and runs through December 2025.

As of December 2025, RealT reported \$161.49 million in total tokenized investment value. Most tokenized properties are occupied single-family homes (67%). They are primarily located in Detroit (75%) and were originally built in the late 1940s (see [Figure A.1](#)). Detroit’s housing market has changed substantially over the past two decades. Following the 2007 financial crisis, transaction prices fell by about 41%, reaching their lowest point around 2012. Prices subsequently increased by about 165% through 2025 (see, e.g., the House Price Index for Detroit from the US Federal Housing Finance Agency). Nevertheless, property price growth and housing demand vary substantially across locations within the same city (see, e.g., Urban Institute, 2017, Redfin, 2025, and Zillow, 2025)

2.2 Primary market and property appraisals

After registering on RealT’s website and completing KYC, investors can trade directly with RealT.⁴ In this primary market, RealT performs a dealer function in both issuance and repurchases ([Treyner, 1987](#)). In the initial crowdfunding offering, each token is sold to investors at approximately \$50 (see [Table 1](#)). RealT typically divides the initial property value by \$50 to determine the number of tokens offered. This number remains fixed over time. RealT then reappraises property values over time, and changes in appraised value lead to corresponding adjustments in the primary market token price, which is also the price at which RealT repurchases tokens. Investors can sell back up to \$2,000 per week at the most recent appraisal-based primary market price.⁵

⁴Because tokenholders are linked to verified identities, cash-flow rights can be assigned, while all transfers of RealT-issued tokens are restricted to whitelisted/KYC-approved wallets.

⁵A 3% fee applies, and settlement typically takes up to 10 days.

2.3 Decentralized exchanges vs. over-the-counter market

Once issued, tokens are integrated into DeFi and can be traded on secondary markets. The Gnosis blockchain provides two main venues, which differ in how prices are determined and how liquidity is supplied. We discuss these pricing mechanisms below. This distinction is central to our tests because secondary markets may differ in their ability to aggregate information and coordinate investor behavior. [Table 2](#) reports summary statistics for on-chain activity. [Table A.3](#) describes the different markets and defines the key terms used in the analysis.

[[Table 2](#) about here]

Decentralized exchanges DEXs consist of liquidity pools. In a two-asset pool, liquidity providers deposit equal dollar values of both assets, for example, a real estate token X and a stablecoin Y , in the pool’s current value ratio. Traders can then buy or sell the real estate token by swapping it against the stablecoin in the pool. Each pool’s quoted price is determined mechanically by the inventories of the two deposited assets, l_X and l_Y . Specifically, the price of the real estate token X in units of the stablecoin Y at timestamp t is l_Y/l_X . Under a constant-product pricing rule, trades change the pool’s inventories along the invariant $l_X l_Y = k$, thereby mechanically changing the quoted pool price l_Y/l_X . Execution prices therefore depend mechanically on the pool’s current inventory, and larger trades generate larger price impact when pool depth is limited. We measure execution price impact (slippage) as the percentage difference between the trade execution price and the pre-trade pool price. We use this measure as a proxy for transaction costs on DEXs.

Over-the-counter market In January 2023, RealT launched the You-and-Me (YAM) platform, where investors submit take-it-or-leave-it buy or sell offers by specifying quantity and price. Trades occur when a counterparty accepts a quoted price, and offers remain listed until accepted. Price discovery is therefore quote-driven by the posting side,

similar to an OTC market. Unlike DEXs, trades do not execute continuously against a standing liquidity pool, and time to execution varies with liquidity and immediacy. YAM is therefore slower and less liquid, but accepted offers may contain more property-specific information if buyers conduct additional due diligence before accepting a posted quote.

To compare price levels across trading venues, [Figure A.3](#) plots transaction level buy and sell prices for one real-estate backed token. DEX prices are relatively continuous and concentrated around \$50, although they display occasional large deviations. By contrast, YAM prices are substantially more dispersed and cluster at discrete price levels. Most YAM trades execute as buys at the ask price, implying that trading on YAM is primarily buyer-initiated. To measure how much blockchain prices deviate from fundamental value, we define the price premium or discount as the difference between secondary market trade prices and the latest primary market price.

2.4 DeFi lending and collateralized borrowing

The final DeFi integration is collateralized borrowing against tokenized real estate. It works as follows. First, depositors provide stablecoins to the lending platform. They do so to earn interest on their deposits, similar to a savings account. Second, borrowers pledge real estate tokens as collateral to the lending platform. They can then borrow stablecoins up to a maximum LTV ratio and pay interest. Because interest accrues continuously over time, the outstanding debt increases even if the borrower does not take out a new loan. Since loans must remain overcollateralized, the value of the deposited collateral must exceed the value of the borrowed stablecoins.

The main difference from traditional lending is that borrowing constraints are enforced automatically by smart contracts. There is no bank or intermediary screening the borrower. Instead, an algorithm monitors whether the collateral value remains sufficiently high relative to the outstanding debt. This liquidation threshold works like a maintenance

margin. If the debt becomes too large relative to the collateral, the position can be liquidated. Third-party liquidators or arbitrageurs then step in, repay part of the borrower's debt, and receive the collateral at a discount ([Lehar and Parlour, 2022](#)). To avoid liquidation, borrowers must manage their leverage by repaying interest payments or depositing additional collateral. As long as the position remains sufficiently overcollateralized, the loan can remain open indefinitely.

Interest rates adjust algorithmically in response to the platform's credit utilization. In other words, when borrowing demand increases relative to available deposits, interest rates rise, discouraging borrowing and attracting more stablecoin deposits to the platform. When liquidity is abundant, interest rates fall.

RealT money market (RMM) In April 2022, RealT launched the RealT money market (RMM V2), a lending platform based on Aave V2 that allows investors to borrow stablecoins against tokenized real estate. In RMM V2, only 53 selected real estate tokens could be used as collateral, and investors could borrow up to 50% of the collateral value. In February 2024, RealT upgraded to RMM V3 (based on Aave V3), which expanded the eligible collateral set to 623 real estate tokens and increased the LTV limit to 75%.

To provide a first overview, we plot daily average investor leverage (defined as borrowing divided by collateral) and total borrowing in \$ (see [Figure A.2](#)). In RMM V2, borrowing grew gradually during 2022-2023 and peaked at around \$2-3 million. It then fell sharply during the transition to RMM V3 in early 2024. Under RMM V3, borrowing increased substantially, reaching approximately \$10-15 million by late 2025. Daily average investor leverage is typically around 20-35%, but becomes higher and more volatile under RMM V3.

Both versions of the RealT lending platform have three distinctive features. First, collateral values are based on the most recent primary market price. This design differs from many DeFi lending platforms, where collateral values are based on secondary market

prices. Second, once real estate tokens are deposited as collateral, they cannot themselves be borrowed by other users. This setting also differs from many DeFi lending platforms. The main idea is to limit collateral rehypothecation ([Bottazzi et al., 2012](#); [Mitchell and Pulvino, 2012](#)). Third, borrowers continue to receive rental income while their tokens are pledged as collateral. These features make borrowing against tokenized real estate a practical alternative to selling real estate tokens for liquidity.

3 Are Token Prices Linked to Fundamentals?

A key institutional feature of our setting is that we observe three related prices for the same underlying asset. The first is the transaction price of the tokenized property in the real estate market. The second is RealT’s primary market token price, which should, in principle, reflect the property’s real economic value. This price also serves two roles in DeFi. It provides the benchmark for measuring secondary market price premia, and RealT’s DeFi lending platform uses it to value collateral. Understanding how these three prices are determined and how they relate to each other is therefore central to our empirical analysis.

3.1 Tokenized vs non-tokenized property transaction prices

We begin by examining whether RealT-tokenized properties differ from comparable non-tokenized properties in the same local housing markets. This comparison requires caution because we compare two price series from different data sources and measurement procedures. RealT-listed property values are reported by the platform and exclude maintenance and renovation reserves, which are included in RealT’s total investment value. The comparison prices come from Zillow transactions matched to official deed records. Furthermore, we restrict the analysis to single-family homes in Detroit (i.e., RealT’s largest market). This restriction improves measurement because multi-family properties are often

not observed as transactions of entire buildings. To test for price differences, we estimate

$$\ln \text{Property Transaction Price}_{izq} = \beta_1 \cdot \text{Tokenized}_{iq} + \beta_2' X_i + \nu_{zq} + \varepsilon_{izq}, \quad (1)$$

where the dependent variable is the transaction price of property i in ZIP code z and quarter q . The variable Tokenized_{iq} equals one for RealT-tokenized properties and zero for non-tokenized properties. The vector X_i contains property characteristics. We include ZIP-code-by-quarter fixed effects and cluster standard errors at the ZIP-code level.

In Panel A of [Table 3](#), tokenized properties are listed at a substantial premium (of approx. up to 43%) relative to comparable non-tokenized house sales. To obtain a closer transaction price comparison, Panel B uses the deed-confirmed acquisition prices paid for properties that were later tokenized by RealT and compares them with deed-confirmed Zillow transaction prices. These acquisition prices are, on average, about 21% below the RealT-listed tokenized property values. Once we use acquisition prices rather than listed tokenized values, we find no statistically significant price difference relative to comparable Zillow transactions.

As a robustness check, we repeat the analysis using propensity score matching (see [Table A.4](#)). Each tokenized property is matched to four comparable non-tokenized properties in the same local market and quarter. Matching substantially improves comparability, although balance is weaker in the smaller deed-record sample. We therefore additionally control for the underlying property characteristics in the matched-sample regressions. The estimated difference in acquisition prices remains small and statistically insignificant.

Overall, the evidence indicates that RealT acquires properties at market prices similar to comparable local housing transactions. The premium arises mainly at the initial sale stage, when RealT offers tokenized properties to investors at prices above comparable local transaction prices. RealT states that this difference reflects acquisition costs (e.g., due diligence, valuation, renovation, and sales commissions).

[Table 3 about here]

3.2 Are primary market prices predictable?

We next examine whether RealT’s manual price changes are predictable from US house price growth, property fundamentals, and order imbalance. Although property valuations appear to occur at regular intervals, RealT updates primary market prices discretely. If these platform-reported prices reflect information about the underlying real estate, price changes should be related to fundamentals. If they also respond to investor demand, they should be related to primary market order imbalance. To test these predictions, we estimate the following panel regression

$$\ln P_{is,t+h} - \ln P_{is,t} = \beta_1 \cdot \Delta \ln \text{House Price Index}_{st} + \beta_2' X_{it} + \alpha_i + \delta_t + \varepsilon_{ist}, \quad (2)$$

where the dependent variable is the cumulative log primary market price change of token i , whose underlying property is located in states, from month t to month $t + h$. The main explanatory variable is the monthly change in the log Zillow state house price index. The vector X_{it} includes time-varying controls. Token fixed effects absorb time-invariant differences across properties. Month fixed effects absorb aggregate shocks common to all tokens. Standard errors are clustered at the token level.

Table 4 shows that the house price growth positively predicts cumulative RealT primary market price changes. The coefficients are positive across all specifications and increase with the forecast horizon. After adding time-varying property controls, a 1% increase in the state house price index predicts a 0.6% increase in RealT primary market prices over the next month and a 5.3% increase over the next six months. For a real estate-backed token priced at \$50, this corresponds to an increase of approximately \$0.30 over one month and \$2.65 over six months. By contrast, primary market order imbalance does not positively predict price increases. Its coefficient is negative across all horizons, suggesting

that RealT primary market prices are linked to housing market growth and fundamentals, but are not mechanically adjusted upward in response to net buying pressure.

[[Table 4 about here](#)]

3.3 Do secondary markets produce property information?

Next, we examine whether secondary markets anticipate future changes in RealT-reported prices. If they do, secondary markets produce useful information for property and collateral valuation before it is incorporated by RealT and the DeFi lending platform.

Our institutional setting allows us to compare two trading venues (DEXs vs. the YAM marketplace) that play different roles in price discovery. For instance, DEX prices are public and update continuously with trades, which supports efficient price discovery, especially when arbitrageurs trade against outdated pool prices. However, DEX prices are also mechanically affected by pool depth and trade size. When liquidity is limited, even small trades can move prices substantially ([Lehar and Parlour, 2025](#); [Barbon and Ranaldo, 2026](#); [Capponi et al., 2026](#)). DEX prices can therefore reflect both information about asset value and pool-specific price impact (slippage) effects.

YAM, by contrast, is closer to a quote-driven OTC market, where prices typically adjust more slowly because of search frictions, bargaining, and lower transparency ([Duffie et al., 2005](#)). However, YAM prices may contain more property-specific information because investors can evaluate individual offers before accepting a quote. Prior work shows that OTC prices need not be dominated by exchange prices when assets are heterogeneous, difficult to value, or when investors want to trade large amounts less visibly ([Madhavan, 1995](#); [Viswanathan and Wang, 2002](#); [Hendershott and Madhavan, 2015](#)).

We build on [Equation 2](#) and test whether DEX and YAM prices separately predict future primary market price changes. Our main explanatory variables are secondary market premiums (defined as the log secondary market price minus the log primary market

price), which measure whether secondary markets value a token above or below RealT’s current primary market benchmark. If liquidity and continuous trading are central to price discovery, DEX premiums should have stronger predictive power. If property-specific due diligence is more important, YAM premiums should also predict future platform price updates, especially for harder-to-value properties.

RealT’s DeFi lending platform transition from RMM V2 to RMM V3 provides additional institutional variation. We use this expansion to test whether the predictive content of secondary market prices changes when tokens become integrated into the lending platform. Specifically, we interact secondary market premiums with collateral and RMM-version indicators and compare predictability across tokens and periods.

[Table 5 about here]

Table 5 reports the DEX results. In all specifications, the DEX premium is statistically significant and positively predicts future cumulative primary market price changes, suggesting that DEX prices contain information that RealT has not yet incorporated into its platform price. A 10% DEX premium predicts about a 0.065% primary market price increase after one month and about a 0.29% increase after six months. The result is also robust to controlling for DEX order imbalance, liquidity, and price impact.

Interestingly, this predictability disappears once real estate-backed tokens become collateral eligible. The total effects of the DEX premium for collateral-eligible tokens are close to zero and statistically insignificant. One explanation is that DEX prices for these tokens also reflect credit demand and leverage constraints. At the same time, when tokens are pledged to the lending platform, DEX trading naturally becomes thinner, making DEX prices less informative. We examine these mechanisms in the following section.

Table 6 reports the corresponding results for the OTC/YAM market. The YAM premium is marginally positive and statistically significant at the one-month horizon, but the effect is weak and not robust across collateral regimes. Overall, these results suggest

that YAM prices contain less timely information about future platform price updates than DEX prices.

[\[Table 6 about here\]](#)

3.4 Do secondary markets produce credit information?

The previous section shows that collateral eligibility can change the economic content of secondary market prices because these prices may begin to incorporate DeFi credit market conditions. We examine this mechanism more directly by estimating regressions of secondary market premiums on lagged leverage demand and constraints,

$$\ln P_{it}^{SM} - \ln P_{it}^{PM} = \sum_{\nu} \beta'_{1\nu} (\text{Credit Conditions}_{it-1} \times \text{RMM}_{it}^{\nu}) + \beta'_2 X_{it-1} + \alpha_i + \delta_t + \varepsilon_{it}. \quad (3)$$

The main explanatory variables measure lagged credit conditions for token i , measured on day $t - 1$, which include the log outstanding debt (in \$), the log amount of collateral deposited (in \$), leverage, unused borrowing capacity, and constraints. Leverage is defined as debt divided by collateral. It ranges from zero to the maximum permitted LTV ratio, where higher values indicate that the collateral is used more intensively for borrowing. Unused borrowing capacity is defined as maximum borrowing capacity minus outstanding debt, and constraints are defined as debt divided by maximum borrowing capacity. The variable ranges from zero to one, where zero indicates that no borrowing capacity is used and one indicates that the borrowing limit is fully used.

All these variables are interacted with RMM_{it}^{ν} , where $\nu \in \{V2, V3\}$. This indicator equal to one if token i is in RMM version ν on day t . We estimate [Equation 3](#) separately for DEX and YAM. The controls include market-specific microstructure variables, including order imbalance, liquidity, and proxies for transaction costs. All specifications include token and day fixed effects, and standard errors are clustered by token and day.

Panel A in [Table 7](#) shows that DEX price premiums are positively related to credit demand, collateral use, and borrowing capacity, specifically in RMM V2. This result implies that investors assign higher value to real estate-backed tokens used more intensively as collateral. The magnitudes are economically meaningful. In the leverage specification, a 10% relative increase in leverage is associated with a 1.15 percentage point higher DEX premium. For a token priced at \$50, this result corresponds to about \$0.55 per token.

Although our estimates are measured at a higher frequency and in a much less liquid market, their magnitudes are somewhat of a similar order to leverage premia documented in traditional markets. The closest qualitative benchmark is [Dam et al. \(2024\)](#), who study closed-end fund premia relative to net asset value using monthly fund-level data. They show that levered closed-end funds trade at a 2.55 percentage point higher premium than unlevered funds. They also show that a one standard deviation increase in leverage is associated with roughly 0.77-1.30 percentage points higher premia, depending on the leverage measure and specification. Another example is [Ballensiefen et al. \(2023\)](#), who show that assets used as collateral in repo markets earn different returns because investors value their collateral services, estimating a 0.42% annual collateral carry premium.

As a robustness test, Panel B reports the corresponding results for YAM. The coefficients have the same positive sign, but only the RMM V3 interactions are positive and statistically significant across all credit condition measures. It appears that, after the expansion of collateral eligibility under RMM V3, credit conditions are more visible in YAM prices than in DEX prices.

[[Table 7](#) about here]

4 Do Secondary Markets Discipline DeFi Lending?

If secondary market prices contain information about credit conditions and collateral, does this information affect behavior in the credit market? The RealT ecosystem provides

a uniquely transparent setting to study this question because many market participants engage in trading, borrowing, and lending, often across multiple activities, and we observe every transaction.

Our starting point is the structure of decentralized lending, which typically consists of two types of market participants. Lenders deposit stablecoins into the platform and earn interest. Borrowers pledge real estate-backed tokens as collateral, borrow stablecoins against them, and pay interest. This disintermediation creates different incentives for borrowers and lenders.

When the lending platform overvalues the collateral relative to the secondary market,

$$P_{it}^{PM} > P_{it}^{SM}$$

borrowers receive more borrowing capacity than the market valuation of the collateral would imply. Two responses can then occur. First, borrowers can take on more debt relative to the amount for which the asset could be sold. If they do, collateral overvaluation increases credit risk and, as a result, the lender’s safety margin declines. If the valuation difference is sufficiently large, liquidations may be insufficient to repay the loan in full.⁶ To mitigate this credit risk, lenders can use secondary market valuations as a signal and reduce their supply of liquidity. The resulting increase in utilization and interest rates makes borrowing more expensive.

Second, borrowers themselves can respond to the information contained in secondary market prices. A secondary market discount signals that the collateral valuation is potentially too high and could subsequently be revised downward. Such a revision would reduce

⁶For example, in November 2022, Aave incurred approximately \$1.5-1.9 million in bad debt after the liquidation of a large borrowing position. A trader borrowed a large amount of CRV tokens through Aave and sold them. When the CRV price increased, the value of the trader’s debt increased, and the position had to be liquidated. Similarly, in May 2021, the price of XVS, the native token of the Venus lending platform, increased by almost 90% over a short period. Because the higher price increased the value of XVS used as collateral, borrowers were able to substantially increase their borrowing. When the XVS price subsequently declined, the collateral was insufficient to repay the loans, leaving Venus with more than \$95 million in bad debt.

borrowing capacity and the borrower’s liquidation buffer, moving the position closer to liquidation. Borrowers can therefore respond actively by repaying debt or adding collateral. In this case, secondary market prices discipline borrowing directly.

Conversely, if

$$P_{it}^{PM} < P_{it}^{SM}$$

the lending platform undervalues collateral. In this case, lenders are better protected, but borrowers receive less borrowing capacity than the secondary market value would justify. They have then an incentive to reduce borrowing and repay their debt, which will algorithmically decrease credit utilization and interest rates.

4.1 Credit Demand

To test these market discipline mechanisms, we examine whether secondary market price premia predict subsequent borrowing against real estate-backed tokens. Specifically, we estimate

$$\ln Y_{i,t+h} - \ln Y_{it} = \beta_1 \cdot (\ln P_{it}^{SM} - \ln P_{it}^{PM}) + \alpha_i + \delta_t + \varepsilon_{it}, \quad (4)$$

where Y_{it} denotes the respective measure of borrowing behavior for token i on day t , including debt, collateral, leverage, unused borrowing capacity, and debt relative to borrowing capacity, and $h \in \{1, 7, 30\}$ days. To ensure that our estimates do not capture mechanical changes in borrowing associated with the migration from RMM V2 to RMM V3, we exclude the transition period from January 31 to February 29, 2024. During this period, borrowing declined sharply in RMM V2 and increased in RMM V3 as positions were transferred between the two versions. Including these observations could therefore overstate the sensitivity of borrowing to secondary market valuation differences.

We estimate the regressions separately using DEX and YAM market prices. Because positive and negative price premia create different borrowing incentives, we additionally decompose the price premium into collateral overvaluation as $\max \{\ln P_{it}^{PM} - \ln P_{it}^{SM}, 0\}$

and collateral undervaluation as $\max \{\ln P_{it}^{SM} - \ln P_{it}^{PM}, 0\}$. All specifications include token and day fixed effects, and standard errors are clustered by token and day.

The results in [Table 8](#) and [Table 9](#) show that collateral valuation differences predict subsequent borrowing behavior. On both DEX and YAM, this relationship is concentrated in periods when the platform undervalues collateral relative to the secondary market. A DEX price 10% above the collateral valuation is associated with approximately 4% lower borrowing after one week and 17.5% lower borrowing after one month. By contrast, borrowers appear reluctant to adjust their debt positions when the platform values collateral above the secondary market price. Collateral overvaluation through YAM shows a small negative response after one day, but this effect does not persist over longer horizons.

[\[Table 8 about here\]](#)

[\[Table 9 about here\]](#)

We add a battery of tests to the appendix to examine whether these relationships change with borrowing constraints or rental yield. Overall, we find that the results are consistent and, under some conditions, become substantially stronger (see [Table A.5](#), [Table A.6](#), [Table A.7](#), [Table A.8](#), [Table A.9](#), [Table A.10](#)).

We first interact the collateral valuation differences with the different RMM versions. The results are consistent with the baseline findings but substantially stronger when borrowing is more restricted in RMM V2. Under both collateral undervaluation and overvaluation, borrowers reduce their debt positions, with stronger effects for DEX prices than for YAM prices.

We next interact the collateral valuation differences with rental yield as a proxy for the strength of the property’s rental cash flows. Because property valuations are updated infrequently, variation in rental yield primarily reflects changes in rental income rather than changes in property values. We find that the market discipline effect becomes weaker for properties with higher rental yields. This finding is consistent with the idea

that borrowers are generally concerned that the platform valuation will be revised and that their positions could move closer to liquidation. Such concerns are weaker when the underlying property generates stronger rental income.

Next, we examine which secondary market price borrowers respond to more strongly when DEX and YAM price signals are observed simultaneously. The results show a particularly strong role for DEX prices when the platform overvalues collateral. Conditional on the YAM valuation, borrowers subsequently delever even though the platform valuation mechanically gives them greater borrowing capacity.

Finally, we test whether agreement or disagreement between DEX and YAM about the direction of the valuation gap predicts subsequent borrowing. We find little evidence that agreement or disagreement itself matters. Borrower adjustment is instead more closely related to the magnitude of the valuation difference and to the market from which the price signal originates.

4.2 Credit Supply

To examine whether lenders use information from secondary market prices to discipline borrowers, we re-estimate the specification in [Equation 4](#) using lender-side measures of credit supply. The dependent variables are stablecoin deposits and withdrawals, available liquidity measured as stablecoin deposits minus stablecoin withdrawals, deposit coverage measured as available liquidity relative to outstanding stablecoin borrowing, and the borrowing interest rate. Because borrowing and lending rates in DeFi are jointly determined by credit utilization (and borrowing rates always exceed lending rates), the borrowing rate provides an additional measure of credit market tightness. Since these outcomes are measured at the lending platform level, all specifications include platform and day fixed effects.

The results are reported in [Table 10](#) and [Table 11](#). Contrary to our hypothesis, we find little evidence that secondary market overvaluation does induce lenders to tighten

credit supply. When the platform valuation exceeds the YAM price, withdrawal activity declines, increasing available stablecoin liquidity. The resulting increase in liquidity relative to outstanding stablecoin borrowing raises the deposit coverage ratio and is mechanically followed by lower borrowing rates.

DEX price signals show less clear results. However, when the platform undervalues collateral relative to DEX prices, withdrawal activity increases. Overall, it appears that lender behavior runs counter to a credit risk-based discipline mechanism. They withdraw more when the platform undervalues collateral and retain more liquidity when it overvalues collateral. A plausible explanation is that lenders simply do not respond to credit risk and primarily care about the expected profitability of supplying stablecoins. When the platform overvalues collateral, borrowers have greater borrowing capacity, which can create greater potential demand for stablecoin loans. Lenders therefore have an incentive to keep liquidity in the pool rather than withdraw it. Conversely, when the platform undervalues collateral, borrowing capacity and potential loan demand are lower, making the pool less attractive to lenders and increasing withdrawals.

[\[Table 10 about here\]](#)

[\[Table 11 about here\]](#)

5 Do Credit and Token Prices Reinforce Each Other?

An extremely large literature documents that asset prices and credit reinforce each other and that this feedback can amplify initial shocks and create financial instability (see e.g., [Kiyotaki and Moore, 1997](#); [Brunnermeier and Pedersen, 2009](#); [Geanakoplos, 2010](#); [Schularick and Taylor, 2012](#)). Studying whether this mechanism emerges in crypto markets is particularly beneficial because, once real world assets enter the blockchain, their tokens immediately play a dual role (i.e., they trade in secondary markets and simultaneously

serve as collateral in DeFi), creating potential circular valuation dynamics that affect the information production and/or market discipline roles of secondary market prices. Furthermore, since DeFi is continuously marked to market, changes in prices or borrowing capacity can generate feedback loops almost immediately, with potentially important but still unexplored consequences for cryptoasset markets and the real economy.

To examine this credit-price feedback mechanism, we construct a token-day dataset and follow [Jordà \(2005\)](#) in estimating local projections that relate changes in leverage to subsequent secondary market prices. We estimate the following regression separately for DEX and YAM prices,

$$\begin{aligned} \ln P_{i,t+h}^{SM} - \ln P_{it}^{SM} = & \beta_{1h} \cdot \Delta \ln \text{Leverage}_{it} + \beta_{2h} \cdot \Delta \ln \text{Leverage}_{i,t-1} \\ & + \beta_{3h} \cdot \Delta \ln P_{i,t-1}^{SM} + \alpha_i + \delta_t + \varepsilon_{i,t+h}, \end{aligned} \quad (5)$$

where P_{it}^{SM} denotes the secondary market price of token i on day t , and Leverage_{it} measures total debt divided by collateral associated with token i . We consider again horizons of $h \in \{1, 7, 30\}$ days. We include one lag of leverage growth and secondary market returns, as well as token and day fixed effects. Standard errors are clustered by token and day. To examine the reverse part of the feedback mechanism, we also test whether secondary market returns and the secondary market price premium predict future changes in leverage.

The results provide no evidence of a self-reinforcing credit-price feedback loop. In [Table 12](#), we observe that the DEX price premium is associated with lower future leverage, consistent with the findings in [Table 8](#) and [Table 9](#) that borrowers reduce leverage when secondary market valuations diverge from collateral valuations on the DeFi lending platform. Leverage changes, by contrast, do not predict real estate-backed token prices. In [Table 13](#), the YAM marketplace does not show any significant results.

[\[Table 12 about here\]](#)

[[Table 13](#) about here]

In the appendix, we include all coefficients (see [Table A.11](#) and [Table A.12](#)).

5.1 Do borrowers spend their loans on real estate tokens?

The absence of a credit-price feedback loop raises the question of why higher credit does not translate into secondary market prices. A necessary condition is that borrowers use the additional credit to purchase tokenized assets. If borrowers instead retain the stablecoins or use them outside the RealT ecosystem, borrowing need not affect token prices. We therefore examine what borrowers actually do with their newly obtained credit.

To do this, we construct a borrower-day dataset and estimate whether borrowing on day t predicts purchases by the same wallet over the next 1, 7, and 30 days. We distinguish between two measures of credit. Total debt captures the borrower’s outstanding loan position across RMM V2 and V3, while new debt captures new borrowing on day t . We again exclude the transition period from RMM V2 to V3 to avoid mechanically affecting the measured borrowing activity. For each market m , we estimate

$$\ln \text{Purchase value}_{b,t+1:t+h}^m = \beta_h \ln \text{Debt}_{bt} + \mu_b + \delta_t + \varepsilon_{b,t+h}, \quad (6)$$

where Debt_{bt} is alternatively the borrower’s total debt or new borrowing on day t . The dependent variable is alternatively the total value of real estate token purchases across all markets, as well as DEX, YAM, and primary market purchases separately. We control for borrower and day fixed effects. Standard errors are clustered by borrower and day.

The results are reported in [Table 14](#). The total debt position is not positively associated with subsequent RealT investments. It even lowers new token purchases after 7 and 30 days. By contrast, new borrowing strongly predicts subsequent real estate token purchases, specifically in the primary market. At the mean positive loan amount

of approximately \$724, a doubling of new borrowing is associated with an 8% increase in primary market purchases over the following day. The relationship is strongest over the following week, indicating that the additional purchasing associated with new credit does not occur only immediately after borrowing.

[\[Table 14 about here\]](#)

The results appear counterintuitive at first. If borrowers use their loans to purchase real estate tokens, why do we observe lower debt, collateral, and leverage by the end of the day, as shown in [Table 8](#) and [Table 9](#)?

Analyzing transaction level data reveals substantial heterogeneity in how borrowers use and manage their loans. First, some wallets actively manage their debt and collateral positions. In other words, they repeatedly borrow and repay debt or deposit and withdraw collateral, thereby keeping leverage under control over the following 1, 7, and 30 days. Second, some wallets engage in stablecoin looping, i.e., they deposit stablecoins as collateral, borrow against them, and repeat the process to increase leverage ([Park and Stinner, 2023](#)). Third, following this idea, some wallets engage in leveraged buying and real estate looping. For instance, they use borrowed funds to purchase real estate tokens, pledge these tokens as collateral, and borrow again to finance additional purchases. Finally, some wallets combine stablecoin and real estate token looping.

To determine how common these strategies are, we classify each new borrowing observation based on the borrower’s debt, collateral, and investment activity over the following 1, 7, and 30 days. We also retain several intermediate strategies rather than forcing every borrower into one of these groups. For example, some borrowers use their loans to purchase real estate tokens but do not obtain additional credit against these positions within the horizon. Others primarily repay debt, continue borrowing without completing a loop, or show little activity after taking out the loan.

[\[Table A.13 about here\]](#)

[[Table A.14](#) about here]

[Table A.13](#) and [Table A.14](#) show that borrower behavior changes considerably with time. Within the first day, the most common strategy is to use borrowed funds to purchase RealT, i.e., 32.7% of new loans are classified as leveraged RealT purchases, while 22.2% show little further activity. Active debt management accounts for 18%, and fully developed borrowing loops remain relatively uncommon.

Over longer horizons, borrowers increasingly adjust and reuse their credit positions. After 30 days, 35.2% of new loans are associated with active debt management, 8.6% with stablecoin looping, 23.2% with real estate token looping, and 14.6% with both forms of looping. Together, these strategies account for about 82% of new borrowing. By contrast, only 11.8% remain simple leveraged real estate token purchases, and 2.0% show little further activity.

Active debt management accounts for 48.8% of initial loan volume, indicating that these wallets tend to start with larger loans. Over the following 30 days, borrowing classified as active debt management accumulates an average of \$8,786 in gross borrowing, including the initial loan and any additional borrowing. After subtracting repayments, average net borrowing is only \$1,883. Their average net real estate token purchases (defined as purchases minus sales over the same period) are relatively small at \$1,034.

Real estate token looping accounts for only 12.8% of initial loan volume, while hybrid looping accounts for 6.4%. These strategies therefore tend to start with smaller loans but generate substantial additional borrowing over time. For stablecoin looping, average cumulative gross borrowing reaches \$18,760 over 30 days, while average net borrowing after repayments is only \$1,048. Real estate token looping accumulate an average of \$9,676 in gross borrowing and retain \$4,627 in net borrowing. Over the same period, borrowers purchase an average of \$7,370 of RealT and sell \$993. Hybrid looping generates the largest amounts. Average cumulative gross borrowing reaches \$44,725 over 30 days, while net borrowing remains \$19,825. These borrowers also purchase an average of \$39,595 of RealT

and sell \$8,816, resulting in average net purchases of \$30,779.

The difference between short- and longer-horizon classifications also shows that strategies develop gradually. Among borrowers showing little activity after one day, 38.8% become active debt managers within 30 days, while only 8.9% remain inactive. Among borrowers who initially purchase real estate tokens, 31.2% become real estate token loopers, 9.8% become hybrid loopers, and 33.3% become active debt managers. Looping strategies also become more complex over time. 48.8% of initial stablecoin loopers and 40.0% of initial real estate token loopers eventually combine both forms of looping.

This heterogeneity helps explain the absence of an aggregate credit-price feedback loop. Although some investors repeatedly use credit to increase their real estate exposure, these strategies are concentrated in relatively smaller initial loans. A large share of borrowing volume is instead associated with active management of debt and collateral. Credit can therefore amplify individual positions without generating sufficiently strong aggregate buying pressure to systematically affect secondary market prices.

5.2 How do DeFi markets process news shocks?

In June 2021, Detroit experienced historic flooding, affecting an estimated 30,000 households.⁷ In July 2025, the City of Detroit filed a large nuisance abatement lawsuit against RealT. The complaint identified a group of particularly problematic properties with serious physical deficiencies, including fire or flood damage, missing doors or windows, lack of heat, and structural problems.⁸

We use the lawsuit as a negative real economy information shock. Our data identify 54 tokenized properties named in the legal records, of which 52 can be matched to the lending platform and had outstanding collateral and debt exposure immediately before the lawsuit. We use July 2, 2025, when the lawsuit was filed and publicly reported, as

⁷See City of Detroit, *Mayor, City Leaders Highlight Private Sewer Repair Program For Detroiters Impacted By 2021 Flooding Disaster*, August 29, 2024

⁸City of Detroit, Nuisance abatement lawsuit, June 30, 2025

the main information date. We then trace the response of secondary market price premia and borrower leverage around the announcement.

We estimate a matched difference-in-differences regression. For each outcome Y , we measure the cumulative change from day t to day $t+h$, for $h \in \{1, 7, 30\}$, and test whether these forward changes differ between lawsuit-affected and matched unaffected properties Detroit the announcement on July 2.

$$\Delta_h Y_{it} = \beta_h \cdot (\text{Treated}_i \times \text{Post}_t) + \alpha_i + \delta_t + \varepsilon_{i,t+h}, \quad (7)$$

where Y includes price premia and changes in debt, collateral, and leverage. Treated_i equals one for the 52 Detroit tokens named in the lawsuit and zero for the 150 matched, unaffected Detroit tokens. The regressions include token and day fixed effects. Standard errors are clustered by token and day.

The clearest response in [Table 15](#) occurs in the secondary market. Following the lawsuit, affected properties experience approximately 3.8% larger declines in their YAM price premium over seven-day horizons and 5.2% larger declines over 30-day horizons relative to matched unaffected Detroit properties. Furthermore, affected tokens experience approximately 1.8% larger declines in debt (and 1.0% larger declines in collateral) over seven-day horizons, while leverage declines by about 0.3 percentage points relative to matched unaffected Detroit properties. These effects are not statistically significant under randomization inference, meaning that effects of similar or greater magnitude frequently arise when the lawsuit label is randomly assigned.

Before the lawsuit, affected and control tokens had very similar primary market prices (\$54 vs. \$52.75), leverage (0.390 vs. 0.392), and average YAM price premia (0.075 vs. 0.076). The affected properties, however, had substantially larger credit positions. Their average debt was \$49,697, compared with \$22,653 for the control properties, while average collateral was \$132,694, compared with \$61,123. As a result, the post-lawsuit

collateral response cannot be cleanly separated from differences that were already present before the lawsuit.

[\[Table 15 about here\]](#)

6 Conclusion

This paper examines whether decentralized markets can perform information and monitoring functions traditionally associated with financial intermediaries when real world assets are both traded and used as collateral. The RealT ecosystem allows us to study this question in a unique setting for the same asset, for which we observe a fundamental value and transaction-level trading, lending, and borrowing across many participants.

Overall, our results highlight both the potential and the limits of integrating tokenized real-world assets into decentralized financial markets. Secondary markets provide informative price signals, and borrowers appear to use them to manage credit risk even without traditional intermediary monitoring. Yet automated lending does not generate the conventional price-credit cycles. In traditional markets, rising collateral values relax borrowing constraints, increase leverage, and induce intermediaries to expand credit. In our setting, higher collateral valuations also expand borrowing capacity, but borrowers do not systematically lever up, while lender liquidity moves countercyclically to credit risk.

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Tables

Table 1: Token and Property Characteristics for All RealT-Tokenized Assets

This table reports token characteristics in Panel A and property characteristics in Panels B and C for all 823 available RealT smart contracts. Deprecated tokens are earlier versions of smart contracts that were replaced by new contracts for the same underlying properties. Each token belongs to one product category (i.e., rental property, equity, loan income, or factoring profit share). Rental property tokens represent fractional interests in LLC/SPV structures holding specific real estate properties and provide investors with rental income and exposure to changes in property value. Loan income tokens finance an underlying loan or note and provide investors with interest income. Factoring profit share tokens finance the purchase of invoices and provide investors with a share of the resulting profits. Equity tokens represent equity investments through RWA Holdings S.A., a Swiss company established to acquire shares in RealToken Technologies Inc. Regulation S identifies token offerings conducted outside the US, while Regulation D identifies token offerings in the US to accredited investors. Tokens without an explicit Regulation S or D classification include LLC/SPV structures or pre-construction loans for properties in Panama, Mexico, and Colombia. Single-family identifies rental properties with a maximum of one rented unit, while multi-home identifies properties with more than one rented unit. Appraisal equals one if the primary market price increased at least once through December 31, 2025, while revision equals one if the primary market price decreased at least once over the same period.

	N	Mean	Std	Min	Median	Max
<i>A. Token characteristics</i>						
Rental property token	823	0.960	0.196	0	1	1
Equity token	823	0.001	0.035	0	0	1
Loan income token	823	0.015	0.120	0	0	1
Factoring profit share token	823	0.024	0.154	0	0	1
SEC Regulation S	823	0.906	0.291	0	1	1
SEC Regulation D	823	0.023	0.150	0	0	1
No SEC Regulation S/D	823	0.070	0.256	0	0	1
Deprecated smart contract	823	0.044	0.205	0	0	1
Listed on DEXs	823	0.789	0.409	0	1	1
Listed on YAM	823	0.923	0.266	0	1	1
Collateral in RMM V2	823	0.064	0.246	0	0	1
Collateral in RMM V3	823	0.757	0.429	0	1	1
<i>B. Tokenized asset locations</i>						
Michigan	823	0.750	0.433	0	1	1
Ohio	823	0.111	0.314	0	0	1
Illinois	823	0.030	0.172	0	0	1
Texas	823	0.015	0.120	0	0	1
Florida	823	0.006	0.078	0	0	1
Missouri	823	0.019	0.138	0	0	1
Alabama	823	0.010	0.098	0	0	1
Georgia	823	0.005	0.070	0	0	1
New York	823	0.002	0.049	0	0	1
Indiana	823	0.001	0.035	0	0	1
Panama	823	0.018	0.134	0	0	1
Colombia	823	0.006	0.078	0	0	1
Mexico	823	0.001	0.035	0	0	1
Switzerland	823	0.001	0.035	0	0	1
<i>C. Property characteristics</i>						
Single-family	823	0.673	0.469	0	1	1
Multi-home	823	0.267	0.443	0	0	1
Property value (in \$)	823	175,910.08	238,750.15	0.00	70,000.00	1,610,000.00

Table 1 – continued

	N	Mean	Std	Min	Median	Max
#Tokens created per property	822	4,144.54	6,368.42	750.03	1,650.00	100,000.00
Annual rent (in \$)	823	19,651.61	27,289.15	0.00	8,425.28	199,411.20
Rented units	823	2.85	4.97	0.00	1.00	36.00
Rental yield (in %)	822	9.69	2.78	0.00	9.78	18.21
Listed on Zillow	823	0.648	0.478	0	1	1
Property age (in years)	785	79.11	27.48	1.00	84.00	158.00
Bedrooms	377	3.34	2.57	0.00	3.00	29.00
Bathrooms	518	1.77	3.72	0.00	1.00	63.00
Living area (in square feet)	795	2,948.57	4,454.46	322.92	1,334.72	45,305.30
Lot size (in square feet)	771	7,150.13	7,937.23	796.53	4,789.94	84,711.97
Official deed record available	823	0.684	0.465	0	1	1
Lawsuit	823	0.066	0.248	0	0	1
Appraisal	823	0.305	0.461	0	0	1
Revision	823	0.007	0.085	0	0	1

Table 2: Summary Statistics

This table reports summary statistics for the variables used in the empirical analysis. Panel A reports token-day market and credit characteristics, Panel B reports platform-day lending characteristics, Panel C reports borrower-day characteristics, and Panel D reports transaction-level characteristics.

Variable	N	Mean	Std	Min	Median	Max
A. Token-day						
<i>A.1 Primary market and fundamentals</i>						
Primary market price (in \$)	459,016	52.19	7.83	46.65	50.68	185.80
$\ln P_{it}^{PM}$	459,016	3.949	0.090	3.843	3.926	5.225
Primary market order imbalance	416,725	0.004	0.413	-1.000	0.000	1.000
House price index	411,420	254,630.46	19,690.17	198,874.91	253,779.03	426,843.29
$\Delta \ln$ House price index	411,420	0.0033	0.0030	-0.0070	0.0029	0.0277
Renovation reserve (in \$)	416,725	4,378.56	15,056.89	0.00	0.00	420,000.00
Renovation event	416,725	0.024	0.154	0.000	0.000	1.000
$\Delta \ln$ Renovation reserve	410,006	-0.2169	1.3816	-12.9480	0.0000	0.0000
Maintenance reserve (in \$)	416,725	1,977.25	4,976.51	0.00	0.00	52,600.00
Maintenance event	416,725	0.027	0.163	0.000	0.000	1.000
$\Delta \ln$ Maintenance reserve	410,006	-0.2120	1.3188	-10.8705	0.0000	8.9873
Rented units	416,725	3.57	5.65	0.00	1.00	36.00
Δ Rented units	410,006	0.002	0.201	-9.000	0.000	5.000
Rent-paid	416,725	0.944	0.230	0.000	1.000	1.000
Rental yield	415,686	0.1030	0.0186	0.0000	0.1007	0.1821
Treated (lawsuit-affected) tokens	459,016	0.102	0.303	0.000	0.000	1.000
Post (July 2, 2025)	459,016	0.248	0.432	0.000	0.000	1.000
<i>A.2 Secondary market</i>						
DEX price (in \$)	38,528	56.11	9.88	1.00	53.96	136.54
DEX price premium	38,528	0.0718	0.1706	-3.9374	0.0557	0.9133
DEX collateral undervaluation	38,528	0.1008	0.1226	0.0000	0.0557	0.9133
DEX collateral overvaluation	38,528	0.0291	0.0908	0.0000	0.0000	3.9374
DEX trading volume (in \$)	23,282	22.42	77.47	3.78e-15	6.72	3,778.89
DEX order imbalance	23,282	-0.047	0.944	-1.000	-0.137	1.000
DEX pre-trade liquidity (in \$)	23,282	571.20	370.23	95.81	402.74	2,593.63
$\ln$ DEX liquidity	23,282	6.167	0.597	4.573	6.001	7.861
DEX price-impact/slippage	23,282	-0.0012	0.0518	-0.9830	-0.0030	0.4443
YAM price (in \$)	124,576	55.91	14.62	6.17e-11	52.69	265.00
YAM price premium	124,576	0.0399	0.4214	-27.4219	0.0294	1.0718
YAM collateral undervaluation	124,576	0.0760	0.1090	0.0000	0.0294	1.0718
YAM collateral overvaluation	124,576	0.0361	0.4002	-0.0000	0.0000	27.4219
YAM trading volume (in \$)	75,599	314.80	2,008.06	5.10e-17	62.67	221,515.89
YAM order imbalance	75,599	0.963	0.256	-1.000	1.000	1.000
YAM bid-ask spread	75,599	0.0643	0.2429	-1.3281	0.0166	1.9993
YAM listing duration (in days)	75,599	9.17	28.39	0.00	1.12	673.06
$\ln$ YAM listing duration	75,599	1.195	1.283	0.000	0.752	6.513
DEX-YAM valuation agreement	21,294	0.877	0.328	0.000	1.000	1.000
DEX-YAM valuation disagreement	21,294	0.123	0.328	0.000	0.000	1.000
<i>A.3 Lending market</i>						
Debt (in \$)	459,016	16,924.00	29,338.68	0.00	6,301.97	292,812.71
$\ln$ Debt	459,016	7.394	3.853	0.000	8.749	12.587
Collateral (in \$)	459,016	48,166.18	85,664.08	0.00	16,039.13	672,531.12
$\ln$ Collateral	459,016	8.176	4.245	0.000	9.683	13.419
Leverage	459,016	0.3025	0.1607	0.0000	0.3658	0.5796
$\ln$ Leverage	459,016	0.2558	0.1342	0.0000	0.3117	0.4572
Maximum borrowing capacity (in \$)	459,016	33,925.48	59,333.33	0.00	11,784.87	504,398.34
Capacity-debt (in \$)	459,016	17,001.48	31,174.30	0.00	5,465.01	237,042.13
$\ln$ Capacity-debt	459,016	7.323	3.835	0.000	8.606	12.376
Debt/capacity	459,016	0.4158	0.2223	0.0000	0.4988	0.8908
$\ln$ Debt/capacity	459,016	0.3335	0.1751	0.0000	0.4046	0.6370
Collateral in RMM V2	459,016	0.163	0.369	0.000	0.000	1.000
Collateral in RMM V3	459,016	0.837	0.369	0.000	1.000	1.000

Table 2 – continued

Variable	N	Mean	Std	Min	Median	Max
B. Platform-day						
Stablecoin deposits (in \$)	2,070	11,598,269.65	9,000,127.66	0.00	11,689,575.64	39,123,888.57
ln Deposits	2,070	15.325	3.302	0.000	16.274	17.482
Stablecoin withdrawals (in \$)	2,070	10,691,999.26	8,298,804.72	0.00	11,579,450.40	35,863,556.07
ln Withdrawals	2,070	15.195	3.326	0.000	16.265	17.395
Deposits-withdrawals	2,070	906,270.39	966,172.10	0.00	758,613.14	3,434,791.53
ln Deposits-withdrawals	2,070	12.126	3.160	0.000	13.539	15.049
Stablecoin borrowing (in \$)	2,070	3,847,039.49	4,689,361.93	0.00	2,206,736.88	14,700,468.33
Deposits/borrowing	1,985	0.5501	0.5223	0.1110	0.3060	2.1203
ln Deposits/borrowing	1,985	0.3930	0.2847	0.1052	0.2670	1.1379
Borrowing interest rate (in %)	2,069	15.465	12.737	0.000	10.589	52.742
C. Borrower-day						
Borrower debt (in \$)	2,393,694	3,149.96	14,843.80	0.00	184.16	963,481.62
ln Borrower debt	2,393,694	4.353	3.551	0.000	5.221	13.778
New borrowing (in \$)	2,393,694	26.72	875.11	0.00	0.00	567,970.45
ln New borrowing	2,393,694	0.128	0.859	0.000	0.000	13.250
Repayments (in \$)	2,393,694	20.69	806.59	0.00	0.00	567,970.44
ln Repayments	2,393,694	0.136	0.807	0.000	0.000	13.250
Collateral (in \$)	2,393,694	47.36	1,355.28	0.00	0.00	686,231.69
ln Collateral	2,393,694	0.244	1.108	0.000	0.000	13.439
Total RealT purchases (in \$)	2,393,694	27.44	511.40	0.00	0.00	199,570.86
ln Total RealT purchases	2,393,694	0.322	1.244	0.000	0.000	12.204
DEX purchases (in \$)	2,393,694	0.21	14.83	0.00	0.00	14,787.94
ln DEX purchases	2,393,694	0.007	0.172	0.000	0.000	9.602
YAM purchases (in \$)	2,393,694	9.04	320.93	0.00	0.00	135,210.04
ln YAM purchases	2,393,694	0.073	0.630	0.000	0.000	11.815
Primary market purchases (in \$)	2,393,694	18.18	391.04	0.00	0.00	199,570.86
ln Primary market purchases	2,393,694	0.249	1.090	0.000	0.000	12.204
D. Transactions						
Transaction value (in \$)	604,676	51.92	448.52	5.70e-17	2.00	89,970.16
Price per token (in \$)	604,676	52.92	11.59	5.08e-11	52.18	299.98
Price premium	604,676	0.0085	0.2967	-27.6310	0.0265	1.7917
Buyer-initiated transaction	604,676	0.663	0.473	0.000	1.000	1.000
Transaction size	604,676	0.972	8.406	1.00e-18	0.044	1,771.000
Borrower strategy classified	604,676	0.275	0.447	0.000	0.000	1.000
Active debt manager	166,573	0.339	0.473	0.000	0.000	1.000
Stablecoin leverage loop	166,573	0.074	0.261	0.000	0.000	1.000
Real-estate-token leverage loop	166,573	0.230	0.421	0.000	0.000	1.000
Hybrid RealT/stablecoin loop	166,573	0.156	0.363	0.000	0.000	1.000
Leveraged RealT buyer	166,573	0.193	0.395	0.000	0.000	1.000
Deleverager	166,573	0.002	0.045	0.000	0.000	1.000
Passive borrower	166,573	0.001	0.034	0.000	0.000	1.000
Credit expansion	166,573	0.002	0.042	0.000	0.000	1.000
Other mixed strategy	166,573	0.003	0.052	0.000	0.000	1.000

Table 3: RealT-listed properties relative to comparable neighborhood properties

This table compares the transaction prices of RealT-tokenized single-family homes in Detroit with comparable non-tokenized real estate transaction prices from the Zillow transactions database, following Equation 1. All Zillow-based sale dates are verified using deed records. In Panel A, we compare the transaction prices of the underlying properties reported by RealT with comparable Zillow transaction prices within the same ZIP code and year-quarter (“All Properties”). The “Propensity Score-Matched Properties” sample includes tokenized and non-tokenized transactions matched based on hedonic characteristics (number of bedrooms and bathrooms, property age, living area, lot size, school distance and rating), ZIP code and year-quarter. It is reported in Appendix Table A.4. In Panel B, we compare the transaction prices paid by RealT, as identified from deed records with comparable Zillow transaction prices. Standard errors are clustered at the ZIP-code level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	ln Property Transaction Price _{izt}							
	All properties				Propensity score-matched properties			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>A. RealT vs. Zillow-listed transaction prices</i>								
Tokenized _{izt}	0.361*** (0.053)	0.361*** (0.052)	0.358*** (0.045)	0.372*** (0.051)	0.363*** (0.072)	0.367*** (0.074)	0.374*** (0.068)	0.381*** (0.070)
Bedrooms _i			0.018 (0.021)	0.026 (0.020)			-0.012 (0.032)	-0.002 (0.043)
Bathrooms _i			0.224*** (0.012)	0.231*** (0.013)			0.175*** (0.029)	0.169*** (0.030)
ln Living Area _i			0.577*** (0.069)	0.562*** (0.073)			0.551*** (0.087)	0.582*** (0.071)
ln Lot Size _i			0.221*** (0.061)	0.210*** (0.065)			0.112 (0.088)	0.129 (0.085)
School Distance _i			-0.022 (0.059)	-0.021 (0.058)			0.026 (0.062)	-0.012 (0.059)
School Rating _i			0.058*** (0.017)	0.058*** (0.017)			0.034 (0.028)	0.048* (0.028)
Property Age _i			-0.001 (0.002)	-0.002 (0.002)			-0.005* (0.003)	-0.006** (0.002)
N	6,239	6,239	3,919	3,919	951	951	951	951
Adjusted R ²	0.124	0.150	0.273	0.307	0.203	0.220	0.285	0.313
ZIP FE	✓	—	✓	—	✓	—	✓	—
Quarter FE	✓	—	✓	—	✓	—	✓	—
ZIP × Quarter FE	—	✓	—	✓	—	✓	—	✓
<i>B. Deed records vs. Zillow-listed transaction prices</i>								
Tokenized _{izt}	0.083 (0.071)	0.103 (0.067)	0.095 (0.076)	0.127 (0.090)	0.132 (0.105)	0.124 (0.101)	0.143 (0.112)	0.134 (0.108)
N	5,910	5,910	3,614	3,614	228	228	228	228
Adjusted R ²	0.121	0.148	0.280	0.315	0.080	0.108	0.108	0.129
Controls	—	—	✓	✓	—	—	✓	✓
ZIP FE	✓	—	✓	—	✓	—	✓	—
Quarter FE	✓	—	✓	—	✓	—	✓	—
ZIP × Quarter FE	—	✓	—	✓	—	✓	—	✓

Table 4: Predicting future primary market prices with fundamentals

This table shows the regression results of estimating Equation 2. The dependent variable is the cumulative primary market price change from month t to month $t + h$ ($\ln P_{it+h}^{PM} - \ln P_{it}^{PM}$) for $h \in 1, 3, 6$ months. The main explanatory variable is the monthly change in the log Zillow state house price index. Controls include renovation and maintenance reserves, rented units, rent-paid status, and primary market order imbalance, defined as investor buy volume minus sell volume divided by their sum and set to zero when both are zero. All regressions include token and month fixed effects. Standard errors are clustered by token and month and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Primary market return = $\ln P_{it+h}^{PM} - \ln P_{it}^{PM}$					
	$h = 1$		$h = 3$		$h = 6$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \ln \text{House price index}_{st}$	0.5662 (0.3529)	0.5846* (0.3492)	2.1627 (1.3605)	2.1778 (1.3603)	5.2601* (3.1249)	5.2812* (3.1284)
$\Delta \ln \text{Renovation reserve}_{it}$		-0.0002** (0.0001)		-0.0000 (0.0002)		-0.0004* (0.0003)
$\Delta \ln \text{Maintenance reserve}_{it}$		0.0001 (0.0001)		0.0000 (0.0003)		0.0002 (0.0003)
$\Delta \text{Rented units}_{it}$		0.0032 (0.0031)		0.0034 (0.0032)		0.0039 (0.0030)
Rent-paid_{it}		-0.0000 (0.0002)		0.0004 (0.0004)		0.0012 (0.0008)
$\text{Primary market order imbalance}_{it}$		-0.0004*** (0.0001)		-0.0010*** (0.0002)		-0.0019*** (0.0003)
N	24,003	24,003	22,444	22,444	20,119	20,119
#Tokens	780	780	778	778	772	772
Adjusted R^2	0.047	0.052	0.101	0.104	0.195	0.198
Token FE	✓	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓	✓

Table 5: Predicting future primary market prices with DEX price premia

This table shows the regression results for Equation 2. The dependent variable is the cumulative primary market price change from month t to month $t + h$ ($\ln P_{it+h}^{PM} - \ln P_{it}^{PM}$) for $h \in 1, 3, 6$ months. The main explanatory variable is DEX price premium, defined as the difference between the DEX price and primary market price. Controls include DEX order imbalance, pre-trade liquidity, and price-impact (slippage). Collateral V2 identifies tokens eligible as collateral in RMM V2, while Collateral V3 identifies tokens eligible as collateral in RMM V3 but not previously in RMM V2. All regressions include token and month fixed effects. Standard errors are clustered by token and month and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Primary market return = $\ln P_{it+h}^{PM} - \ln P_{it}^{PM}$					
	$h = 1$		$h = 3$		$h = 6$	
	(1)	(2)	(3)	(4)	(5)	(6)
DEX price premium = $\ln P_{it}^{SM} - \ln P_{it}^{PM}$	0.0065** (0.0031)	0.0065** (0.0031)	0.0156** (0.0065)	0.0155** (0.0064)	0.0291** (0.0119)	0.0288** (0.0116)
<i>A. Collateral eligibility and platform version</i>						
Price premium $_{it} \times$ Collateral V2 $_i \times$ RMM V2 $_t$	-0.0059 (0.0038)	-0.0058 (0.0038)	-0.0150** (0.0067)	-0.0149** (0.0066)	-0.0254** (0.0118)	-0.0249** (0.0117)
Price premium $_{it} \times$ Collateral V2 $_i \times$ RMM V3 $_t$	-0.0060* (0.0031)	-0.0058* (0.0031)	-0.0146** (0.0061)	-0.0141** (0.0061)	-0.0327*** (0.0115)	-0.0295*** (0.0113)
Price premium $_{it} \times$ Collateral V3 $_i \times$ RMM V3 $_t$	-0.0056* (0.0032)	-0.0054* (0.0032)	-0.0145** (0.0061)	-0.0139** (0.0061)	-0.0276** (0.0107)	-0.0251** (0.0106)
Collateral V2 $_i \times$ RMM V2 $_t$	-0.0007* (0.0004)	-0.0008** (0.0004)	-0.0027*** (0.0008)	-0.0029*** (0.0008)	-0.0061*** (0.0015)	-0.0066*** (0.0016)
Collateral V2 $_i \times$ RMM V3 $_t$	-0.0010** (0.0004)	-0.0010** (0.0004)	-0.0018 (0.0017)	-0.0018 (0.0015)	-0.0007 (0.0040)	-0.0014 (0.0038)
Collateral V3 $_i \times$ RMM V3 $_t$	-0.0007** (0.0003)	-0.0007** (0.0003)	-0.0012 (0.0015)	-0.0011 (0.0013)	0.0002 (0.0034)	-0.0001 (0.0031)
<i>B. Secondary market</i>						
DEX order imbalance $_{it}$	-0.0001 (0.0001)	-0.0001 (0.0001)	-0.0001 (0.0003)	-0.0001 (0.0004)	0.0001 (0.0006)	0.0003 (0.0006)
$\ln$ DEX liquidity $_{it}$	-0.0003 (0.0004)	-0.0005 (0.0005)	-0.0026** (0.0012)	-0.0033** (0.0016)	-0.0066** (0.0030)	-0.0083** (0.0036)
DEX price impact (slippage) $_{it}$	-0.0030 (0.0045)	-0.0031 (0.0045)	-0.0060 (0.0043)	-0.0063 (0.0042)	-0.0121 (0.0097)	-0.0140 (0.0096)
<i>C. Primary market and fundamentals</i>						
$\Delta \ln$ House price index $_{st}$	0.0553 (0.0417)	0.0540 (0.0419)	0.1195 (0.1207)	0.1079 (0.1245)	0.0151 (0.2367)	-0.0226 (0.2540)
$\Delta \ln$ Renovation reserve $_{it}$		-0.0001 (0.0001)		-0.0000 (0.0002)		-0.0002 (0.0004)
$\Delta \ln$ Maintenance reserve $_{it}$		0.0001 (0.0001)		0.0001 (0.0002)		0.0001 (0.0003)
Δ Rented units $_{it}$		-0.0000 (0.0001)		0.0000 (0.0002)		0.0007 (0.0005)
Rent-paid $_{it}$		0.0007 (0.0005)		0.0021*** (0.0008)		0.0051*** (0.0015)
Primary market order imbalance $_{it}$		0.0002 (0.0002)		0.0003 (0.0002)		0.0002 (0.0004)
N	10,097	10,097	9,159	9,159	7,733	7,733
#Tokens	611	611	601	601	550	550
Adjusted R^2	0.088	0.089	0.103	0.104	0.202	0.206
Token FE	✓	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓	✓

Table 6: Predicting future primary market prices with YAM price premia

This table shows the regression results for Equation 2. The dependent variable is the cumulative primary market price change from month t to month $t + h$ ($\ln P_{it+h}^{PM} - \ln P_{it}^{PM}$) for $h \in 1, 3, 6$ months. The main explanatory variable is the YAM price premium, defined as the difference between the YAM price and the primary market price. Controls include YAM order imbalance, bid-ask spread, and listing duration. Collateral V2 identifies tokens eligible as collateral in RMM V2, while Collateral V3 identifies tokens eligible as collateral in RMM V3 but not previously in RMM V2. All regressions include token and month fixed effects. Standard errors are clustered by token and month and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Primary market return = $\ln P_{it+h}^{PM} - \ln P_{it}^{PM}$					
	$h = 1$		$h = 3$		$h = 6$	
	(1)	(2)	(3)	(4)	(5)	(6)
YAM price premium = $\ln P_{it}^{SM} - \ln P_{it}^{PM}$	0.0005* (0.0003)	0.0005** (0.0002)	0.0007 (0.0007)	0.0007 (0.0007)	0.0012 (0.0008)	0.0012* (0.0007)
<i>A. Collateral eligibility and platform version</i>						
Price premium $_{it} \times$ Collateral V2 $_i \times$ RMM V2 $_t$	-0.0033*** (0.0009)	-0.0037*** (0.0004)	-0.0027 (0.0027)	-0.0031 (0.0024)	-0.0004 (0.0064)	-0.0009 (0.0061)
Price premium $_{it} \times$ Collateral V2 $_i \times$ RMM V3 $_t$	0.0010 (0.0013)	0.0012 (0.0012)	0.0013 (0.0023)	0.0015 (0.0024)	-0.0033 (0.0043)	-0.0026 (0.0045)
Price premium $_{it} \times$ Collateral V3 $_i \times$ RMM V3 $_t$	-0.0006 (0.0005)	-0.0005 (0.0004)	-0.0006 (0.0009)	-0.0006 (0.0010)	-0.0006 (0.0011)	-0.0005 (0.0011)
Collateral V2 $_i \times$ RMM V2 $_t$	-0.0004 (0.0005)	-0.0004 (0.0005)	-0.0003 (0.0004)	-0.0003 (0.0004)	-0.0006 (0.0006)	-0.0006 (0.0006)
Collateral V2 $_i \times$ RMM V3 $_t$	0.0016 (0.0016)	0.0012 (0.0013)	-0.0120 (0.0137)	-0.0123 (0.0142)	-0.0261 (0.0301)	-0.0267 (0.0307)
Collateral V3 $_i \times$ RMM V3 $_t$	0.0013 (0.0015)	0.0010 (0.0012)	-0.0134 (0.0135)	-0.0137 (0.0140)	-0.0300 (0.0299)	-0.0305 (0.0305)
<i>B. Secondary market</i>						
YAM order imbalance $_{it}$	-0.0016 (0.0016)	-0.0017 (0.0015)	-0.0021 (0.0019)	-0.0022 (0.0019)	-0.0022 (0.0014)	-0.0022 (0.0014)
$\ln$ YAM listing duration $_{it}$	-0.0000 (0.0001)	-0.0001 (0.0001)	-0.0000 (0.0001)	-0.0001 (0.0001)	0.0000 (0.0002)	-0.0001 (0.0002)
YAM bid-ask spread $_{it}$	-0.0017* (0.0009)	-0.0019** (0.0008)	-0.0018 (0.0014)	-0.0020 (0.0013)	-0.0016 (0.0017)	-0.0019 (0.0015)
<i>C. Primary market and fundamentals</i>						
$\Delta \ln$ House price index $_{st}$	-0.0790 (0.2352)	-0.0414 (0.1889)	-0.5621 (0.6913)	-0.5349 (0.6340)	-0.8131 (0.9037)	-0.7969 (0.8464)
$\Delta \ln$ Renovation reserve $_{it}$		-0.0002 (0.0001)		-0.0001 (0.0002)		-0.0004 (0.0004)
$\Delta \ln$ Maintenance reserve $_{it}$		-0.0000 (0.0002)		-0.0000 (0.0002)		0.0000 (0.0003)
Δ Rented units $_{it}$		0.0037 (0.0036)		0.0037 (0.0037)		0.0040 (0.0032)
Rent-paid $_{it}$		0.0001 (0.0003)		0.0008* (0.0005)		0.0014 (0.0009)
Primary market order imbalance $_{it}$		-0.0001 (0.0002)		0.0003 (0.0003)		-0.0002 (0.0005)
N	16,971	16,971	15,659	15,659	13,555	13,555
#Tokens	721	721	719	719	700	700
Adjusted R^2	0.043	0.056	0.081	0.086	0.191	0.195
Token FE	✓	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓	✓

Table 7: Secondary market price premia to credit conditions

This table shows the regression results for Equation 3. The dependent variable is the secondary market price premium relative to the primary market price. Panel A uses the DEX price premium ($\ln P_{it}^{DEX} - \ln P_{it}^{PM}$) and Panel B uses the YAM price premium ($\ln P_{it}^{YAM} - \ln P_{it}^{PM}$). The explanatory variables are measures of credit conditions in the lending market, including total debt, collateral, leverage, maximum borrowing capacity minus debt, and the debt-to-capacity ratio, each interacted with the RMM V2 and RMM V3 regimes. Controls include venue-specific market characteristics, including DEX order imbalance, pre-trade liquidity, and price impact (slippage) in Panel A, as well as YAM order imbalance, bid-ask spread, and listing duration in Panel B. All regressions include token and day fixed effects. Standard errors are clustered by token and day and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

<i>Dependent variable:</i>	DEX price premium = $\ln P_{it}^{SM} - \ln P_{it}^{PM}$				
	Debt	Collateral	Leverage	Capacity-Debt	Debt/Capacity
	(1)	(2)	(3)	(4)	(5)
$\ln \text{Credit condition}_{it-1} \times \text{RMM V2}_{it}$	0.0044*** (0.0007)	0.0040*** (0.0007)	0.1550*** (0.0263)	0.0047*** (0.0008)	0.0883*** (0.0149)
$\ln \text{Credit condition}_{it-1} \times \text{RMM V3}_{it}$	-0.0000 (0.0008)	-0.0000 (0.0007)	-0.0117 (0.0215)	0.0000 (0.0008)	-0.0091 (0.0170)
DEX order imbalance $_{it-1}$	-0.0194*** (0.0029)	-0.0194*** (0.0029)	-0.0195*** (0.0029)	-0.0194*** (0.0029)	-0.0195*** (0.0029)
$\ln \text{DEX liquidity}_{it-1}$	0.1921*** (0.0321)	0.1921*** (0.0321)	0.1925*** (0.0320)	0.1919*** (0.0322)	0.1925*** (0.0320)
DEX price impact/slippage $_{it-1}$	0.1305*** (0.0270)	0.1305*** (0.0270)	0.1304*** (0.0270)	0.1305*** (0.0270)	0.1304*** (0.0270)
N	24,505	24,505	24,505	24,505	24,505
#Tokens	525	525	525	525	525
Adjusted R^2	0.179	0.179	0.179	0.179	0.179
Token FE	✓	✓	✓	✓	✓
Day FE	✓	✓	✓	✓	✓
<i>Dependent variable:</i>	YAM price premium = $\ln P_{it}^{SM} - \ln P_{it}^{PM}$				
	Debt	Collateral	Leverage	Capacity-Debt	Debt/Capacity
	(1)	(2)	(3)	(4)	(5)
$\ln \text{Credit condition}_{it-1} \times \text{RMM V2}_{it}$	0.0066 (0.0057)	0.0057 (0.0050)	0.2882 (0.2466)	0.0062 (0.0054)	0.1598 (0.1370)
$\ln \text{Credit condition}_{it-1} \times \text{RMM V3}_{it}$	0.0056*** (0.0014)	0.0051*** (0.0012)	0.1313*** (0.0367)	0.0057*** (0.0014)	0.1041*** (0.0290)
YAM order imbalance $_{it-1}$	0.0913*** (0.0153)	0.0913*** (0.0153)	0.0914*** (0.0153)	0.0913*** (0.0153)	0.0914*** (0.0153)
YAM bid-ask spread $_{it-1}$	0.1323 (0.1351)	0.1322 (0.1351)	0.1331 (0.1355)	0.1320 (0.1350)	0.1331 (0.1354)
$\ln \text{YAM listing duration}_{it-1}$	0.0307*** (0.0020)	0.0307*** (0.0020)	0.0307*** (0.0020)	0.0307*** (0.0020)	0.0307*** (0.0020)
N	78,340	78,340	78,340	78,340	78,340
#Tokens	623	623	623	623	623
Adjusted R^2	0.012	0.012	0.012	0.012	0.012
Token FE	✓	✓	✓	✓	✓
Day FE	✓	✓	✓	✓	✓

Table 8: Borrowing behavior in response to DEX price premia

This table shows the regression results for Equation 4. The dependent variable is the cumulative change from day t to day $t+h$ in borrowing behavior for $h \in 1, 7, 30$ days. Borrowing behavior is measured by debt, collateral, leverage, borrowing capacity minus debt, and the debt-to-capacity ratio. The main explanatory variable is the secondary market price premium relative to the primary market price ($\ln P_{it}^{DEX} - \ln P_{it}^{PM} = q_{it}$). The asymmetric specification separates collateral undervaluation ($\max\{q_{it}, 0\}$) from collateral overvaluation ($\max\{-q_{it}, 0\}$). Observations during the transition from RMM V2 to RMM V3 (between January 31 and February 29, 2024) are excluded. All regressions include token and day fixed effects. Standard errors are clustered by token and day and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	$\ln Y_{it+h} - \ln Y_{it}$				
	Debt	Collateral	Leverage	Capacity-Debt	Debt/capacity
	(1)	(2)	(3)	(4)	(5)
<i>A. $h = 1$</i>					
DEX price premium = $\ln P_{it}^{SM} - \ln P_{it}^{PM} = q_{it}$	-0.0232 (0.0168)	-0.0251 (0.0171)	-0.0006 (0.0007)	-0.0209 (0.0149)	-0.0011 (0.0009)
Collateral undervaluation = $\max\{q_{it}, 0\}$	-0.0580* (0.0305)	-0.0594* (0.0324)	-0.0021* (0.0012)	-0.0480* (0.0282)	-0.0035** (0.0017)
Collateral overvaluation = $\max\{-q_{it}, 0\}$	-0.0053 (0.0139)	-0.0030 (0.0141)	-0.0006 (0.0007)	-0.0012 (0.0122)	-0.0009 (0.0009)
Adjusted R^2	0.287	0.289	0.182	0.291	0.222
N	24,545	24,545	24,545	24,545	24,545
<i>B. $h = 7$</i>					
DEX price premium = $\ln P_{it}^{SM} - \ln P_{it}^{PM} = q_{it}$	-0.1909*** (0.0714)	-0.2076*** (0.0781)	-0.0060*** (0.0023)	-0.1723** (0.0670)	-0.0100*** (0.0037)
Collateral undervaluation = $\max\{q_{it}, 0\}$	-0.4232*** (0.1428)	-0.4583*** (0.1567)	-0.0144*** (0.0047)	-0.3749*** (0.1345)	-0.0236*** (0.0073)
Collateral overvaluation = $\max\{-q_{it}, 0\}$	0.0004 (0.0372)	0.0021 (0.0409)	-0.0009 (0.0014)	0.0061 (0.0368)	-0.0012 (0.0019)
Adjusted R^2	0.306	0.310	0.194	0.314	0.242
N	24,486	24,486	24,486	24,486	24,486
<i>C. $h = 30$</i>					
DEX price premium = $\ln P_{it}^{SM} - \ln P_{it}^{PM} = q_{it}$	-0.8374*** (0.3019)	-0.9471*** (0.3367)	-0.0273*** (0.0098)	-0.7973*** (0.2912)	-0.0433*** (0.0148)
Collateral undervaluation = $\max\{q_{it}, 0\}$	-2.0187*** (0.4980)	-2.2606*** (0.5536)	-0.0686*** (0.0160)	-1.9179*** (0.4837)	-0.1045*** (0.0238)
Collateral overvaluation = $\max\{-q_{it}, 0\}$	-0.1895 (0.1728)	-0.1949 (0.1878)	-0.0085 (0.0053)	-0.1769 (0.1601)	-0.0099 (0.0084)
Adjusted R^2	0.235	0.232	0.205	0.232	0.222
N	23,770	23,770	23,770	23,770	23,770
#Tokens	525	525	525	525	525
Token FE	✓	✓	✓	✓	✓
Day FE	✓	✓	✓	✓	✓

Table 9: Borrowing behavior in response to YAM price premia

This table shows the regression results for Equation 4. The dependent variable is the cumulative change from day t to day $t+h$ in borrowing behavior for $h \in 1, 7, 30$ days. Borrowing behavior is measured by debt, collateral, leverage, borrowing capacity minus debt, and the debt-to-capacity ratio. The main explanatory variable is the secondary market price premium relative to the primary market price ($\ln P_{it}^{YAM} - \ln P_{it}^{PM} = q_{it}$). The asymmetric specification separates collateral undervaluation ($\max\{q_{it}, 0\}$) from collateral overvaluation ($\max\{-q_{it}, 0\}$). Observations during the transition from RMM V2 to RMM V3 (between January 31 and February 29, 2024) are excluded. All regressions include token and day fixed effects. Standard errors are clustered by token and day and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	$\ln Y_{it+h} - \ln Y_{it}$				
	Debt	Collateral	Leverage	Capacity-Debt	Debt/capacity
	(1)	(2)	(3)	(4)	(5)
<i>A. $h = 1$</i>					
YAM price premium = $\ln P_{it}^{SM} - \ln P_{it}^{PM} = q_{it}$	0.0004 (0.0006)	0.0002 (0.0007)	0.0001** (0.0000)	-0.0001 (0.0007)	0.0001** (0.0000)
Collateral undervaluation = $\max\{q_{it}, 0\}$	-0.0274* (0.0141)	-0.0288* (0.0157)	-0.0010* (0.0006)	-0.0261* (0.0144)	-0.0013* (0.0007)
Collateral overvaluation = $\max\{-q_{it}, 0\}$	-0.0016* (0.0009)	-0.0015 (0.0011)	-0.0001*** (0.0000)	-0.0011 (0.0010)	-0.0002*** (0.0001)
Adjusted R^2	0.320	0.320	0.177	0.315	0.230
N	78,443	78,443	78,443	78,443	78,443
<i>B. $h = 7$</i>					
YAM price premium = $\ln P_{it}^{SM} - \ln P_{it}^{PM} = q_{it}$	-0.0049 (0.0047)	-0.0064 (0.0053)	0.0001 (0.0002)	-0.0070 (0.0048)	0.0001 (0.0002)
Collateral undervaluation = $\max\{q_{it}, 0\}$	-0.1588*** (0.0601)	-0.1770*** (0.0674)	-0.0051** (0.0024)	-0.1612*** (0.0605)	-0.0066** (0.0031)
Collateral overvaluation = $\max\{-q_{it}, 0\}$	-0.0022 (0.0041)	-0.0014 (0.0046)	-0.0003* (0.0002)	0.0000 (0.0043)	-0.0004** (0.0002)
Adjusted R^2	0.276	0.276	0.175	0.269	0.229
N	78,061	78,061	78,061	78,061	78,061
<i>C. $h = 30$</i>					
YAM price premium = $\ln P_{it}^{SM} - \ln P_{it}^{PM} = q_{it}$	-0.0117 (0.0219)	-0.0141 (0.0245)	-0.0002 (0.0008)	-0.0135 (0.0220)	-0.0003 (0.0010)
Collateral undervaluation = $\max\{q_{it}, 0\}$	-0.9346*** (0.2362)	-1.0314*** (0.2618)	-0.0341*** (0.0085)	-0.9240*** (0.2359)	-0.0436*** (0.0108)
Collateral overvaluation = $\max\{-q_{it}, 0\}$	-0.0301 (0.0200)	-0.0319 (0.0223)	-0.0013* (0.0008)	-0.0276 (0.0200)	-0.0017* (0.0010)
Adjusted R^2	0.225	0.227	0.184	0.225	0.204
N	76,206	76,206	76,206	76,206	76,206
#Tokens	623	623	623	623	623
Token FE	✓	✓	✓	✓	✓
Day FE	✓	✓	✓	✓	✓

Table 10: Lending behavior in response to DEX price premia

This table shows the regression results for Equation 4. The dependent variable is the cumulative change from day t to day $t + h$ in lending behavior on RMM V2 and RMM V3 for $h \in 1, 7, 30$ days. Lending behavior is measured by stablecoin deposits, stablecoin withdrawals, available liquidity (deposits minus withdrawals), deposit coverage measured as available liquidity relative to outstanding stablecoin borrowing, and the borrowing interest rate. The main explanatory variable is the secondary market price premium relative to the primary market price. It is calculated as the weighted average of $(\ln P_{it}^{DEX} - \ln P_{it}^{PM})$ across tokens, where each token is weighted by its share of collateral deposited in the respective RMM platform. The asymmetric specification separates collateral undervaluation ($\max q_{\nu t}, 0$) from collateral overvaluation ($\max -q_{\nu t}, 0$). Observations during the transition from RMM V2 to RMM V3 (between January 31 and February 29, 2024) are excluded. All regressions include platform and day fixed effects. Standard errors are clustered by day and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	$\ln Y_{\nu t+h} - \ln Y_{\nu t}$				$r_{\nu t+h} - r_{\nu t}$
	Deposits	Withdrawals	Deposits-Withdrawals	Deposit coverage	Interest rate
	(1)	(2)	(3)	(4)	(5)
<i>A. $h = 1$</i>					
DEX premium = $q_{\nu t}$	1.4811 (1.1126)	2.0834 (1.5165)	0.1149 (0.1163)	0.0361 (0.0428)	17.0550** (8.2471)
Collateral undervaluation = $\max\{q_{\nu t}, 0\}$	1.8983 (1.4907)	2.4993 (2.0250)	0.1343 (0.1644)	0.0450 (0.0606)	16.9185 (10.4639)
Collateral overvaluation = $\max\{-q_{\nu t}, 0\}$	-0.2143 (1.3781)	-0.8203 (2.0224)	-0.0561 (0.0513)	-0.0090 (0.0163)	-17.4696 (10.7908)
Adjusted R^2	-0.041	0.059	-0.009	-0.004	0.001
N	1,208	1,208	1,210	1,210	1,210
<i>B. $h = 7$</i>					
DEX premium = $q_{\nu t}$	1.1970 (2.1179)	14.8996*** (4.9966)	0.0003 (0.3069)	0.0199 (0.1226)	11.4689 (12.3719)
Collateral undervaluation = $\max\{q_{\nu t}, 0\}$	0.8343 (2.8435)	14.9080** (6.2232)	0.1324 (0.4257)	0.0688 (0.1774)	7.2024 (15.3219)
Collateral overvaluation = $\max\{-q_{\nu t}, 0\}$	-2.3488 (2.8393)	-14.8728 (9.0663)	0.4196 (0.4960)	0.1356 (0.1814)	-25.0229 (19.9145)
Adjusted R^2	-0.034	0.055	0.038	0.014	0.008
N	1,184	1,184	1,198	1,198	1,198
<i>C. $h = 30$</i>					
DEX premium = $q_{\nu t}$	1.4968 (2.9184)	6.7738** (3.2983)	-0.5567 (0.8023)	0.0994 (0.2761)	-0.1632 (9.8405)
Collateral undervaluation = $\max\{q_{\nu t}, 0\}$	3.1630 (3.7550)	3.0824 (3.7978)	-0.3066 (1.2771)	0.3533 (0.4496)	0.9748 (12.9664)
Collateral overvaluation = $\max\{-q_{\nu t}, 0\}$	4.9517 (8.2905)	-21.0603*** (7.2650)	1.5371 (1.7452)	0.8913 (0.6867)	4.6244 (27.4352)
Adjusted R^2	-0.013	0.070	-0.062	0.080	-0.002
N	1,094	1,094	1,154	1,152	1,154
Platform FE	✓	✓	✓	✓	✓
Day FE	✓	✓	✓	✓	✓

Table 11: Lending behavior in response to YAM price premia

This table shows the regression results for Equation 4. The dependent variable is the cumulative change from day t to day $t + h$ in lending behavior on RMM V2 and RMM V3 for $h \in 1, 7, 30$ days. Lending behavior is measured by stablecoin deposits, stablecoin withdrawals, available liquidity (deposits minus withdrawals), deposit coverage measured as available liquidity relative to outstanding stablecoin borrowing, and the borrowing interest rate. The main explanatory variable is the secondary market price premium relative to the primary market price. It is calculated as the weighted average of $(\ln P_{it}^{YAM} - \ln P_{it}^{PM})$ across tokens, where each token is weighted by its share of collateral deposited in the respective RMM platform. The asymmetric specification separates collateral undervaluation ($\max q_{\nu t}, 0$) from collateral overvaluation ($\max -q_{\nu t}, 0$). Observations during the transition from RMM V2 to RMM V3 (between January 31 and February 29, 2024) are excluded. All regressions include platform and day fixed effects. Standard errors are clustered by day and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	$\ln Y_{\nu t+h} - \ln Y_{\nu t}$				$r_{\nu t+h} - r_{\nu t}$
	Deposits	Withdrawals	Deposits-Withdrawals	Deposit coverage	Interest rate
	(1)	(2)	(3)	(4)	(5)
<i>A. $h = 1$</i>					
YAM price premium = $q_{\nu t}$	0.4890 (0.3436)	3.6704*** (1.1909)	-0.1297** (0.0532)	-0.0658*** (0.0248)	-3.3890 (3.0754)
Collateral undervaluation = $\max\{q_{\nu t}, 0\}$	-2.5283 (2.4969)	6.0084 (3.9564)	-0.0245 (0.1475)	-0.0149 (0.0581)	2.5029 (17.9916)
Collateral overvaluation = $\max\{-q_{\nu t}, 0\}$	-0.7795** (0.3764)	-3.4453*** (1.1747)	0.1399** (0.0577)	0.0707*** (0.0269)	3.9562 (3.1510)
Adjusted R^2	-0.039	0.067	-0.006	0.006	-0.005
N	1,308	1,308	1,310	1,310	1,310
<i>B. $h = 7$</i>					
YAM premium = $q_{\nu t}$	0.1021 (0.8689)	9.1781*** (2.5070)	-0.4576*** (0.0633)	-0.2412*** (0.0301)	31.3767*** (8.1978)
Collateral undervaluation = $\max\{q_{\nu t}, 0\}$	4.0092 (6.2932)	4.1888 (12.7290)	0.4379 (0.6705)	0.2320 (0.2584)	3.6465 (32.0146)
Collateral overvaluation = $\max\{-q_{\nu t}, 0\}$	0.2689 (0.9492)	-9.6519*** (2.2189)	0.5427*** (0.0865)	0.2862*** (0.0377)	-34.0130*** (7.8710)
Adjusted R^2	-0.043	0.039	0.044	0.046	0.025
N	1,284	1,284	1,298	1,298	1,298
<i>C. $h = 30$</i>					
YAM premium = $q_{\nu t}$	5.7764** (2.4100)	-0.7412 (1.9508)	-0.5714* (0.3204)	-0.2375*** (0.0689)	23.4665*** (9.0949)
Collateral undervaluation = $\max\{q_{\nu t}, 0\}$	12.0711 (10.7154)	-0.8278 (13.1326)	-1.6101 (4.5665)	1.0007 (1.0064)	-91.1797* (47.2826)
Collateral overvaluation = $\max\{-q_{\nu t}, 0\}$	-5.2097** (2.4716)	0.7334 (2.1827)	0.4754** (0.2258)	0.3507*** (0.1260)	-34.0551*** (3.5345)
Adjusted R^2	-0.011	0.045	-0.054	0.083	0.033
N	1,194	1,194	1,254	1,252	1,254
Platform FE	✓	✓	✓	✓	✓
Day FE	✓	✓	✓	✓	✓

Table 12: Feedback between DEX prices and leverage

This table shows the regression results for Equation 5. The dependent variables are future changes in DEX returns ($\Delta \ln P_{it}^{DEX}$) and leverage in Panel A, and the DEX price premium ($\ln P_{it}^{DEX} - \ln P_{it}^{PM}$) and leverage in Panel B, over horizons of $h \in 1, 7, 30$ days. The main explanatory variables are current changes in leverage, DEX returns, and the DEX price premium, with one day lags included as controls. Columns (4)-(6) additionally control for lagged DEX order imbalance, liquidity, and price impact (slippage). Observations during the transition from RMM V2 to RMM V3 (between January 31 and February 29, 2024) are excluded. All coefficients are reported in Table A.11. All regressions include token and day fixed effects. Standard errors are clustered by token and calendar day and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	$\ln Y_{it+h} - \ln Y_{it}$					
	$h = 1$	$h = 7$	$h = 30$	$h = 1$	$h = 7$	$h = 30$
	(1)	(2)	(3)	(4)	(5)	(6)
A. DEX returns $\rightarrow$ Leverage						
$\Delta \ln P_{it}^{DEX}$	-0.0000 (0.0015)	-0.0018 (0.0017)	-0.0024 (0.0051)	-0.0002 (0.0019)	-0.0014 (0.0021)	-0.0071 (0.0073)
N	13,275	13,237	12,771	10,666	10,633	10,274
#Tokens	416	415	398	416	415	398
Adjusted R^2	0.246	0.257	0.277	0.185	0.252	0.276
Leverage $\rightarrow$ DEX returns						
$\Delta \ln \text{Leverage}_{it}$	-0.0248 (0.0202)	-0.0252 (0.0917)	-0.1286 (0.1172)	-0.0327 (0.0295)	-0.0813 (0.1245)	-0.2009 (0.1671)
N	9,017	6,101	5,947	6,408	5,014	4,902
#Tokens	325	207	178	235	193	172
Adjusted R^2	0.417	0.523	0.543	0.467	0.567	0.589
B. DEX price premium $\rightarrow$ Leverage						
$\ln P_{it}^{SM} - \ln P_{it}^{PM}$	-0.0020** (0.0009)	-0.0135*** (0.0047)	-0.0635*** (0.0151)	-0.0010 (0.0012)	-0.0173*** (0.0061)	-0.0851*** (0.0208)
N	13,275	13,237	12,771	10,666	10,633	10,274
#Tokens	416	415	398	416	415	398
Adjusted R^2	0.246	0.258	0.280	0.185	0.254	0.281
Leverage $\rightarrow$ DEX price premium						
$\Delta \ln \text{Leverage}_{it}$	-0.0248 (0.0202)	-0.0253 (0.0917)	-0.1287 (0.1172)	-0.0327 (0.0295)	-0.0814 (0.1245)	-0.2011 (0.1672)
N	9,017	6,101	5,947	6,408	5,014	4,902
#Tokens	325	207	178	235	193	172
Adjusted R^2	0.417	0.523	0.543	0.467	0.566	0.589
Controls	—	—	—	✓	✓	✓
Token FE	✓	✓	✓	✓	✓	✓
Day FE	✓	✓	✓	✓	✓	✓

Table 13: Feedback between YAM prices and leverage

This table shows the regression results for Equation 5. The dependent variables are future changes in YAM returns ($\Delta \ln P_{it}^{YAM}$) and leverage in Panel A, and the YAM price premium ($\ln P_{it}^{YAM} - \ln P_{it}^{PM}$) and leverage in Panel B, over horizons of $h \in 1, 7, 30$ days. The main explanatory variables are current changes in leverage, YAM returns, and the YAM price premium, with one day lags included as controls. Columns (4)-(6) additionally control for lagged YAM order imbalance, listing duration and bid-ask spread. Observations during the transition from RMM V2 to RMM V3 (between January 31 and February 29, 2024) are excluded. All coefficients are reported in Table A.12. All regressions include token and day fixed effects. Standard errors are clustered by token and calendar day and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	$\ln Y_{it+h} - \ln Y_{it}$					
	$h = 1$	$h = 7$	$h = 30$	$h = 1$	$h = 7$	$h = 30$
	(1)	(2)	(3)	(4)	(5)	(6)
A. YAM returns $\rightarrow$ Leverage						
$\Delta \ln P_{it}^{YAM}$	-0.0000 (0.0001)	0.0001 (0.0001)	-0.0004 (0.0008)	-0.0000 (0.0001)	0.0000 (0.0002)	-0.0013 (0.0017)
N	50,140	49,900	48,565	38,320	38,150	37,129
#Tokens	622	622	622	622	622	622
R^2	0.215	0.200	0.245	0.209	0.211	0.252
Leverage $\rightarrow$ YAM returns						
$\Delta \ln \text{Leverage}_{it}$	0.0277 (0.0281)	0.0876 (0.0959)	-0.1668 (0.3239)	0.0577 (0.0353)	-0.0634 (0.1002)	-0.2672 (0.4151)
N	34,905	24,968	21,115	23,085	19,373	16,364
#Tokens	622	615	611	617	612	610
Adjusted R^2	0.133	0.237	0.237	0.162	0.269	0.226
B. YAM price premium $\rightarrow$ Leverage						
$\ln P_{it}^{SM} - \ln P_{it}^{PM}$	0.0000 (0.0000)	0.0002 (0.0002)	-0.0004 (0.0014)	0.0000 (0.0001)	-0.0000 (0.0002)	-0.0014 (0.0019)
N	50,140	49,900	48,565	38,320	38,150	37,129
#Tokens	622	622	622	622	622	622
Adjusted R^2	0.215	0.200	0.245	0.209	0.211	0.252
Leverage $\rightarrow$ YAM price premium						
$\Delta \ln \text{Leverage}_{it}$	0.0276 (0.0281)	0.0893 (0.0957)	-0.1695 (0.3235)	0.0574 (0.0353)	-0.0627 (0.1002)	-0.2725 (0.4143)
N	34,905	24,968	21,115	23,085	19,373	16,364
#Tokens	622	615	611	617	612	610
Adjusted R^2	0.133	0.237	0.237	0.162	0.269	0.226
Controls	—	—	—	✓	✓	✓
Token FE	✓	✓	✓	✓	✓	✓
Day FE	✓	✓	✓	✓	✓	✓

Table 14: Leveraged buying by wallet

This table shows the regression results for Equation 6. The dependent variable is the log value of real estate-backed token purchases by borrower b from day t to day $t + h$, where total purchases include secondary markets (DEX, YAM) and primary market purchases. Columns (1)-(3) use the borrower's total outstanding RMM V2 and RMM V3 debt on day t as the main explanatory variable, while Columns (4)-(6) use new borrowing on day t . All regressions include borrower and day fixed effects. Standard errors are clustered by borrower wallet and day and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	$\ln \sum_{\tau=t+1}^{t+h} \sum_i \text{Token volume}_{bi\tau} \times \text{Token price}_{bi\tau}$					
	Total debt (in \$)			New debt (in \$)		
	$h = 1$	$h = 7$	$h = 30$	$h = 1$	$h = 7$	$h = 30$
	(1)	(2)	(3)	(4)	(5)	(6)
<i>A. Total RealT</i>						
$\ln \text{Borrower Debt}_{bt}$	-0.0012 (0.0015)	-0.0204*** (0.0048)	-0.0353*** (0.0071)	0.1639*** (0.0086)	0.2083*** (0.0084)	0.1592*** (0.0075)
N	2,388,216	2,356,172	2,236,382	2,388,216	2,356,172	2,236,382
#Borrowers	3,908	3,858	3,764	3,908	3,858	3,764
#Tokens	768	768	768	768	768	768
Adjusted R^2	0.176	0.386	0.514	0.187	0.391	0.515
<i>B. DEX</i>						
$\ln \text{Borrower Debt}_{bt}$	0.0002 (0.0004)	0.0005 (0.0009)	0.0004 (0.0014)	0.0015* (0.0008)	0.0042* (0.0023)	0.0061* (0.0032)
N	2,388,216	2,356,172	2,236,382	2,388,216	2,356,172	2,236,382
#Borrowers	3,908	3,858	3,764	3,908	3,858	3,764
#Tokens	649	649	649	649	649	649
Adjusted R^2	0.208	0.386	0.484	0.208	0.386	0.484
<i>C. YAM</i>						
$\ln \text{Borrower Debt}_{bt}$	0.0019* (0.0010)	0.0033 (0.0028)	0.0016 (0.0048)	0.0570*** (0.0053)	0.1025*** (0.0072)	0.1088*** (0.0073)
N	2,388,216	2,356,172	2,236,382	2,388,216	2,356,172	2,236,382
#Borrowers	3,908	3,858	3,764	3,908	3,858	3,764
#Tokens	759	759	759	759	759	759
Adjusted R^2	0.164	0.310	0.432	0.170	0.314	0.434
<i>D. Primary market</i>						
$\ln \text{Borrower Debt}_{bt}$	-0.0033*** (0.0010)	-0.0263*** (0.0043)	-0.0424*** (0.0067)	0.1108*** (0.0084)	0.1370*** (0.0081)	0.1021*** (0.0068)
N	2,388,216	2,356,172	2,236,382	2,388,216	2,356,172	2,236,382
#Borrowers	3,908	3,858	3,764	3,908	3,858	3,764
#Tokens	768	768	768	768	768	768
Adjusted R^2	0.166	0.388	0.525	0.173	0.390	0.525
Borrower FE	✓	✓	✓	✓	✓	✓
Day FE	✓	✓	✓	✓	✓	✓

Table 15: Information shocks to tokenized properties and DeFi behavior

This table shows the regression results for Equation 7. The shock date is July 2, 2025, when the Detroit lawsuit was first filed and publicly reported. Treated properties are the 52 Detroit RealT tokens named in the lawsuit and deposited as collateral on the lending platform. Control properties are similar properties located in Detroit but not named in the lawsuit. The dependent variable is the cumulative change in Y from day t to day $t + h$, where $h \in \{1, 7, 30\}$ days. Y includes the YAM price premium, debt, collateral, and leverage. All regressions include token and day fixed effects. Standard errors are clustered by token and calendar day and reported in parentheses. Randomization p -values are based on 999 reassignments of the treated label within the matched Detroit sample. Pre-trend p -values test whether the treated-control coefficients from event days -30 to -2 , relative to day -1 , are jointly zero. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	$\ln Y_{it+h} - \ln Y_{it}$		
	(1) $h = 1$	(2) $h = 7$	(3) $h = 30$
<i>A. YAM price premium</i>			
Treated _{i} $\times$ Post _{t}	-0.0146*** (0.0024)	-0.0378*** (0.0063)	-0.0530*** (0.0135)
N	3,478	3,225	3,177
#Tokens	201	200	201
Adjusted R^2	-0.041	0.048	0.031
Randomization p	0.264	0.057	0.124
Pre-trend joint p -value	0.084	0.084	0.084
<i>B. Debt</i>			
Treated _{i} $\times$ Post _{t}	-0.0011 (0.0010)	-0.0179*** (0.0021)	0.0275*** (0.0031)
N	12,322	12,322	12,322
#Tokens	202	202	202
Adjusted R^2	0.104	0.126	0.450
Randomization p	0.985	0.276	0.063
Pre-trend joint p -value	0.126	0.126	0.126
<i>C. Collateral</i>			
Treated _{i} $\times$ Post _{t}	-0.0049*** (0.0006)	-0.0102*** (0.0016)	0.0180*** (0.0025)
N	12,322	12,322	12,322
#Tokens	202	202	202
Adjusted R^2	0.055	0.156	0.490
Randomization p	0.064	0.302	0.075
Pre-trend joint p -value	0.037	0.037	0.037
<i>D. Leverage</i>			
Treated _{i} $\times$ Post _{t}	0.0010*** (0.0002)	-0.0022*** (0.0003)	0.0024*** (0.0003)
N	12,322	12,322	12,322
#Tokens	202	202	202
Adjusted R^2	0.152	0.141	0.373
Randomization p	0.347	0.386	0.212
Pre-trend joint p -value	0.274	0.274	0.274
Token FE	✓	✓	✓
Day FE	✓	✓	✓

Appendix

Figure A.1: Spatial distribution of tokenized real estate in Detroit

The map shows the city of Detroit, Michigan, with red markers indicating the locations of residential properties that have been tokenized.

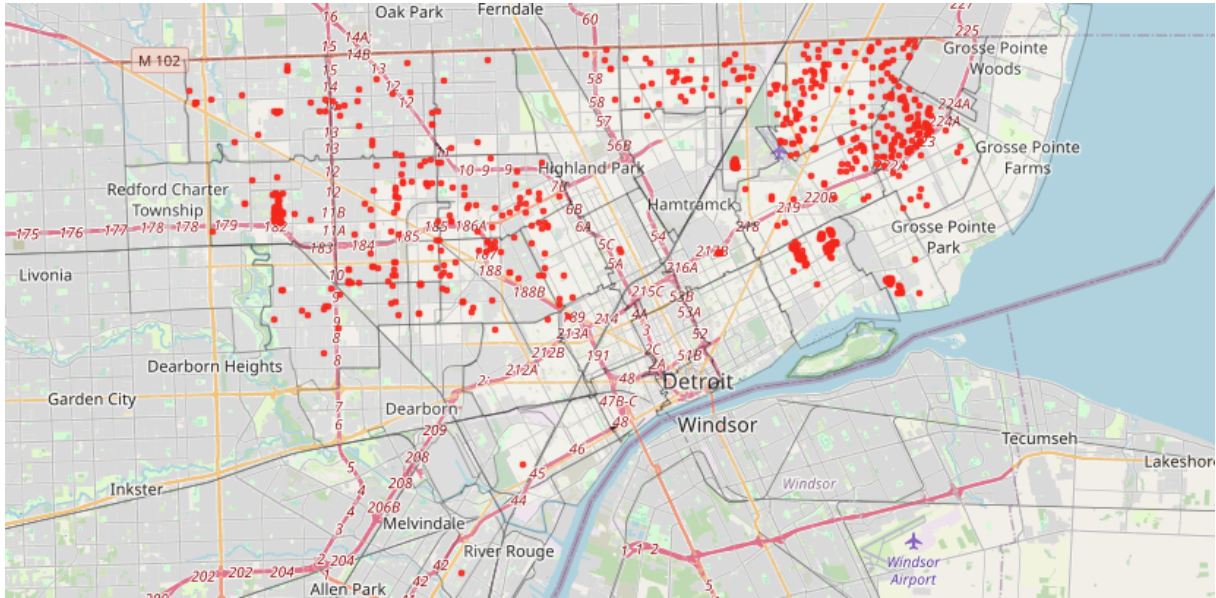


Figure A.2: Credit demand in tokenized real estate lending market

This figure illustrates daily investor leverage and borrowing amounts in \$ in the tokenized real estate lending market. The sample period runs from April 2022 to December 2025. From April 14, 2022 to January 30, 2024, the market operates under RMM V2, and from January 31, 2024 onward, it operates under RMM V3. The solid blue line (RMM V2) and the dashed blue line (RMM V3) plot daily average investor leverage (left axis, in %). The shaded areas show how much individual investor leverage varies around the daily average, using one standard deviation above and below the mean. The red lines plot the borrowing amount in \$ (right axis) for each version. Vertical dashed lines mark major changes in the RealT ecosystem. RMM V2 launched in early 2022, followed by the introduction of the OTC/YAM marketplace in January 2023. At the end of January 2024, RMM V2 was replaced by RMM V3, which expanded eligible collateral from 53 tokens to the majority of RealT's 823 real estate tokens. Furthermore, RMM V3 relaxed borrowing constraints by increasing the LTV from 50% to 75%.

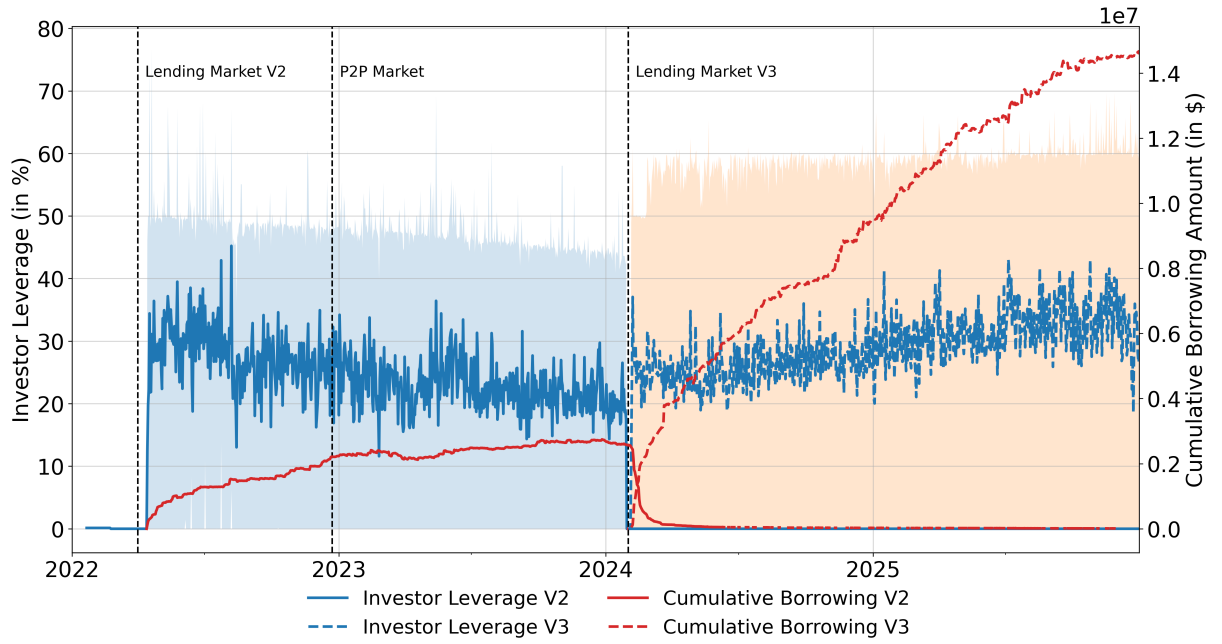
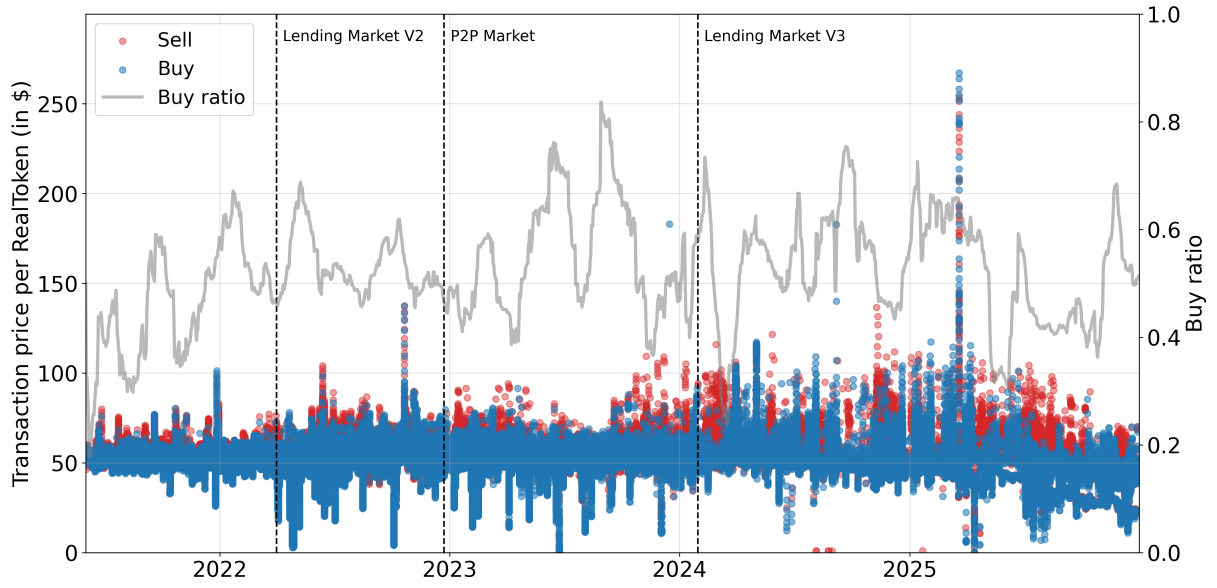


Figure A.3: Price dynamics of tokenized real estate on secondary markets

This figure illustrates transaction level prices of tokenized real estate on the secondary market. Buy transactions are shown as blue markers and sell transactions as red markers. The upper panel shows trades executed in DEX liquidity pools, and the lower panel shows trades on the OTC/YAM marketplace. The gray line on the right axis plots a 30-day rolling average of the daily buy ratio, which is defined as the proportion of buy transactions to total transactions. This measure provides an indication of buy-side trading intensity over time. Vertical dashed lines mark major changes in the RealT ecosystem, i.e., the introduction of the RMM V2 lending market in early 2022, the launch of the OTC/YAM marketplace, and the replacement of RMM V2 by the RMM V3 lending market in January 2024.

Panel A: DEX liquidity pools



Panel B: OTC/YAM marketplace

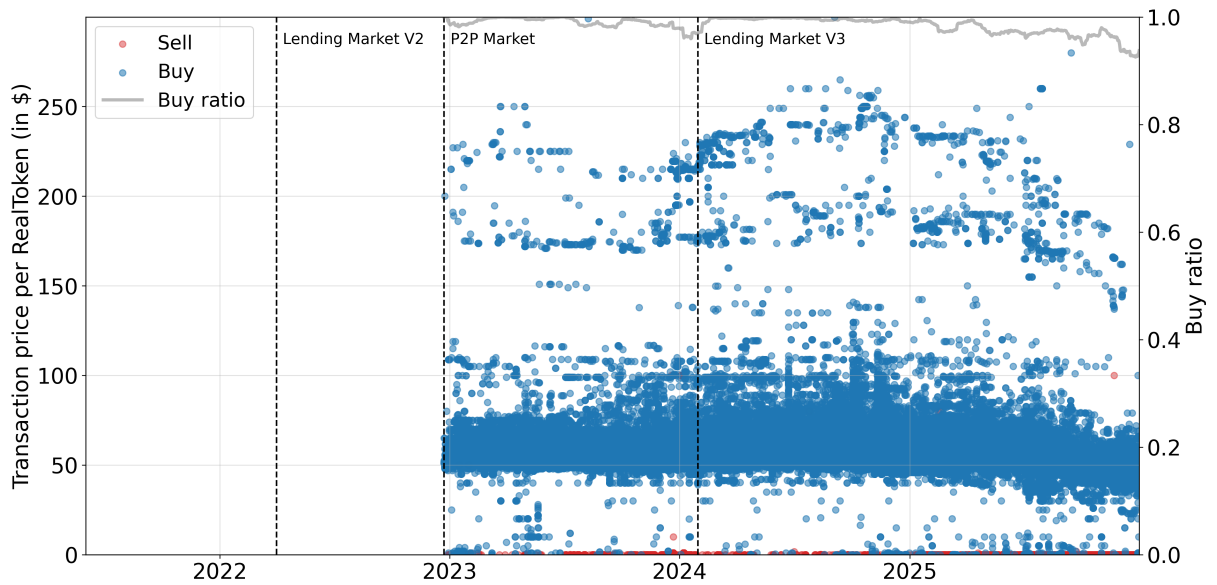


Table A.1: Three ways to own and trade fractional real estate

This table compares direct or fractional property ownership through shared-equity mortgages, publicly traded real estate investment trusts (REITs), and tokenized property ownership across key economic dimensions. High, medium, and low indicate qualitative relative assessments across the three ownership structures.

	Direct/Shared Ownership	REITs	Tokenized Property
Liquidity	LOW Requires to complete a bilateral property transaction.	HIGH Listed REIT shares trade on public stock exchanges.	MEDIUM Tokens can trade on secondary markets, but liquidity varies substantially across properties.
Entry cost	HIGH Substantial capital requirements.	LOW-MEDIUM Minimum investment of one share through a brokerage account, or \$1,000-\$2,500 for non-traded REITs.	LOW Properties are divided into tokens, and investors can also buy fractions of a token, allowing for very small investment amounts.
Regulation	MEDIUM Property law and local real estate regulations.	HIGH REITs are subject to securities regulation, disclosure requirements, and REIT-specific legal and tax rules.	HIGH In US, real estate tokens require securities registration or an applicable exemption (Regulation S or Regulation D). In Europe, tokens qualifying as financial instruments are subject to existing EU securities regulation.
Control	HIGH Owners retain direct decision rights over the property, subject to agreements among co-owners.	LOW Investment and operating decisions are delegated to professional REIT management. Investors have no direct control.	LOW Property and operating decisions are generally delegated to the token issuer (e.g. RealT). Token holders have no direct control.
Cash flow	DIRECT Owners receive rental income and directly participate in changes in the value of the property.	INDIRECT Investors receive dividends generated by a diversified portfolio of properties.	DIRECT Token holders receive their proportional share of net rental income generated by the underlying property.
Liability	MEDIUM-HIGH Liability depends on the ownership structure, and direct owners may bear legal and financial obligations associated with the property.	LOW REIT shareholders generally have limited liability.	LOW The LLC or SPV generally bears the property's legal obligations, while token holders have limited liability.
Idiosyncratic risk	HIGH Investors are directly exposed to property-specific risk.	LOW REIT portfolios generally consist of multiple properties, data centers, and infrastructure projects.	MEDIUM Each token is linked to a specific property, so investors remain exposed to property-specific risk unless they diversify across tokens.

Table A.2: The asset tokenization market for real estate

In this table, we summarize the real estate tokenization landscape (as of December 2025). We list each platform’s number of tokenized properties, assets (in \$ millions), and provide a brief description, and the blockchains they use.

Company	#	Assets in \$ million	Description	Blockchain
RealT	823	161.49	Since 2019, RealT has tokenized U.S. single-family rentals by issuing fractional tokens linked to an LLC that owns each home. Most properties are in Detroit, and rent is paid out in stablecoins.	Gnosis, Ethereum
Tangible	192	41.83	Since 2022, Tangible has been converting real estate into redeemable non-fungible tokens (NFTs) that represent rights to a specific property. These tokens are held within an special purpose vehicle company, allowing investors to earn rental yield and trade on the Tangible marketplace.	Arbitrum, Polygon, Optimism
Lofty	150	98.53	Founded in 2018 (marketplace launched 2021), Lofty sells fractional tokens tied to property-owning entities and distributes rent. It focuses on residential homes in Chicago, Cleveland, Pittsburgh, Texas and Florida.	Ethereum
Binaryx Platform	26	6.63	Since 2024, Binaryx has been offering fractional tokens of resort hotels in Indonesia and Montenegro. Investors can earn rental income and exit through the company’s marketplace.	Polygon
WorldEs	9	0.57	Since 2023, WorldEs is tokenizing U.S. residential units at the Pradera Oaks development in Texas. Investors can buy real-estate tokens and track transactions and changes to property information on the blockchain.	Arbitrum
Estate Protocol	7	9.2	Estate Protocol was launched in 2024 and fractionalizes single-family rentals in Texas, Arizona, and Georgia into tokens with monthly rent.	Arbitrum
Propbase	4	0.89	Since 2023, Propbase has tokenized hotel properties in Bangkok, Thailand. Investors purchase fractional tokens and receive a share of the hotel’s revenue.	Aptos
RealtyX	3	1.36	Since 2024, RealtyX tokenizes real estate in Dubai. Property token holders receive rental distributions via the platform.	Base, Plume
Landshare	4	0.62	Since 2021, Landshare has issued fractional tokens backed by U.S. rental homes through a special purpose vehicle company. The company focuses on Midwestern markets, such as Ohio, Michigan, and North Dakota.	Binance
Homebase	2	0.2	Since 2023, Homebase has been tokenizing single-family rentals in Texas. Investors purchase non-fungible tokens representing shares in the LLC holding title and receive rental income on-chain.	Solana
ELYFI	2	0.4	Since 2021, ELYFI is a real-estate-backed DeFi lending platform. It uses tokenized property assets from the ELYSIA protocol as collateral and has offered tokenized real-estate loan products in the USA and South Korea	Ethereum
LaProp	2	n/a	Since 2022, LaProp has sold tokenized shares of rental apartments. It launched offerings for two residential properties in Medellín, Colombia, with automated, on-chain rent payouts.	Ethereum
CitaDAO	2	0	Since 2022, CitaDAO tokenizes commercial properties into ERC-20 style fractions that reflect economic rights; notable assets include buildings in London and Singapore.	Ethereum
Roofstock Onchain	2	n/a	Since 2022, Roofstock onChain sells U.S. single-family homes as a single NFT representing 100% membership in the home’s LLC	Ethereum
HouseBit	1	0.2	Since 2022, HouseBit tokenized a Miami condo by issuing 1,000 ownership tokens.	Ethereum

Table A.3: RealT’s ecosystem

This table provides an overview of the primary, secondary, and lending markets for real estate-backed tokens that RealT operates. All transactions are recorded on the Gnosis blockchain. We also provide definitions of all key terms in this ecosystem.

Primary Market	Buying and selling tokens from/to RealT	Gnosis
Secondary Market	1. Decentralized Exchanges (DEXs) 2. OTC/You-and-Me (YAM) marketplace	
Lending Market	RealT’s Money Market (RMM)/ Lending platform based on Aave	

Name	Definition
Decentralized Exchange	
AMM	Automated Market Maker, i.e., an inventory-based market maker that uses a fixed pricing curve. Traders trade against a pool of two assets. There is no dealer and no order book. The pool quotes prices by a simple pricing rule. A common one keeps the product of token balances constant $x \cdot y = k$, so larger orders move the price more and the price impact (slippage) is predictable. Each trade pays a fee that is distributed to the pool’s asset suppliers (liquidity providers)
1inch	A platform that searches through many DEX liquidity pools to find the best overall price. It splits trades across pools to reduce price impact and fees. Users can connect their wallets and swap assets without creating an account or using a custodian.
Liquidity Pool in DEX	An inventory of usually two tokens (sometimes three) that enables continuous trading. Liquidity providers add tokens to the pool and earn trading fees based on the amount they supplied. Although depositing liquidity seems similar to an interest-bearing savings account, it carries economic risks. One key risk is impermanent loss, i.e., the token price decrease from pool rebalancing versus buy-and-hold. For instance, in a 50/50 pool of token X and Y , if Y doubles, the constant-product rule causes the pool to sell Y for X , leaving the liquidity provider with less Y and more X than buy-and-hold.
Uniswap (Levenswap)	An AMM-DEX that consists of many two-asset liquidity pools. Anyone can create a liquidity pool for any pair of assets. Levenswap is a Uniswap V2 copy deployed on Gnosis. Users connect wallets and trade without an account or custodian. Newer versions of Uniswap pools (e.g., V3, V4) concentrate liquidity near the current price to reduce the price impact for typical trade sizes.
YAM	You-and-Me Market (see yam.realtoken.network), i.e., RealT’s simple exchange platform where users post bids and asks. If an offer is accepted, the trade settles via a smart contract that transfers tokens directly between wallets. Price discovery comes from posted quotes rather than continuous market making.
Decentralized Lending	
Aave	A multi-asset money market in which each asset has its own lending pool (see aave.com). In addition, borrowers must pledge collateral worth more than the value of their loans. The LTV is set between 50-85%, depending on the provided collateral asset. With a single collateral position, a borrower can borrow several assets at once, each from its own lending pool and at its own interest rate. Aave has several versions of its money market. The newest version, V3, adds efficiency and safety features, such as higher LTVs for correlated assets, isolation of risky collateral, supply and borrow limits, and easier movement of liquidity between blockchains. Aave V2, the older core system, lacks these features.
Lending Pool	A one-asset pool, where lenders deposit an asset into it and borrowers withdraw the same asset. Within each lending pool, interest rates adjust automatically with supply and demand (utilization), i.e., when a larger share of the pool is lent out, borrowing costs and deposit yields rise, and when liquidity is high, interest rates fall.
Liquidation	If the loan exceeds a fixed threshold, a liquidation process is initiated, i.e, arbitrageurs step in to repay part of the debt, receive collateral at a discount, and sell it for profit.
LTV	The loan-to-value ratio is the maximum borrowing amount divided by the collateral value. DeFi lending platforms also set a liquidation threshold at which the forced liquidation process begins. For example, an LTV of 60% and a liquidation threshold of 70% means that \$100 of collateral allows for a loan of up to \$60 and is liquidated if the loan exceeds \$70 of allowable collateral value.
RMM	RealT’s money market is built on Aave mechanics (see rmm.realtoken.network). It is the only DeFi lending platform that accepts RealT’s real estate-backed tokens as collateral and lends out stablecoins. There are two versions. The first is based on Aave V2 and allows only 53 real estate tokens to be used as collateral. The newer version is based on Aave V3 and allows 623 real estate tokens to be used as collateral.
Assets	
Stablecoins	Tokens backed by fiat currencies, typically \$ and treasury bills, to provide more price stability. There are two main types: (i) fiat-backed claims on reserves held by an issuer (e.g., USDT, USDC) and (ii) overcollateralized crypto-backed stablecoins (e.g., DAI).
DAI	A \$-pegged stablecoin from Sky (formerly MakerDAO). Users pledge approved collateral (e.g., ETH or other cryptocurrencies) to mint/create DAI against it. The created DAI represents the borrowed amount. Users pay interest on the debt and burn/destroy the DAI when they repay it. There is no fixed term, and users can repay anytime. If the loan exceeds a liquidation threshold, the loan is liquidated to cover the debt. This procedure establishes a stable unit of account that can be used for trading, lending, and making payments on public blockchains.

Name	Definition
LEVIN	LEVIN is Levinswap's governance and revenue-claim token. In other words, it gives the holder residual control rights over platform rules and a pro-rata claim on fee revenues. LEVIN is now effectively inactive because secondary-market trading and liquidity have largely disappeared. According to community documentation, the lead developer left in 2022. After this, the application was maintained on a community basis. In early February 2024, RealT withdrew around 80% of its liquidity support, leaving LEVIN-related pools empty (see community-realt.gitbook.io).
xDAI	On Gnosis, xDAI is the <i>native cryptocurrency</i> , pegged 1:1 to the stablecoin DAI.
wxDAI	On Gnosis, a <i>wrapped</i> form of xDAI is pegged 1:1 to the native token xDAI. The benefit of a wrapped version of xDAI is that it can be used in DEX and DeFi lending platforms.
Native	A blockchain's built-in native currency pays transaction fees and rewards validators or stakers. Examples of native cryptocurrencies include BTC on Bitcoin, ETH on Ethereum, and xDAI on Gnosis.
Wrapped	Many cryptocurrencies have wrapped versions (e.g., WETH, WBTC, wxDAI), i.e., the original cryptocurrency is converted into a new token on a 1:1 basis and is redeemable through the wrapping platform. Wrapping makes native cryptocurrencies compatible with DeFi and, in some cases, usable on other blockchains.
Blockchain	
Gnosis	A separate blockchain with its own consensus and validators, focused on low fees and fast settlement. Gnosis is compatible with Ethereum, meaning Ethereum's smart contracts and wallets can be deployed and used on Gnosis.
Validators	Operators who run network nodes, propose blocks, and validate transactions to reach consensus.
Stakers	Token holders who stake tokens (directly or via delegation) to secure the network.

Table A.4: Tokenized vs. non-tokenized property characteristics

This table compares the average hedonic characteristics of tokenized and Zillow-based non-tokenized single-family homes in Detroit before and after matching. Panel A compares all RealT-listed transaction prices with non-tokenized transaction prices from Zillow. Panel B compares deed-confirmed RealT transaction prices with non-tokenized transaction prices from Zillow. Propensity score matching uses nearest-neighbor matching with a 4:1 ratio and a caliper of 0.2 standard deviations of the propensity score. Matching is based on the number of bedrooms and bathrooms, living area, lot size, distance to the nearest school, school rating, building age, ZIP code, and sale quarter.

	Tokenized	Non-Tokenized		
	Mean	Mean	Std. Mean Diff.	Var. Ratio
	(1)	(2)	(3)	(4)
<i>A. RealT vs. Zillow-listed transaction prices</i>				
<i>A.1 All properties</i>				
Bedrooms _i	3.02	3.04	-0.05	0.64
Bathrooms _i	1.22	1.45	-0.49	0.60
Living Area _i	1273.29	1244.32	0.02	22.23
Lot Size _i	4889.46	5165.49	-0.18	0.49
School Distance _i	0.63	0.72	-0.22	0.83
School Rating _i	3.75	3.68	0.08	0.65
Building Age _i	77.82	83.07	-0.23	2.16
<i>A.2 Propensity score-matched properties</i>				
Bedrooms _i	3.00	2.99	0.02	0.94
Bathrooms _i	1.24	1.24	0.00	1.27
Living Area _i	1172.00	1181.56	-0.01	1.67
Lot Size _i	4768.81	4831.15	-0.04	1.37
School Distance _i	0.64	0.65	-0.01	1.06
School Rating _i	3.75	3.75	0.01	0.70
Building Age _i	82.37	82.84	-0.02	1.21
All	361	3,558		
Matched	289	662		
Unmatched	72	2,896		
<i>B. Deed records vs. Zillow-listed transaction prices</i>				
<i>B.1 All properties</i>				
Bedrooms _i	3.02	3.15	-0.18	0.15
Bathrooms _i	1.23	1.26	-0.05	0.64
Living Area _i	1205.16	1235.87	-0.04	0.73
Lot Size _i	4915.10	5022.26	-0.07	1.07
School Distance _i	0.58	0.55	0.11	0.77
School Rating _i	3.64	3.70	-0.08	0.61
Property Age _i	84.70	84.42	0.02	1.74
<i>B.2 Propensity score-matched properties</i>				
Bedrooms _i	3.14	3.04	0.14	1.41
Bathrooms _i	1.27	1.45	-0.35	0.78
Living Area _i	1334.73	1244.32	0.13	3.72
Lot Size _i	4825.34	5165.49	-0.23	0.46
School Distance _i	0.58	0.72	-0.47	0.44
School Rating _i	3.71	3.68	0.05	0.63
Property Age _i	85.11	83.07	0.15	0.79
All	55	3,558		
Matched	50	178		
Unmatched	5	3,380		

Table A.5: Borrowing behavior in response to DEX price premia and collateral

This table shows the regression results for Equation 4. The dependent variable is the cumulative change from day t to day $t+h$ in borrowing behavior for $h \in 1, 7, 30$ days. Borrowing behavior is measured by debt, collateral, leverage, borrowing capacity minus debt, and the debt-to-capacity ratio. The main explanatory variable is the secondary market price premium relative to the primary market price ($\ln P_{it}^{DEX} - \ln P_{it}^{PM} = q_{it}$). The asymmetric specification separates collateral undervaluation ($\max\{q_{it}, 0\}$) from collateral overvaluation ($\max\{-q_{it}, 0\}$). Observations during the transition from RMM V2 to RMM V3 (between January 31 and February 29, 2024) are excluded. All regressions include token and day fixed effects. Standard errors are clustered by token and day and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	$\ln Y_{it+h} - \ln Y_{it}$				
	Debt	Collateral	Leverage	Capacity-Debt	Debt/capacity
	(1)	(2)	(3)	(4)	(5)
<i>A. $h = 1$</i>					
Collateral undervaluation	0.0158 (0.0301)	0.0152 (0.0329)	-0.0004 (0.0017)	0.0187 (0.0286)	-0.0008 (0.0021)
Collateral undervaluation $\times$ Collateral V2 _{i}	-0.1746*** (0.0647)	-0.1775*** (0.0679)	-0.0039 (0.0029)	-0.1585*** (0.0606)	-0.0064 (0.0039)
Collateral overvaluation	0.0137 (0.0194)	0.0184 (0.0201)	-0.0002 (0.0010)	0.0181 (0.0180)	-0.0002 (0.0013)
Collateral overvaluation $\times$ Collateral V2 _{i}	-0.1131 (0.0758)	-0.1254 (0.0862)	-0.0024 (0.0035)	-0.1130 (0.0765)	-0.0037 (0.0046)
N	24,545	24,545	24,545	24,545	24,545
Adjusted R^2	0.288	0.289	0.182	0.291	0.222
<i>B. $h = 7$</i>					
Collateral undervaluation	0.0031 (0.1526)	0.0009 (0.1676)	-0.0041 (0.0060)	0.0290 (0.1511)	-0.0068 (0.0077)
Collateral undervaluation $\times$ Collateral V2 _{i}	-1.0003*** (0.3072)	-1.0767*** (0.3278)	-0.0240** (0.0112)	-0.9483*** (0.2895)	-0.0392** (0.0153)
Collateral overvaluation	0.0940 (0.0582)	0.1013 (0.0631)	0.0011 (0.0019)	0.0961 (0.0590)	0.0018 (0.0024)
Collateral overvaluation $\times$ Collateral V2 _{i}	-0.5738** (0.2578)	-0.6097** (0.2774)	-0.0126 (0.0087)	-0.5500** (0.2488)	-0.0190 (0.0118)
Adjusted R^2	0.307	0.311	0.194	0.315	0.243
N	24,486	24,486	24,486	24,486	24,486
<i>C. $h = 30$</i>					
Collateral undervaluation	-1.3304** (0.6104)	-1.4836** (0.6773)	-0.0586*** (0.0219)	-1.2524** (0.6062)	-0.0799*** (0.0287)
Collateral undervaluation $\times$ Collateral V2 _{i}	-1.4757** (0.7158)	-1.6623** (0.7861)	-0.0198 (0.0242)	-1.4217** (0.6977)	-0.0513 (0.0338)
Collateral overvaluation	-0.3032** (0.1202)	-0.3336** (0.1334)	-0.0145*** (0.0049)	-0.3006** (0.1221)	-0.0173*** (0.0060)
Collateral overvaluation $\times$ Collateral V2 _{i}	0.4393 (0.7623)	0.5477 (0.8217)	0.0279 (0.0229)	0.4933 (0.6987)	0.0326 (0.0368)
Adjusted R^2	0.236	0.233	0.206	0.232	0.223
N	23,770	23,770	23,770	23,770	23,770
Token FE	✓	✓	✓	✓	✓
Day FE	✓	✓	✓	✓	✓
#Tokens	525	525	525	525	525

Table A.6: Borrowing behavior in response to YAM price premia and collateral

This table shows the regression results for Equation 4. The dependent variable is the cumulative change from day t to day $t+h$ in borrowing behavior for $h \in 1, 7, 30$ days. Borrowing behavior is measured by debt, collateral, leverage, borrowing capacity minus debt, and the debt-to-capacity ratio. The main explanatory variable is the secondary market price premium relative to the primary market price ($\ln P_{it}^{YAM} - \ln P_{it}^{PM} = q_{it}$). The asymmetric specification separates collateral undervaluation ($\max\{q_{it}, 0\}$) from collateral overvaluation ($\max\{-q_{it}, 0\}$). Observations during the transition from RMM V2 to RMM V3 (between January 31 and February 29, 2024) are excluded. All regressions include token and day fixed effects. Standard errors are clustered by token and day and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	$\ln Y_{it+h} - \ln Y_{it}$				
	Debt	Collateral	Leverage	Capacity-Debt	Debt/capacity
	(1)	(2)	(3)	(4)	(5)
<i>A. $h = 1$</i>					
Collateral undervaluation	-0.0199 (0.0160)	-0.0209 (0.0179)	-0.0006 (0.0007)	-0.0196 (0.0164)	-0.0008 (0.0008)
Collateral undervaluation $\times$ Collateral V2 _{i}	-0.0392* (0.0235)	-0.0409 (0.0249)	-0.0018* (0.0011)	-0.0337 (0.0223)	-0.0023* (0.0014)
Collateral overvaluation	-0.0020 (0.0013)	-0.0021 (0.0015)	-0.0001** (0.0001)	-0.0016 (0.0014)	-0.0002** (0.0001)
Collateral overvaluation $\times$ Collateral V2 _{i}	0.0017 (0.0018)	0.0022 (0.0020)	0.0001 (0.0001)	0.0020 (0.0019)	0.0001 (0.0001)
Adjusted R^2	0.320	0.320	0.177	0.315	0.230
N	78,443	78,443	78,443	78,443	78,443
<i>B. $h = 7$</i>					
Collateral undervaluation	-0.0866 (0.0644)	-0.0986 (0.0720)	-0.0022 (0.0027)	-0.0928 (0.0645)	-0.0029 (0.0034)
Collateral undervaluation $\times$ Collateral V2 _{i}	-0.3792*** (0.1081)	-0.4117*** (0.1180)	-0.0156*** (0.0043)	-0.3586*** (0.1062)	-0.0200*** (0.0054)
Collateral overvaluation	-0.0007 (0.0054)	-0.0005 (0.0061)	-0.0002 (0.0002)	0.0001 (0.0055)	-0.0002 (0.0002)
Collateral overvaluation $\times$ Collateral V2 _{i}	-0.0086 (0.0075)	-0.0061 (0.0084)	-0.0007** (0.0003)	-0.0023 (0.0077)	-0.0012*** (0.0004)
Adjusted R^2	0.276	0.277	0.175	0.269	0.229
N	78,061	78,061	78,061	78,061	78,061
<i>C. $h = 30$</i>					
Collateral undervaluation	-0.7412*** (0.2377)	-0.8183*** (0.2633)	-0.0277*** (0.0086)	-0.7311*** (0.2373)	-0.0353*** (0.0110)
Collateral undervaluation $\times$ Collateral V2 _{i}	-1.0111*** (0.2507)	-1.1138*** (0.2762)	-0.0335*** (0.0094)	-1.0083*** (0.2491)	-0.0430*** (0.0120)
Collateral overvaluation	-0.0364 (0.0238)	-0.0390 (0.0268)	-0.0016* (0.0009)	-0.0338 (0.0241)	-0.0020* (0.0011)
Collateral overvaluation $\times$ Collateral V2 _{i}	0.0242 (0.0226)	0.0270 (0.0255)	0.0011 (0.0009)	0.0233 (0.0232)	0.0014 (0.0011)
Adjusted R^2	0.225	0.227	0.184	0.225	0.204
N	76,206	76,206	76,206	76,206	76,206
Token FE	✓	✓	✓	✓	✓
Day FE	✓	✓	✓	✓	✓
#Tokens	623	623	623	623	623

Table A.7: Borrowing behavior in response to DEX price premia and rental yield

This table shows the regression results for Equation 4. The dependent variable is the cumulative change from day t to day $t+h$ in borrowing behavior for $h \in 1, 7, 30$ days. Borrowing behavior is measured by debt, collateral, leverage, borrowing capacity minus debt, and the debt-to-capacity ratio. The main explanatory variable is the secondary market price premium relative to the primary market price ($\ln P_{it}^{DEX} - \ln P_{it}^{PM} = q_{it}$). The asymmetric specification separates collateral undervaluation ($\max\{q_{it}, 0\}$) from collateral overvaluation ($\max\{-q_{it}, 0\}$). Observations during the transition from RMM V2 to RMM V3 (between January 31 and February 29, 2024) are excluded. All regressions include token and day fixed effects. Standard errors are clustered by token and day and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	$\ln Y_{it+h} - \ln Y_{it}$				
	Debt	Collateral	Leverage	Capacity-Debt	Debt/capacity
	(1)	(2)	(3)	(4)	(5)
A. $h = 1$					
Collateral undervaluation	-0.0994 (0.1271)	-0.0717 (0.1347)	-0.0044 (0.0058)	-0.0448 (0.1173)	-0.0076 (0.0078)
Collateral undervaluation $\times$ RentalYield $_{it}$	0.0041 (0.0092)	0.0018 (0.0099)	0.0002 (0.0004)	0.0006 (0.0086)	0.0003 (0.0006)
Collateral overvaluation	-0.0055 (0.0998)	0.0054 (0.1083)	-0.0001 (0.0044)	0.0097 (0.0899)	-0.0011 (0.0062)
Collateral overvaluation $\times$ RentalYield $_{it}$	0.0003 (0.0100)	-0.0005 (0.0109)	-0.0000 (0.0004)	-0.0008 (0.0091)	0.0000 (0.0006)
RentalYield $_{it}$	-0.0008 (0.0024)	-0.0005 (0.0026)	-0.0000 (0.0001)	-0.0006 (0.0022)	-0.0000 (0.0001)
Adjusted R^2	0.294	0.295	0.184	0.297	0.227
N	24,348	24,348	24,348	24,348	24,348
B. $h = 7$					
Collateral undervaluation	-1.8914*** (0.7154)	-1.9813*** (0.7672)	-0.0705*** (0.0229)	-1.5757** (0.6515)	-0.1150*** (0.0362)
Collateral undervaluation $\times$ RentalYield $_{it}$	0.1225** (0.0506)	0.1271** (0.0544)	0.0047*** (0.0016)	0.1005** (0.0463)	0.0076*** (0.0026)
Collateral overvaluation	0.0687 (0.4147)	0.0989 (0.4424)	-0.0032 (0.0145)	0.1325 (0.3776)	-0.0055 (0.0218)
Collateral overvaluation $\times$ RentalYield $_{it}$	-0.0107 (0.0421)	-0.0138 (0.0449)	0.0001 (0.0015)	-0.0161 (0.0384)	0.0002 (0.0022)
RentalYield $_{it}$	-0.0142 (0.0095)	-0.0141 (0.0106)	-0.0006* (0.0004)	-0.0116 (0.0093)	-0.0009* (0.0005)
Adjusted R^2	0.316	0.320	0.199	0.323	0.251
N	24,289	24,289	24,289	24,289	24,289
C. $h = 30$					
Collateral undervaluation	-8.0072*** (2.1070)	-8.8435*** (2.2931)	-0.2433*** (0.0663)	-7.5231*** (2.0113)	-0.3893*** (0.0979)
Collateral undervaluation $\times$ RentalYield $_{it}$	0.5019*** (0.1541)	0.5504*** (0.1679)	0.0147*** (0.0049)	0.4684*** (0.1471)	0.0239*** (0.0072)
Collateral overvaluation	-1.1023 (1.1516)	-1.0389 (1.2198)	-0.0383 (0.0357)	-0.8384 (1.0411)	-0.0576 (0.0556)
Collateral overvaluation $\times$ RentalYield $_{it}$	0.0838 (0.1227)	0.0754 (0.1305)	0.0028 (0.0038)	0.0582 (0.1110)	0.0044 (0.0059)
RentalYield $_{it}$	-0.0724* (0.0390)	-0.0774* (0.0437)	-0.0022* (0.0013)	-0.0660* (0.0393)	-0.0035** (0.0017)
Adjusted R^2	0.234	0.232	0.204	0.231	0.221
N	23,573	23,573	23,573	23,573	23,573
Token FE	✓	✓	✓	✓	✓
Day FE	✓	✓	✓	✓	✓
#Tokens	525	525	525	525	525

Table A.8: Borrowing behavior in response to YAM price premia and rental yield

This table shows the regression results for Equation 4. The dependent variable is the cumulative change from day t to day $t+h$ in borrowing behavior for $h \in 1, 7, 30$ days. Borrowing behavior is measured by debt, collateral, leverage, borrowing capacity minus debt, and the debt-to-capacity ratio. The main explanatory variable is the secondary market price premium relative to the primary market price ($\ln P_{it}^{YAM} - \ln P_{it}^{PM} = q_{it}$). The asymmetric specification separates collateral undervaluation ($\max\{q_{it}, 0\}$) from collateral overvaluation ($\max\{-q_{it}, 0\}$). Observations during the transition from RMM V2 to RMM V3 (between January 31 and February 29, 2024) are excluded. All regressions include token and day fixed effects. Standard errors are clustered by token and day and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	$\ln Y_{it+h} - \ln Y_{it}$				
	Debt	Collateral	Leverage	Capacity-Debt	Debt/capacity
	(1)	(2)	(3)	(4)	(5)
<i>A. $h = 1$</i>					
Collateral undervaluation	-0.0653 (0.0548)	-0.0646 (0.0607)	-0.0019 (0.0024)	-0.0575 (0.0553)	-0.0026 (0.0030)
Collateral undervaluation $\times$ RentalYield _{it}	0.0028 (0.0035)	0.0026 (0.0039)	0.0001 (0.0002)	0.0023 (0.0035)	0.0001 (0.0002)
Collateral overvaluation	-0.0063 (0.0041)	-0.0067 (0.0048)	-0.0003 (0.0002)	-0.0050 (0.0046)	-0.0004 (0.0003)
Collateral overvaluation $\times$ RentalYield _{it}	0.0005 (0.0004)	0.0005 (0.0004)	0.0000 (0.0000)	0.0004 (0.0004)	0.0000 (0.0000)
RentalYield _{it}	0.0009 (0.0018)	0.0012 (0.0020)	0.0000 (0.0001)	0.0010 (0.0018)	0.0001 (0.0001)
Adjusted R^2	0.320	0.320	0.177	0.315	0.230
N	78,187	78,187	78,187	78,187	78,187
<i>B. $h = 7$</i>					
Collateral undervaluation	-0.4325** (0.1959)	-0.4800** (0.2198)	-0.0139* (0.0082)	-0.4324** (0.1981)	-0.0185* (0.0104)
Collateral undervaluation $\times$ RentalYield _{it}	0.0210* (0.0123)	0.0233* (0.0138)	0.0007 (0.0005)	0.0209* (0.0125)	0.0009 (0.0006)
Collateral overvaluation	-0.0319 (0.0282)	-0.0336 (0.0322)	-0.0016* (0.0008)	-0.0274 (0.0304)	-0.0021** (0.0011)
Collateral overvaluation $\times$ RentalYield _{it}	0.0030 (0.0027)	0.0032 (0.0031)	0.0001* (0.0001)	0.0028 (0.0029)	0.0002* (0.0001)
RentalYield _{it}	-0.0011 (0.0076)	-0.0014 (0.0084)	0.0001 (0.0002)	-0.0019 (0.0077)	0.0001 (0.0003)
Adjusted R^2	0.277	0.277	0.176	0.270	0.230
N	77,807	77,807	77,807	77,807	77,807
<i>C. $h = 30$</i>					
Collateral undervaluation	-2.5023*** (0.7177)	-2.7954*** (0.7907)	-0.0835*** (0.0289)	-2.5172*** (0.7058)	-0.1087*** (0.0365)
Collateral undervaluation $\times$ RentalYield _{it}	0.1177** (0.0525)	0.1324** (0.0575)	0.0037* (0.0022)	0.1197** (0.0512)	0.0048* (0.0027)
Collateral overvaluation	-0.0142 (0.0732)	-0.0108 (0.0829)	-0.0009 (0.0027)	-0.0083 (0.0752)	-0.0010 (0.0034)
Collateral overvaluation $\times$ RentalYield _{it}	-0.0018 (0.0064)	-0.0024 (0.0072)	-0.0001 (0.0002)	-0.0022 (0.0065)	-0.0001 (0.0003)
RentalYield _{it}	0.0152 (0.0277)	0.0173 (0.0308)	0.0008 (0.0009)	0.0144 (0.0282)	0.0010 (0.0011)
Adjusted R^2	0.226	0.228	0.185	0.225	0.206
N	75,961	75,961	75,961	75,961	75,961
Token FE	✓	✓	✓	✓	✓
Day FE	✓	✓	✓	✓	✓
#Tokens	622	622	622	622	622

Table A.9: Borrowing behavior in response to DEX and YAM price premia

This table shows the regression results for Equation 4. The dependent variable is the cumulative change from day t to day $t+h$ in borrowing behavior for $h \in 1, 7, 30$ days. Borrowing behavior is measured by debt, collateral, leverage, borrowing capacity minus debt, and the debt-to-capacity ratio. The main explanatory variables are the DEX and YAM secondary market price premia relative to the primary market price ($\ln P_{it}^{SM} - \ln P_{it}^{PM} = q_{it}$). The asymmetric specification separates collateral undervaluation ($\max\{q_{it}, 0\}$) from collateral overvaluation ($\max\{-q_{it}, 0\}$). Observations during the transition from RMM V2 to RMM V3 (between January 31 and February 29, 2024) are excluded. All regressions include token and day fixed effects. Standard errors are clustered by token and day and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	$\ln Y_{it+h} - \ln Y_{it}$				
	Debt	Collateral	Leverage	Capacity-Debt	Debt/capacity
	(1)	(2)	(3)	(4)	(5)
<i>A. $h = 1$</i>					
DEX collateral undervaluation = U_{it}^{DEX}	0.0380 (0.0448)	0.0377 (0.0491)	0.0012 (0.0022)	0.0338 (0.0428)	0.0016 (0.0028)
YAM collateral undervaluation = U_{it}^{YAM}	0.0026 (0.0120)	0.0059 (0.0134)	-0.0003 (0.0007)	0.0064 (0.0121)	-0.0003 (0.0009)
DEX collateral overvaluation = O_{it}^{DEX}	-0.0353** (0.0168)	-0.0315* (0.0164)	-0.0017* (0.0011)	-0.0280* (0.0146)	-0.0022* (0.0013)
YAM collateral overvaluation = O_{it}^{YAM}	-0.0005 (0.0010)	-0.0008 (0.0010)	-0.0000 (0.0001)	-0.0007 (0.0009)	-0.0000 (0.0001)
N	21,911	21,911	21,911	21,911	21,911
#Tokens	525	525	525	525	525
Adjusted R^2	0.357	0.354	0.164	0.351	0.238
<i>B. $h = 7$</i>					
DEX collateral undervaluation = U_{it}^{DEX}	-0.0110 (0.0952)	-0.0134 (0.1057)	-0.0010 (0.0042)	-0.0091 (0.0938)	-0.0013 (0.0053)
YAM collateral undervaluation = U_{it}^{YAM}	0.0328 (0.0448)	0.0404 (0.0503)	0.0007 (0.0020)	0.0376 (0.0436)	0.0009 (0.0025)
DEX collateral overvaluation = O_{it}^{DEX}	-0.1371*** (0.0447)	-0.1483*** (0.0496)	-0.0050** (0.0022)	-0.1311*** (0.0453)	-0.0064** (0.0027)
YAM collateral overvaluation = O_{it}^{YAM}	-0.0042** (0.0017)	-0.0025 (0.0024)	-0.0005* (0.0003)	-0.0002 (0.0031)	-0.0008* (0.0005)
N	21,844	21,844	21,844	21,844	21,844
#Tokens	525	525	525	525	525
Adjusted R^2	0.515	0.512	0.278	0.504	0.394
<i>C. $h = 30$</i>					
DEX collateral undervaluation = U_{it}^{DEX}	-0.2275 (0.2270)	-0.2347 (0.2525)	-0.0180** (0.0091)	-0.1803 (0.2258)	-0.0218* (0.0117)
YAM collateral undervaluation = U_{it}^{YAM}	-0.0929 (0.0871)	-0.1006 (0.0967)	-0.0048 (0.0032)	-0.0854 (0.0877)	-0.0064 (0.0042)
DEX collateral overvaluation = O_{it}^{DEX}	-0.5252*** (0.1765)	-0.5458*** (0.2014)	-0.0168*** (0.0065)	-0.4969*** (0.1837)	-0.0218*** (0.0083)
YAM collateral overvaluation = O_{it}^{YAM}	0.0599 (0.0630)	0.0643 (0.0744)	0.0020 (0.0020)	0.0574 (0.0687)	0.0026 (0.0025)
N	20,838	20,838	20,838	20,838	20,838
#Tokens	525	525	525	525	525
Adjusted R^2	0.300	0.299	0.229	0.293	0.267
Token FE	✓	✓	✓	✓	✓
Day FE	✓	✓	✓	✓	✓

Table A.10: Borrowing behavior in response to DEX and YAM (dis)agreement

This table shows the regression results for Equation 4. The dependent variable is the cumulative change from day t to day $t + h$ in borrowing behavior for $h \in 1, 7, 30$ days. Borrowing behavior is measured by debt, collateral, leverage, borrowing capacity minus debt, and the debt-to-capacity ratio. The main explanatory variable is the secondary market price premium relative to the primary market price ($\ln P_{it}^{DEX} - \ln P_{it}^{PM} = q_{it}$). The asymmetric specification separates collateral undervaluation ($\max\{q_{it}, 0\}$) from collateral overvaluation ($\max\{-q_{it}, 0\}$). Both DEX and YAM agreeing on collateral undervaluation is the omitted category. Observations during the transition from RMM V2 to RMM V3 (between January 31 and February 29, 2024) are excluded. All regressions include token and day fixed effects. Standard errors are clustered by token and day and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	$\ln Y_{it+h} - \ln Y_{it}$				
	Debt	Collateral	Leverage	Capacity-Debt	Debt/capacity
	(1)	(2)	(3)	(4)	(5)
<i>A. $h = 1$</i>					
<i>A.1 Agreement</i>					
DEX & YAM collateral overvaluation $_{it}$	0.0058 (0.0085)	0.0042 (0.0091)	0.0006 (0.0004)	0.0023 (0.0080)	0.0007 (0.0005)
<i>A.2 Disagreement</i>					
DEX collateral valuation < YAM collateral valuation $_{it}$	0.0196 (0.0129)	0.0197 (0.0142)	0.0009 (0.0006)	0.0168 (0.0126)	0.0011 (0.0007)
DEX collateral valuation > YAM collateral valuation $_{it}$	0.0061 (0.0115)	0.0086 (0.0132)	0.0003 (0.0005)	0.0078 (0.0118)	0.0003 (0.0006)
N	21,294	21,294	21,294	21,294	21,294
#Tokens	525	525	525	525	525
Adjusted R^2	0.367	0.364	0.170	0.361	0.247
<i>B. $h = 7$</i>					
<i>B.1 Agreement</i>					
DEX & YAM collateral overvaluation $_{it}$	-0.0389 (0.0278)	-0.0404 (0.0307)	-0.0022* (0.0013)	-0.0320 (0.0270)	-0.0028* (0.0016)
<i>B.2 Disagreement</i>					
DEX collateral valuation < YAM collateral valuation $_{it}$	-0.0090 (0.0255)	-0.0081 (0.0281)	-0.0011 (0.0012)	-0.0032 (0.0244)	-0.0014 (0.0015)
Disagreement: D_{it}^{OU}	0.0342 (0.0287)	0.0381 (0.0321)	0.0018 (0.0011)	0.0334 (0.0290)	0.0021 (0.0014)
N	21,227	21,227	21,227	21,227	21,227
#Tokens	525	525	525	525	525
Adjusted R^2	0.513	0.510	0.276	0.503	0.392
<i>C. $h = 30$</i>					
<i>C.1 Agreement</i>					
DEX & YAM collateral overvaluation $_{it}$	-0.1117 (0.0771)	-0.1201 (0.0849)	-0.0041 (0.0029)	-0.1082 (0.0758)	-0.0051 (0.0037)
<i>C.2 Disagreement</i>					
DEX collateral valuation < YAM collateral valuation $_{it}$	0.0649 (0.0754)	0.0707 (0.0840)	0.0030 (0.0025)	0.0572 (0.0759)	0.0044 (0.0033)
DEX collateral valuation > YAM collateral valuation $_{it}$	0.0606 (0.0687)	0.0704 (0.0758)	0.0019 (0.0026)	0.0680 (0.0679)	0.0021 (0.0034)
N	20,241	20,241	20,241	20,241	20,241
#Tokens	525	525	525	525	525
Adjusted R^2	0.301	0.300	0.227	0.294	0.267
Token FE	✓	✓	✓	✓	✓
Day FE	✓	✓	✓	✓	✓

Table A.11: Feedback between DEX prices and leverage

	$\ln Y_{it+h} - \ln Y_{it}$					
	$h = 1$	$h = 7$	$h = 30$	$h = 1$	$h = 7$	$h = 30$
	(1)	(2)	(3)	(4)	(5)	(6)
A. DEX returns $\rightarrow$ Leverage						
$\Delta \ln P_{it}^{DEX}$	-0.0000 (0.0015)	-0.0018 (0.0017)	-0.0024 (0.0051)	-0.0002 (0.0019)	-0.0014 (0.0021)	-0.0071 (0.0073)
$\Delta \ln P_{it-1}^{DEX}$	0.0005 (0.0012)	0.0009 (0.0019)	-0.0063 (0.0047)	-0.0002 (0.0007)	0.0004 (0.0023)	-0.0009 (0.0063)
$\Delta \ln \text{Leverage}_{it-1}$	0.0069 (0.0101)	0.0157 (0.0259)	-0.1342** (0.0547)	0.0079 (0.0096)	0.0106 (0.0283)	-0.1304** (0.0578)
DEX order imbalance $_{it-1}$				0.0002 (0.0002)	-0.0001 (0.0007)	-0.0024 (0.0017)
$\ln \text{DEX liquidity}_{it-1}$				-0.0027 (0.0017)	-0.0007 (0.0055)	-0.0065 (0.0179)
DEX price impact/slippage $_{it-1}$				0.0021 (0.0021)	0.0002 (0.0108)	-0.0035 (0.0268)
N	13,275	13,237	12,771	10,666	10,633	10,274
#Tokens	416	415	398	416	415	398
Adjusted R^2	0.246	0.257	0.277	0.185	0.252	0.276
Leverage $\rightarrow$ DEX returns						
$\Delta \ln \text{Leverage}_{it}$	-0.0248 (0.0202)	-0.0252 (0.0917)	-0.1286 (0.1172)	-0.0327 (0.0295)	-0.0813 (0.1245)	-0.2009 (0.1671)
$\Delta \ln \text{Leverage}_{it-1}$	-0.0110 (0.0230)	0.0319 (0.0897)	0.0247 (0.1024)	-0.0006 (0.0241)	0.0464 (0.0994)	-0.0199 (0.1054)
$\Delta \ln P_{i,t-1}^{DEX}$	-0.0826*** (0.0277)	-0.1982*** (0.0701)	-0.2287*** (0.0724)	-0.0743** (0.0313)	-0.1788*** (0.0679)	-0.1888*** (0.0730)
DEX order imbalance $_{i,t-1}$				0.0051*** (0.0018)	0.0065** (0.0029)	0.0107*** (0.0035)
$\ln \text{DEX liquidity}_{i,t-1}$				-0.0373** (0.0176)	-0.1297*** (0.0414)	-0.1748*** (0.0466)
DEX price impact/slippage $_{i,t-1}$				-0.0080 (0.0414)	-0.1198 (0.0774)	-0.2216** (0.0938)
N	9,017	6,101	5,947	6,408	5,014	4,902
#Tokens	325	207	178	235	193	172
Adjusted R^2	0.417	0.523	0.543	0.467	0.567	0.589
B. DEX premium $\rightarrow$ Leverage						
$\ln P_{it}^{SM} - \ln P_{it}^{PM}$	-0.0020** (0.0009)	-0.0135*** (0.0047)	-0.0635*** (0.0151)	-0.0010 (0.0012)	-0.0173*** (0.0061)	-0.0851*** (0.0208)
$\Delta \ln P_{i,t-1}^{DEX}$	0.0008 (0.0013)	0.0038** (0.0017)	0.0064 (0.0051)	-0.0000 (0.0008)	0.0034 (0.0021)	0.0136*** (0.0050)
$\Delta \ln \text{Leverage}_{it-1}$	0.0068 (0.0101)	0.0153 (0.0258)	-0.1364** (0.0531)	0.0079 (0.0096)	0.0096 (0.0285)	-0.1351** (0.0576)
DEX order imbalance $_{i,t-1}$				0.0002 (0.0002)	-0.0003 (0.0006)	-0.0036** (0.0018)
$\ln \text{DEX liquidity}_{i,t-1}$				-0.0024 (0.0017)	0.0039 (0.0059)	0.0159 (0.0193)
DEX price impact/slippage $_{i,t-1}$				0.0024 (0.0024)	0.0054 (0.0110)	0.0217 (0.0267)
N	13,275	13,237	12,771	10,666	10,633	10,274
#Tokens	416	415	398	416	415	398
Adjusted R^2	0.246	0.258	0.280	0.185	0.254	0.281
Leverage $\rightarrow$ DEX premium						
$\Delta \ln \text{Leverage}_{it}$	-0.0248 (0.0202)	-0.0253 (0.0917)	-0.1287 (0.1172)	-0.0327 (0.0295)	-0.0814 (0.1245)	-0.2011 (0.1672)
$\Delta \ln \text{Leverage}_{it-1}$	-0.0110 (0.0230)	0.0319 (0.0898)	0.0247 (0.1024)	-0.0006 (0.0241)	0.0463 (0.0994)	-0.0199 (0.1054)
$\Delta \ln P_{i,t-1}^{DEX}$	-0.0826*** (0.0277)	-0.1981*** (0.0702)	-0.2287*** (0.0724)	-0.0743** (0.0313)	-0.1788*** (0.0680)	-0.1887*** (0.0730)
DEX order imbalance $_{i,t-1}$				0.0051*** (0.0018)	0.0065** (0.0029)	0.0106*** (0.0035)
$\ln \text{DEX liquidity}_{i,t-1}$				-0.0373** (0.0176)	-0.1298*** (0.0415)	-0.1750*** (0.0467)
DEX price impact/slippage $_{i,t-1}$				-0.0080 (0.0414)	-0.1172 (0.0778)	-0.2213** (0.0939)
N	9,017	6,101	5,947	6,408	5,014	4,902
#Tokens	325	207	178	235	193	172
Adjusted R^2	0.417	0.523	0.543	0.467	0.566	0.589
Token FE	✓	✓	✓	✓	✓	✓
Day FE	✓	✓	✓	✓	✓	✓

Table A.12: Feedback between YAM prices and leverage

	$\ln Y_{it+h} - \ln Y_{it}$					
	$h = 1$	$h = 7$	$h = 30$	$h = 1$	$h = 7$	$h = 30$
	(1)	(2)	(3)	(4)	(5)	(6)
A. YAM returns $\rightarrow$ Leverage						
$\Delta \ln P_{it}^{YAM}$	-0.0000 (0.0001)	0.0001 (0.0001)	-0.0004 (0.0008)	-0.0000 (0.0001)	0.0000 (0.0002)	-0.0013 (0.0017)
$\Delta \ln P_{it-1}^{YAM}$	0.0000 (0.0000)	-0.0001 (0.0001)	-0.0004 (0.0009)	0.0000 (0.0000)	-0.0001 (0.0001)	-0.0009 (0.0009)
$\Delta \ln \text{Leverage}_{it-1}$	-0.0177** (0.0070)	-0.0404*** (0.0090)	-0.1266*** (0.0305)	-0.0197*** (0.0062)	-0.0393*** (0.0110)	-0.1260*** (0.0289)
YAM order imbalance $_{it-1}$				-0.0000 (0.0003)	0.0004 (0.0005)	-0.0003 (0.0012)
$\ln \text{YAM listing duration}_{it-1}$				0.0001 (0.0001)	0.0004* (0.0002)	0.0010** (0.0004)
YAM bid-ask spread $_{it-1}$				0.0004 (0.0006)	0.0023** (0.0011)	0.0011 (0.0039)
Observations	50,140	49,900	48,565	38,320	38,150	37,129
Token contracts	622	622	622	622	622	622
Adjusted R^2	0.215	0.200	0.245	0.209	0.211	0.252
Leverage $\rightarrow$ YAM returns						
$\Delta \ln \text{Leverage}_{it}$	0.0277 (0.0281)	0.0876 (0.0959)	-0.1668 (0.3239)	0.0577 (0.0353)	-0.0634 (0.1002)	-0.2672 (0.4151)
$\Delta \ln \text{Leverage}_{it-1}$	-0.0737 (0.0830)	0.0446 (0.0646)	-0.2733 (0.2187)	-0.1051 (0.1192)	0.0926 (0.0967)	-0.0580 (0.0726)
$\Delta \ln P_{it-1}^{YAM}$	-0.1817*** (0.0486)	-0.3200*** (0.0794)	-0.2668*** (0.0663)	-0.1853*** (0.0483)	-0.3134*** (0.0742)	-0.2699*** (0.0672)
YAM order imbalance $_{it-1}$				-0.0093 (0.0095)	-0.0323** (0.0164)	-0.0073 (0.0209)
$\ln \text{YAM listing duration}_{it-1}$				-0.0030 (0.0025)	-0.0094** (0.0039)	-0.0065* (0.0034)
YAM bid-ask spread $_{it-1}$				-0.0427 (0.0968)	-0.1449* (0.0834)	0.1195 (0.0808)
N	34,905	24,968	21,115	23,085	19,373	16,364
#Tokens	622	615	611	617	612	610
Adjusted R^2	0.133	0.237	0.237	0.162	0.269	0.226
B. YAM price premium $\rightarrow$ Leverage						
$\ln P_{it}^{SM} - \ln P_{it}^{PM}$	0.0000 (0.0000)	0.0002 (0.0002)	-0.0004 (0.0014)	0.0000 (0.0001)	-0.0000 (0.0002)	-0.0014 (0.0019)
$\Delta \ln P_{it-1}^{YAM}$	0.0000 (0.0000)	-0.0001 (0.0001)	-0.0002 (0.0006)	0.0000 (0.0000)	-0.0001 (0.0001)	-0.0002 (0.0006)
$\Delta \ln \text{Leverage}_{it-1}$	-0.0177** (0.0070)	-0.0404*** (0.0090)	-0.1266*** (0.0305)	-0.0197*** (0.0062)	-0.0393*** (0.0110)	-0.1260*** (0.0289)
YAM order imbalance $_{it-1}$				-0.0000 (0.0003)	0.0004 (0.0005)	-0.0002 (0.0012)
$\ln \text{YAM listing duration}_{it-1}$				0.0001 (0.0001)	0.0004* (0.0002)	0.0010** (0.0004)
YAM bid-ask spread $_{it-1}$				0.0004 (0.0006)	0.0023** (0.0011)	0.0010 (0.0039)
N	50,140	49,900	48,565	38,320	38,150	37,129
#Tokens	622	622	622	622	622	622
Adjusted R^2	0.215	0.200	0.245	0.209	0.211	0.252
Leverage $\rightarrow$ YAM price premium						
$\Delta \ln \text{Leverage}_{it}$	0.0276 (0.0281)	0.0893 (0.0957)	-0.1695 (0.3235)	0.0574 (0.0353)	-0.0627 (0.1002)	-0.2725 (0.4143)
$\Delta \ln \text{Leverage}_{it-1}$	-0.0738 (0.0830)	0.0452 (0.0644)	-0.2760 (0.2184)	-0.1050 (0.1192)	0.0933 (0.0966)	-0.0608 (0.0721)
$\Delta \ln P_{it-1}^{YAM}$	-0.1817*** (0.0486)	-0.3200*** (0.0794)	-0.2668*** (0.0663)	-0.1853*** (0.0483)	-0.3134*** (0.0742)	-0.2699*** (0.0672)
YAM order imbalance $_{it-1}$				-0.0094 (0.0095)	-0.0324** (0.0164)	-0.0073 (0.0209)
$\ln \text{YAM listing duration}_{it-1}$				-0.0030 (0.0025)	-0.0094** (0.0039)	-0.0066* (0.0034)
YAM bid-ask spread $_{it-1}$				-0.0427 (0.0968)	-0.1448* (0.0835)	0.1199 (0.0806)
N	34,905	24,968	21,115	23,085	19,373	16,364
#Tokens	622	615	611	617	612	610
Adjusted R^2	0.133	0.237	0.237	0.162	0.269	0.226
Token FE	✓	✓	✓	✓	✓	✓
Day FE	✓	✓	✓	✓	✓	✓

Table A.13: Borrower strategy classification after taking out a loan

This table shows how borrowers use and manage a new loan over the following 1, 7, and 30 days. We classify each loan based on the actions taken by the same wallet during this period. For example, a stablecoin leverage loop occurs when a borrower takes out a loan, deposits stablecoins as collateral, borrows again, and subsequently deposits additional stablecoins as collateral. A real estate leverage loop occurs when a borrower takes out a loan, purchases real estate tokens, pledges them as collateral, borrows again, and then purchases additional real estate tokens. To exclude very small loops, the amount involved in the loop must be at least 25% of the initial loan. A combined leverage loop uses both stablecoins and real estate tokens. Deleveraging means repaying part or all of the outstanding debt only. Leveraging means taking out further credit without completing a loop. Active debt management captures borrowers who repeatedly adjust their debt and collateral positions (by both leveraging and deleveraging) without completing a leverage loop. The total value of these adjustments must be at least 50% of the initial loan. A leveraged real estate purchase means buying real estate tokens with borrowed funds without completing a leverage loop. Passive borrowers show little follow-up activity after the initial loan. All remaining observations are classified as other mixed strategies. Observations during the transition from RMM V2 to RMM V3 (between January 31 and February 29, 2024) are excluded.

	% of new loans			% of initial loan value		
	$h = 1$	$h = 7$	$h = 30$	$h = 1$	$h = 7$	$h = 30$
Stablecoin leverage loop	3.0%	5.2%	8.6%	3.5%	6.1%	10.1%
Real estate leverage loop	8.1%	15.0%	23.2%	4.7%	8.2%	12.8%
Combined Real estate/stablecoin leverage loop	0.7%	4.2%	14.6%	0.3%	1.9%	6.4%
Deleverage	5.3%	3.4%	1.6%	11.7%	6.5%	3.7%
Leverage	5.1%	2.9%	1.7%	5.2%	3.7%	2.1%
Active debt management (Leverage + Deleverage)	18.0%	33.1%	35.2%	23.2%	41.0%	48.8%
Leveraged real estate purchase	32.7%	26.7%	11.8%	17.0%	14.8%	8.1%
Passive borrowing	22.2%	6.5%	2.0%	27.3%	11.7%	4.0%
Other mixed strategy	5.0%	3.0%	1.3%	7.2%	6.1%	4.0%
New loans	88,286	87,810	85,671			

Table A.14: Average borrowing and holdings by borrower strategy

This table shows how borrowers use and manage a new loan over the following 1, 7, and 30 days. All reported values are conditional means in \$ over the respective horizon. Gross borrowing includes the initial loan and any additional borrowing, while net borrowing subtracts repayments. Real estate token purchases and sales combine DEX, YAM, and primary-market transactions. Real estate token holdings include tokens held in wallets and collateral deposited on the lending platform. Stablecoin holdings include stablecoins (WXDAI and USDC) held in wallets and stablecoin collateral deposited on the lending platform. Holdings are measured at the end of each horizon. Observations during the transition from RMM V2 to RMM V3 (between January 31 and February 29, 2024) are excluded.

	New borrowing		Real estate tokens				Stablecoin	N
	Gross	Net	Purchases	Sales	Purchases-Sales	Holdings	Holdings	
A. $h = 1$								
Stablecoin leverage loop	5,774	1,361	1,235	373	861	52,929	2,572	2,612
Real estate leverage loop	4,319	3,434	4,264	143	4,121	126,897	490	7,118
Combined leverage loop	6,954	5,281	6,274	537	5,737	107,145	1,254	628
Leverager	2,580	2,578	6	7	-1	74,599	780	4,515
Deleverager	1,796	-257	8	81	-73	56,905	1,014	4,710
Active debt manager	3,190	763	899	341	558	74,079	905	15,857
Leveraged real estate buyer	476	408	544	22	521	39,861	707	28,869
Passive borrower	891	890	1	5	-4	41,367	842	19,597
Other mixed strategy	1,073	1,042	20	15	6	44,794	1,156	4,380
B. $h = 7$								
Stablecoin leverage loop	13,252	874	4,257	2,458	1,799	61,726	2,456	4,529
Real estate leverage loop	7,970	5,187	7,326	678	6,648	87,152	533	13,210
Combined leverage loop	25,436	12,183	23,429	3,280	20,149	134,583	1,413	3,695
Leveraged real estate buyer	608	495	684	23	662	31,840	660	23,457
Leverager	4,293	4,288	22	15	7	66,378	727	2,588
Deleverager	1,538	-361	17	166	-149	44,477	855	2,952
Active debt manager	4,989	1,033	1,292	603	689	66,458	1,028	29,075
Passive borrower	1,311	1,307	8	16	-9	28,468	540	5,667
Other mixed strategy	1,513	1,466	56	31	25	40,950	1,163	2,637
C. $h = 30$								
Stablecoin leverage loop	18,760	1,048	6,654	4,499	2,155	63,090	1,894	7,341
Real estate leverage loop	9,676	4,627	7,370	993	6,377	66,361	414	19,907
Combined leverage loop	44,725	19,825	39,595	8,816	30,779	114,037	1,148	12,510
Leveraged real estate buyer	924	767	1,234	43	1,192	26,270	445	10,149
Leverager	2,873	2,869	30	8	22	35,803	460	1,417
Deleverager	1,828	-568	25	302	-277	25,413	454	1,379
Active debt manager	8,786	1,883	1,778	744	1,034	58,031	1,000	30,197
Passive borrower	1,484	1,477	8	35	-27	19,317	305	1,675
Other mixed strategy	2,362	2,255	82	48	34	31,803	560	1,096