BIS Working Papers

No 1311

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Monetary and Economic Department

November 2025

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This publication is available on the BIS website (www.bis.org).

ISSN 1020-0959 (print)
ISSN 1682-7678 (online)

When Bricks Meet Bytes: Does Tokenisation Fill Gaps in Traditional Real Estate Markets?*

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27 November 2025

Abstract

Using novel US data from multiple platforms over 2019–25, I show that real estate tokenisation fills gaps in traditional markets. The supply of tokenised real estate is driven by pricing, demand, liquidity and supply in the physical property market. These factors affect the supply of traditional real estate properties and Real Estate Investment Trust (REIT) portfolios differently. Areas with limited access to credit see more rapid growth in tokenised properties, suggesting tokenisation may bridge gaps in access to real estate. Finally, to test whether tokenisation can address liquidity gaps, I analyse trading activity around natural disasters as an exogenous liquidity shock. Trading in tokenised properties rises by 35% cumulatively over the two days following a disaster. This suggests that tokenisation can preserve liquidity when it typically dries up, but only if platforms provide buyback features, which comes with higher insolvency risk.

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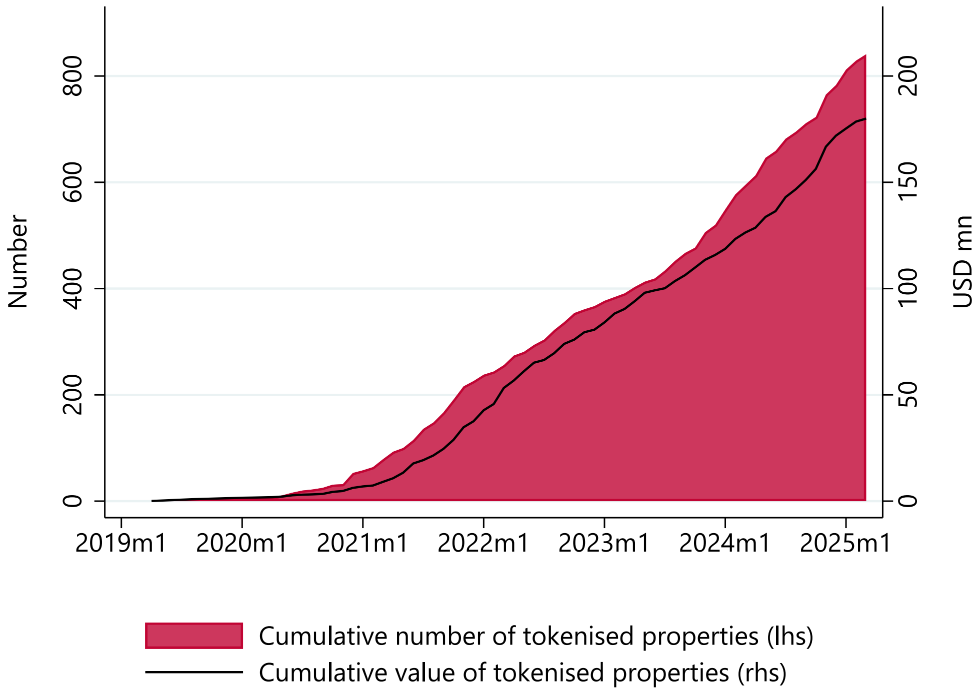
1 Introduction

Is tokenisation the next leap in financial innovation? By leveraging blockchain technology to represent assets – including ownership rights of real-world assets – as digital tokens, tokenisation enables fractional ownership and offers potential benefits such as 24/7 trading and lower barriers to entry across a wide range of asset classes, including art, collectibles, infrastructure, real estate and financial assets such as stocks, bonds and trade finance, to name a few (Aldasoro et al., 2023; Financial Stability Board (FSB), 2023; Schär, 2021). Tokenisation can also introduce greater transparency and efficiency by automating processes through smart contracts, which may reduce transaction costs, minimise the need for intermediaries and enable the contingent performance of actions through programmability – potentially expanding the universe of contracts (Aldasoro et al., 2023) or completing the market (Ross, 1976; Arrow and Debreu, 1954). As tokenisation continues to gain traction, it holds the potential to fundamentally reshape how assets are owned, traded and managed.

Tokenisation could transform real estate, an asset class typically characterised by illiquidity and complex transaction processes. By enabling fractional ownership of properties, tokenisation could make real estate investments more accessible and potentially more liquid, while also enhancing diversification opportunities both across asset classes and within the real estate sector. This innovation has garnered significant attention as it targets key inefficiencies in traditional real estate markets, such as lengthy transaction times, high barriers to entry, the involvement of multiple intermediaries and limited liquidity (Baum, 2021; Yermack, 2017). As the tokenisation of real estate properties gains momentum globally, it is important to understand its drivers, whether it fills any gap in traditional markets, and the fragilities it may introduce. This is relevant for policymakers, investors and market participants.

The market for tokenised real estate is still nascent. In the United States, one of the largest markets for tokenised properties, the notional value of residential and commercial listings enabling tokenised fund- and property-level investments exceeded USD 10 billion. The subset of these listings enabling property-level investment is rapidly approaching 1,000, representing a total value of approximately USD 200 million as of February 2025 (Figure 1). Beyond the United States, jurisdictions such as Switzerland, the United Arab Emirates and Singapore are also witnessing growing adoption of real estate tokenisation. These developments suggest that tokenisation could emerge as a transformative force in real estate investment globally.

Figure 1: **The growth of tokenised real estate in the United States**



Note: The figure shows the cumulative number of property-level tokenised real estate properties (left-hand axis) and the associated cumulative value (right-hand axis) in the United States. Sources: Blocksquare; LoftyAI; RealT; author's calculations.

This paper evaluates the development of tokenised real estate in the US over 2019–25 combining data from multiple platforms, with the aim of establishing whether tokenisation fills gaps in access and in liquidity observed in traditional real estate markets. To address this broader question, I break it down into three interconnected sub-questions. First, do traditional real estate market forces and structural characteristics of credit intermediation drive the development of tokenised real estate? Second, do these forces have a different effect on "conventional" real estate assets such as traditional real estate properties or real estate investment trust (REIT) portfolios? Finally, how does trading activity in tokenised real estate respond to exogenous shocks, such as natural disasters? Specifically, is the premium investors pay for tokenised properties justified by higher liquidity during periods when liquidity typically dries up? These questions are critical for understanding the unique characteristics of real estate tokenisation and its interaction with traditional real estate markets.

While real estate tokenisation may enable broader access to real estate assets, the areas targeted by investors in tokenised properties exhibit distinct characteristics. My findings suggest that investors in tokenised properties tend to focus on undervalued areas where the economic fundamentals of the real estate market are weaker. In contrast, investors in traditional real estate properties prefer areas with stronger fundamentals, reflecting a preference for established residential areas and potentially an intention to reside in the property. Interestingly, but consistent with the intrinsic characteristics of the product, REITs occupy a middle ground. Specifically, as investment vehicles not intended for personal residence, REITs share characteristics with tokenised real estate in terms of liquidity, but diverge in other dimensions.

By targeting areas with distinct features, real estate tokenisation has the potential to enhance financial inclusion. The findings indicate that real estate tokenisation tends to develop in areas with lower bank presence, with fewer bank and non-bank lenders and with higher market concentration, where gaining exposure to real estate, even for diversification purposes, can be more challenging. This evidence is consistent with tokenisation addressing unmet demand left by traditional financial intermediaries and potentially completing the market by introducing an instrument to access real estate in these areas (Ross, 1976; Arrow and Debreu, 1954).

Traditional real estate markets are notoriously affected by lengthy transaction times and fragmented processes that require coordination among multiple parties, who often operate in silos (Saull and Baum, 2019; Agarwal et al., 2019). Tokenisation could enable access to a broader investor base through fractionalisation – the process of dividing ownership of an asset into smaller units, allowing multiple investors to hold fractional ownership. Interestingly, the evidence suggests that it also enhances market liquidity – defined as the availability of a counterparty willing to take the opposite side of a trade – even during periods when liquidity typically dries up, such as after a natural disaster.[1] Ex-ante, the expectation following a natural disaster is that the

[1]Market liquidity is typically defined as the ability to sell an asset on short notice at a minimal price discount and is often proxied by measures based on price spreads and/or transaction volumes (Chordia et al., 2001; Goyenko et al., 2009; Nyborg and Östberg, 2014; Huang and Wang, 2009). I focus on volumes because real estate token prices are not always free-floating but often require a re-appraisal of the property value, which typically takes several

number of transactions will decline (Sheldon and Zhan, 2019; Wesley, 2024). However, the evidence shows an increase. This could be attributed to two mechanisms. First, the easier access to information about the property, which is centralised on the blockchain or the tokenisation platform. Such centralisation allows prospective investors to identify properties that were not damaged by the disaster and could benefit from the mechanically reduced supply in the area. Second, the increase in trading activity could stem from token buyback features offered by the platform, which guarantee an exit option for investors, albeit at the cost of higher insolvency risk for the platform. These buyback features function as a backstop provided by the platform and resemble the sponsor support mechanisms observed in money market funds, where sponsors step in to provide liquidity during periods of stress. However, as documented by Parlatore 2016, sponsor support may prove ineffective during systemic shocks and can even amplify such shocks due to the higher risk-taking of fund managers in the presence of sponsor support (Kacperczyk and Schnabl 2013). Similarly, in the context of tokenised real estate, the reliance on buyback features could exacerbate risks, particularly in the event of a crisis in the housing market.

This paper makes four contributions to the growing literature on tokenisation. First, it is the first study to conduct an empirical analysis of tokenised real estate that combines data from multiple tokenisation platforms. This approach exploits richer geographical variation and it accounts for new data – up to 2025 – which is a major improvement in a nascent but fast-growing market. Second, this paper is the first to document the traditional real estate market forces – such as pricing, demand, liquidity and supply – that drive the development of tokenised properties. Importantly, these drivers exhibit distinct effects compared with traditional real estate properties and REIT portfolios. Moreover, the paper provides novel evidence on the role of access to credit in shaping the growth of tokenised real estate, highlighting how tokenisation may address gaps in access to real estate assets. Finally, this study complements existing research by demonstrating that the higher liquidity offered by tokenisation in the face of exogenous shocks is contingent to specific institutional design features – such as the (limited) buyback of tokens over short periods – which involve a trade-off with higher solvency risks for the platform.

weeks and is carried out on an yearly schedule.

Related literature. This work contributes to the growing literature on tokenisation by documenting its application to the real estate market. The existing literature is predominantly theoretical, addressing issues such as market competition under tokenisation (Goldstein et al., 2024; Chod and Lyandres, 2023), moral hazard (Chod et al., 2022), corporate governance issues (Yermack, 2017) and financing in token-based platforms (Cong et al., 2022). Cornelli et al. 2025 propose a theoretical model and empirically examine the role of governance tokens in driving borrowing through decentralised finance (DeFi) lending platforms. Additionally, Leung et al. 2023 and Aldasoro et al. 2025 study the tokenisation of government bonds.

Specifically, this paper contributes to the literature on the tokenisation of real estate properties, which is still in its infancy. Earlier work on real estate tokenisation is primarily theoretical (Liu et al., 2020; Markheim and Berentsen, 2021) or focuses empirically on specific aspects, such as liquidity under normal market conditions (Swinkels, 2023), or property-specific and broader crypto-market-specific determinants of security token offerings and their secondary markets (Kreppmeier et al., 2023). This study distinguishes itself from these works by documenting the traditional real estate market forces that drive the growth of real estate tokenisation, by examining trading activity around exogenous shock to market liquidity, such as natural disasters, and by highlighting the resulting trade-off with higher insolvency risk.

This study complements the literature on access to credit (see eg Sussman and Zeira 1995; Almazan 2002; Degryse and Ongena 2005; Alessandrini et al. 2009; Agarwal and Hauswald 2010; Knyazeva and Knyazeva 2012; Hollander and Verriest 2016; Eichholtz et al. 2023) by documenting its link with real estate tokenisation.

Finally, I contribute to the literature on the impact of financial innovation in the real estate sector. Chung et al. 2016 and Giacomini et al. 2017 study the dynamics of prices and volatility, as well as leverage in REITs. Howell et al. 2020 find a positive relationship between successful initial coin offerings (ICO) and the operating sector tokenising a real asset. Schweizer and Zhou 2017 study the determinants of real estate crowdfunding. Buchak et al. 2020 document how technology-driven intermediaries choose to intermediate properties with the highest underlying liquidity – those where additional liquidity is least required – in order to mitigate problems of adverse selection. This work adds to this literature by showing the distinct nature of tokenised real estate properties.

The rest of the paper is structured as follows: Section 2 describes the business model of real estate tokenisation, outlining the different approaches adopted by platforms and their implications for investors. Section 3 presents the data and variable construction. Section 4 discusses the analysis; Section 5 concludes.

2 How does real estate tokenisation work?

Real estate tokenisation platforms operate at the intersection of technology, finance and property markets, leveraging blockchain technology to fractionalise ownership of real estate assets. These platforms provide a framework for converting real estate assets into digital tokens, which represent fractional ownership rights or claims on the underlying property.

At a high level, it is possible to distinguish between three models of real estate tokenisation. These models are summarised in Table 1. In the first model, the company tokenising the assets provides tokenisation services on a standalone basis (ie *tokenisation service only*). The company issues a token representing the estate on the blockchain and charges a fee for the tokenisation process. Specifically, this model is equivalent to issuing a non-fungible token (NFT) and represents the least common approach among the three models of real estate tokenisation.

In the second model, the company tokenising properties identifies, acquires and subsequently manages a portfolio of real estate assets. The firm issues tokens representing fractional ownership of the portfolio that offer investors the opportunity to invest in the portfolio of real estate assets and receive a share of income generated by these properties through rent, for instance (ie *portfolio-based tokenisation*). This model closely resembles investment funds, such as REITs.

Finally, in the third model, the company tokenising the assets identifies, acquires, renovates and manages a pool of properties; however, it issues separate tokens for each individual property (ie *property-level tokenisation*). In addition, platforms guarantee the buyback of a limited number of tokens (typically per week) within a few days, thereby enhancing market liquidity (Swinkels, 2023).[2] In a variation to this model, some platforms do not directly purchase properties but simply act as a marketplace, enabling owners to sell a portion of their property on the marketplace to investors.[3] In both cases, each token represents fractional ownership of a specific property. Although platforms provide the option to sell a portion of an estate to finance its purchase, most of the transactions are geared towards buying claims to a share of rental payments and the appreciation in the property's value. Arguably, the third model is the most innovative and holds the highest potential for unlocking the benefits of tokenisation. Therefore, the remainder of the analysis will focus on tokenisation companies that operate under this business model.

Table 1: Real estate tokenisation business models

	Business model		
	Tokenisation service only	Portfolio-based tokenisation	Property-level tokenisation
Description	The platform tokenises a property (often as an NFT) and charges a fee.	The platform acquires and manages a portfolio of properties and issues tokens representing fractional ownership of the entire portfolio.	Each property is tokenised separately. Investors buy fractional ownership in individual assets. Platform may act as marketplace.
Investor exposure	Single asset.	Diversified portfolio, regular income (eg rent).	Tailored selection of individual properties; direct exposure to asset-level cash flows.
Analogy	Digital notary / registry service	Similar to REITs or funds.	Similar to real estate crowdfunding (in terms of fractionalisation).
Liquidity features	Typically none. One-time issuance.	May include buyback or platform-run liquidity mechanisms.	May include buyback options (e.g. limited weekly redemption) and/or secondary trading on DEXs.

NOTES: The table reports a schematic representation of the business models of real estate tokenisation.

Business strategies influence both the clustering and distribution of tokenised real estate properties. Some platforms acquire geographically clustered properties to achieve economies of scale, enhance a neighbourhood through property renovation, and potentially benefit from the resulting positive externalities on the values of the other properties they own in the same area. Others instead diversify their offering to cater to a wider pool of investors more sensitive to diversifying their real estate portfolio. Figure 2

[2]For further details see How to benefit from the deep liquidity of the RealToken ecosystem?

[3]For an example see How the Lofty Marketplace Works.

shows the distribution of the number of tokenised properties per million people (panel (a)) and the total value per capita (panel (b)) by state. While these properties are spread over several states, they are clustered in specific areas within states, as shown in Figure A1 in Appendix A.

Tokenising real estate properties under the property-level tokenisation business model follows a structured process governed by the applicable legal framework. Drawing from Kreppmeier et al. 2023, Figure 3 provides a schematic representation of the different steps involved in this process. Under the Howey test – a legal framework used to determine whether a transaction qualifies as an investment contract – digital assets that meet its qualifying criteria, are deemed securities and are thus subject to regulatory oversight.[4] This means that real estate tokens must comply with registration requirements set by the Securities and Exchange Commission (SEC) and adhere to investor protection laws. Tokenisation platforms typically offer these tokens through unregistered securities offerings, leveraging exemptions such as Regulation D 506(c) for U.S.-accredited investors and Regulation S for non-U.S. investors under the Securities Act.

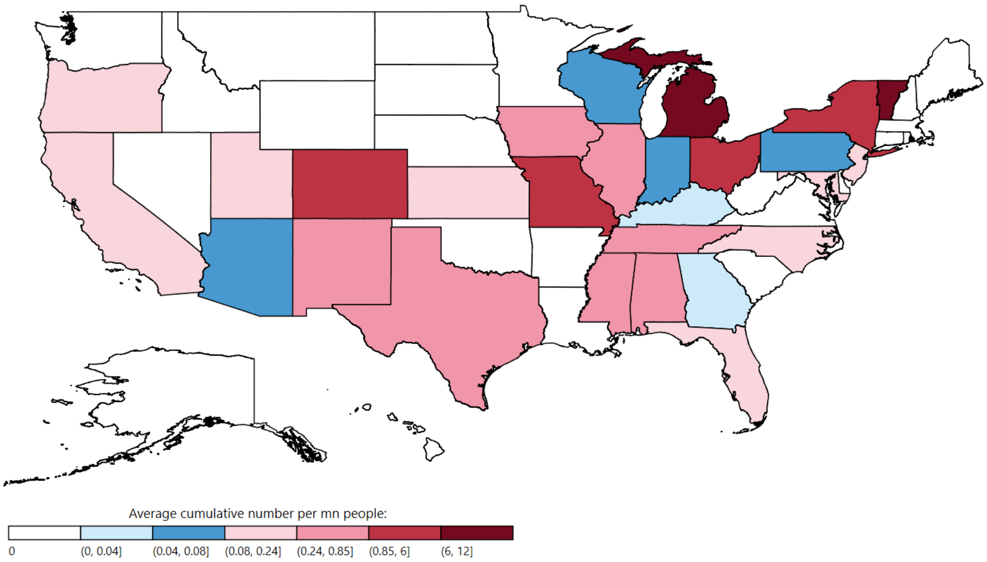
Figure 3 illustrates the process for tokenising a real estate property. The top part of the figure shows that for each property, the platform establishes a special purpose vehicle (SPV) that purchases and owns the property and thus holds the property deed. These SPVs are legally independent entities and the properties they legally own are subsequently tokenised using standardised blockchain protocols, such as the Ethereum ERC-20 token standard.[5] The properties involved are predominantly rented residential buildings (or commercial buildings in some cases), with property management outsourced to local professionals. Investors can acquire tokens during a token offering (ie issuance of the tokens). Upon successful payment and the digital signing of the

[4]The criteria examine whether, for instance, investors pay a monetary value to purchase tokens (ie investment of money); whether the tokens represent a share in a special purpose vehicle that owns the underlying real estate asset (ie common enterprise); whether investors expect to earn returns through rental income or capital appreciation (ie expectation of profits); and whether the returns depend on the managerial efforts of the tokenisation platform, property managers and other third parties (ie efforts of others). For further details see SEC v. W.J. Howey Co., 328 U.S. 293 (1946).

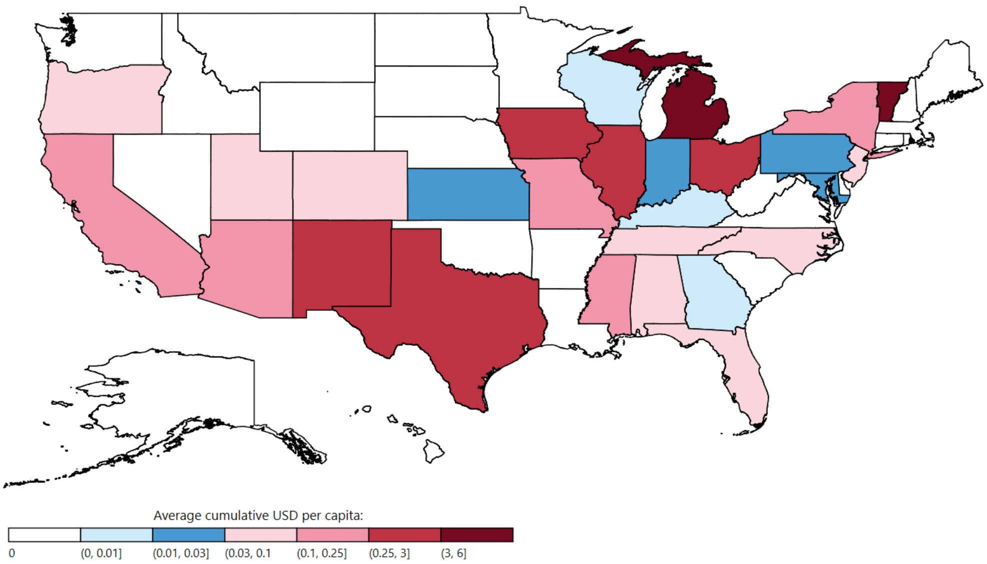
[5]The Ethereum ERC-20 token standard is a technical framework for creating and managing tokens on the Ethereum blockchain. It establishes a set of rules and functions for tokens, ensuring compatibility and interoperability with decentralized applications and other smart contracts on the Ethereum network. For instance, features of the ERC-20 standard include functions for transferring tokens, checking token balances and approving third-party spending.

Figure 2: **Real estate tokenisation across the US**

(a) Number of tokenised real estate properties



(b) Value of tokenised real estate properties

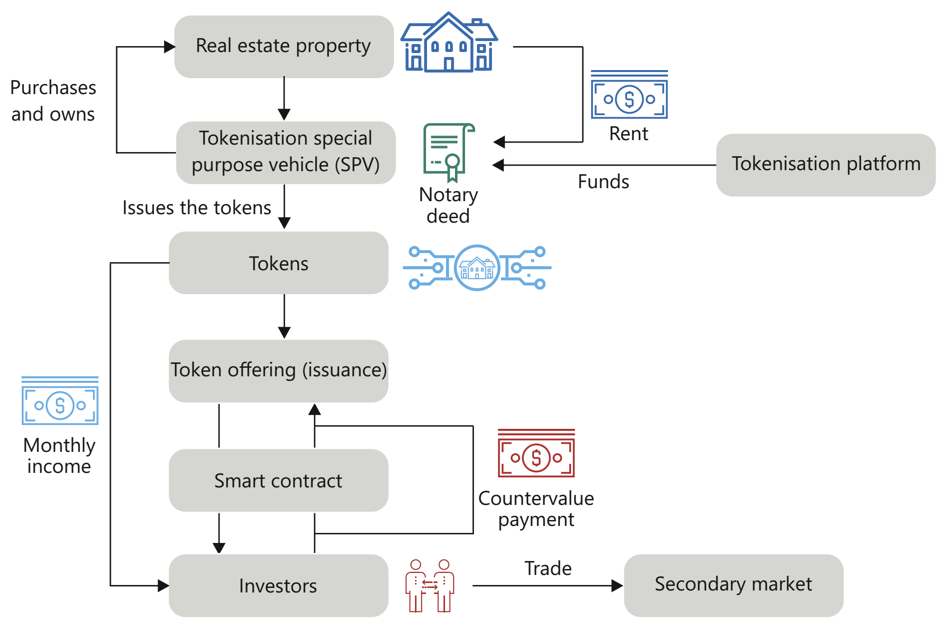


Note: The figure shows the distribution of tokenised real estate properties across states in the US as of March 2025. Panel (a) shows the breakdown by cumulative number (per million people) of properties. Panel (b) shows the breakdown by cumulative value (per capita) of these properties. The use of this map does not constitute, and should not be construed as constituting, an expression of a position by the BIS or the author regarding the legal status of, or sovereignty of any territory or its authorities, to the delimitation of international frontiers and boundaries and/or to the name and designation of any territory, city or area. Sources: Blocksquare; LoftyAI; RealT; author's calculations.

offering memorandum, tokens are automatically transferred to investors' wallets via a smart contract. Transactions on the blockchain incur an additional "gas fee", which covers the computational power and monetary incentives required to process operations and which is covered by investors.

Ownership of tokens grants investors a stake in the tokenised real estate property. Net rental income, calculated after deducting operating costs, insurance and property taxes, is distributed on a weekly basis to token holders through a smart contract linked to the property itself. The token value is determined by dividing the assessed property value (after accounting for a maintenance and repair reserve) by the total number of tokens issued. After issuance, tokens can either be redeemed by the platform or traded on decentralized exchanges (DEX), facilitating participation in DeFi (lower part of Figure 3). Properties are typically revalued annually, with token values adjusted to reflect any appreciation or depreciation in the underlying asset.

Figure 3: **The process for tokenising a real estate property**



Note: The figure shows a simplified and schematic representation of the different steps involved in the real estate tokenisation process analysed in this paper.
Sources: adapted from Kreppmeier et al. 2023.

The total value of the tokens issued (ie "market capitalisation") includes both the property values and the costs incurred by the tokenisation SPV to acquire the property in the "real world". For instance, the most significant part of these expenses is accounted for by sourcing, administrative (eg the cost of the notary validating the transaction) and listing fees. In nearly all aspects, these transactions are traditional real estate transactions. Thus, the values of these fees are sizeable and comparable to the ones in traditional real estate transactions, with additional costs to issue the tokens.[6] Figure 4 panel (a) shows an overview of these one-off fees. Specifically, relative to the average (median) property value which is about USD 215,300 (USD 91,200), the average sourcing fee amounts to USD 21,500 (USD 9,000), administrative fees are on the order of USD 3,000 (USD 1,250) and the listing fee is about USD 125 (50). In addition, investors pay gas fees to get their purchase transactions recorded on the blockchain. In periods of network congestion these fees can be sizeable and waiting times can be long (Boissay et al., 2022). Finally, the last bar in panel (a) shows the expected annual income from the investment. On average, this is about 10% of property value.

Panel (b) of Figure 4 offers an overview of the monthly costs for the average property. Maintenance expenditures, insurance and property management costs correspond to roughly one-third of the monthly income from the property. The last bar of panel (b) shows platform fees. Platforms charge a monthly platform fee on the order of 2% of the monthly income in exchange for enabling a fractionalised investment in a real estate property.[7] Put differently, the platform fee proxies the spread that investors are willing to pay in order to benefit from fractionalisation and the potentially higher liquidity offered by tokens. These platform fees are USD 33 per month on average or USD 15 per month for the median property.

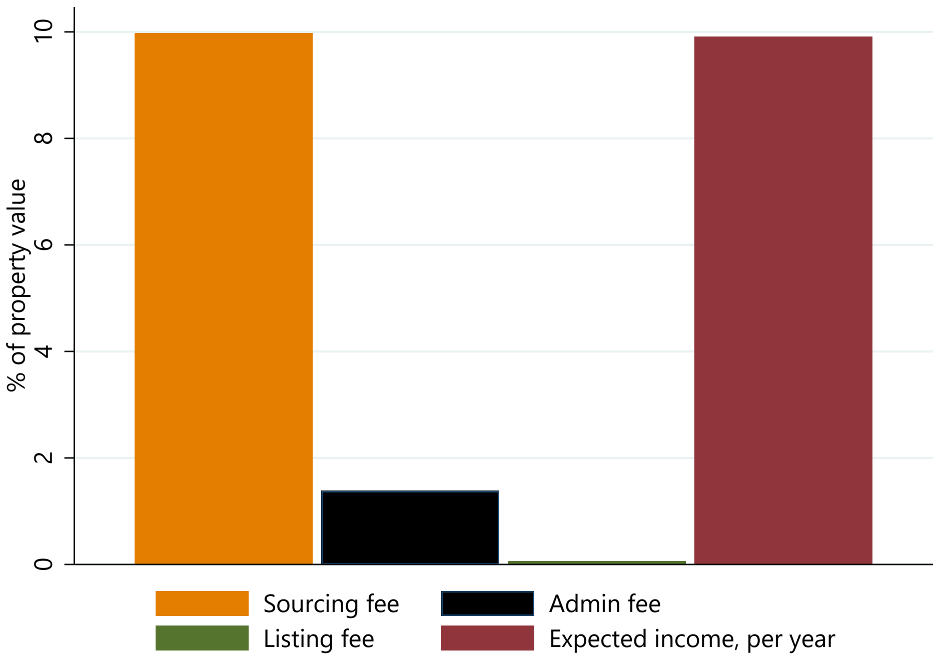
While real estate tokenisation is often touted as a means to reduce property management costs through streamlined processes, these cost savings may not yet be fully realised. Tokenisation can simplify transaction processes by centralising the archiving of all relevant documents on-chain rather than maintaining them in isolated silos across multiple intermediaries involved in the process. However, the evidence from Figure 4 panel (b) shows that the cost savings are not immediately apparent. Anecdotal evidence suggests that av-

[6] While there is no record of the magnitude of the tokenisation costs, these are likely included in the administrative fees.

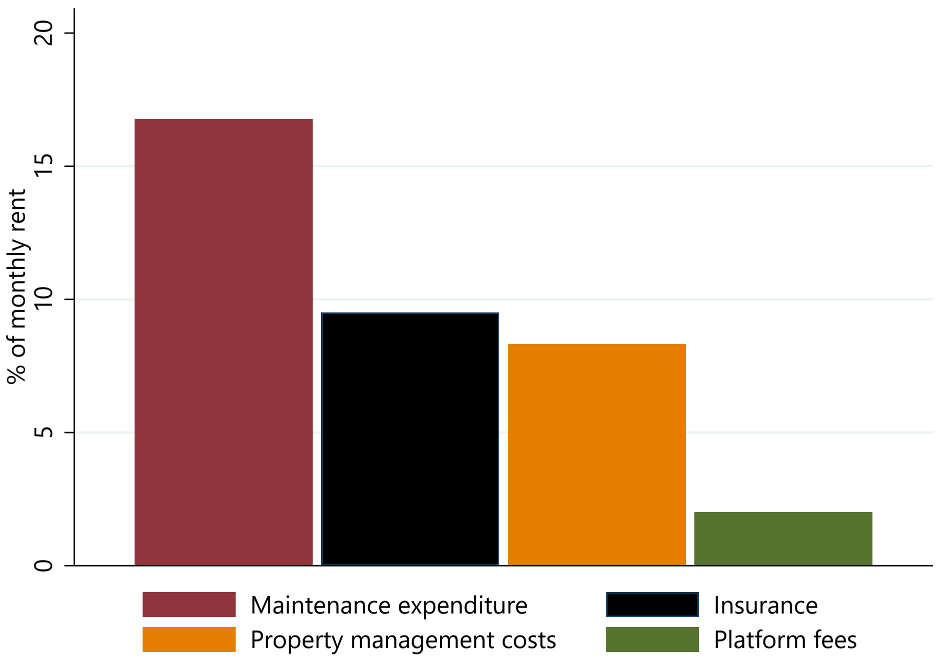
[7] In the model where the platform acts as a marketplace, platform fees typically correspond to a percentage of the value of the property equity sold (eg 3%). For an example see, Easily Pull Equity Out of Your Property.

Figure 4: **Real estate tokenisation: fees, income and costs**

(a) Average purchase fees and expected income



(b) Monthly running costs



Note: The figure shows the average fees and income of tokenised real estate properties in the US across three platforms as of March 2025. Panel (a) shows the one-off fees at purchase/tokens issuance, as well as the yearly expected income. Panel (b) shows the monthly running costs of these properties. Sources: Blocksquare; LoftyAI; RealT; author’s calculations.

erage property management costs for traditional real estate range between 6% and 12% of monthly rent.[8] This compares to an average property management cost of 8.3% for tokenised properties (yellow bar). These costs also appear to be in the same ballpark as those for REITs. For US REITs, the average ratio of total expenses – resulting from operating and maintaining all real estate assets – to total rental revenue is approximately 35%. Specifically, this ratio is about 40% for residential REITs, 36% for office REITs and 27% for industrial REITs (Figure A2 in the appendix). For tokenised properties, the combined costs of maintenance, insurance and property management amount to nearly 35%.

Figure 5 shows some of the characteristics of the tokens associated with tokenised properties. Panel (a) provides insights into the degree of fractionalisation enabled by tokenisation. On average, each property is fractionalised into approximately 2,000 tokens, translating into a minimum investment amount of about USD 50 for the average tokenised property. Ownership is also diversified. Panel (b) shows that, for the average property, the cumulative number of distinct investors holding at least one token at any point in time exceeds 500. Furthermore, the tokens exhibit high liquidity, as evidenced by the more than 2,700 cumulative transfers recorded for the average token over the analysis period.

Figure 6 shows features of investors in tokenised real estate properties. The leftmost part of the figure shows the distribution of the number of tokens held by investors. This indicator gives a sense of the diversification of investors' portfolio. Notably, the distribution is skewed, suggesting that only a few investors hold a large number of different tokens. Assuming that each investor holds a single wallet, the median investor holds 9 tokens (2 tokens for the 25th percentile and about 40 tokens for the 75th percentile) while the average investor holds nearly 80 tokens.[9] Taken together these results suggest that the degree of diversification is still limited, albeit growing over time. The rightmost part of the figure shows the distribution of the cumulative amount invested in tokenised properties. Similarly, the distribution of total amount invested is skewed to the right. The median investor purchased about USD 600 of tokens (USD 150 for the 25th percentile and about USD 3,000 for the 75th percentile). For the average investor, the amount is nearly USD 16,500.

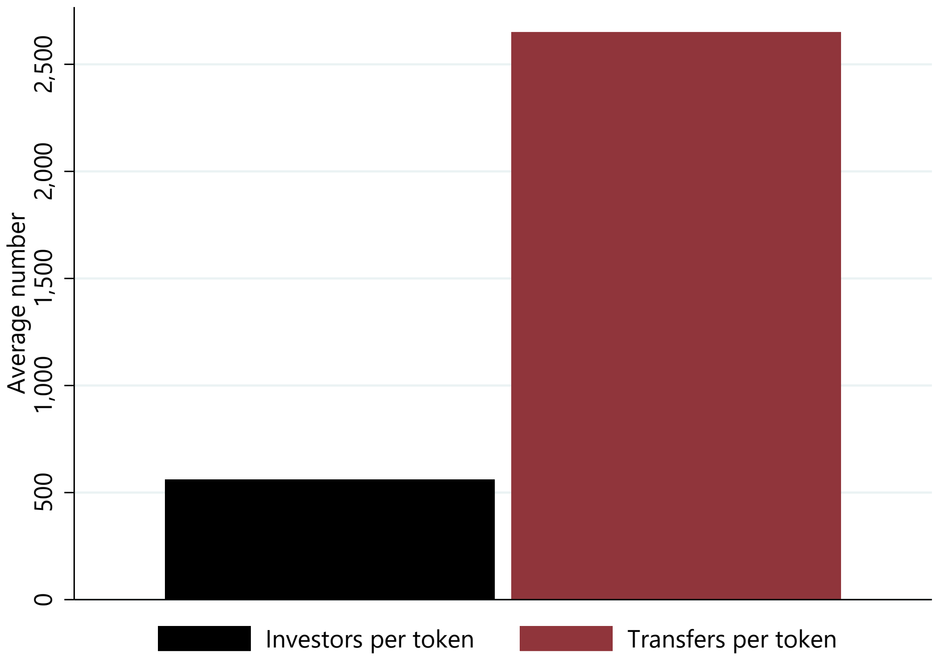
[8] For further details see (Rhode, 2025; Kennedy, 2025; Welty, 2025).

[9] This number is significantly larger than the ten tokens found by Kreppmeier et al. 2023. The discrepancy is likely traceable to the smaller sample of properties and the shorter period covered in their analysis.

Figure 5: **Real estate tokenisation: token characteristics**

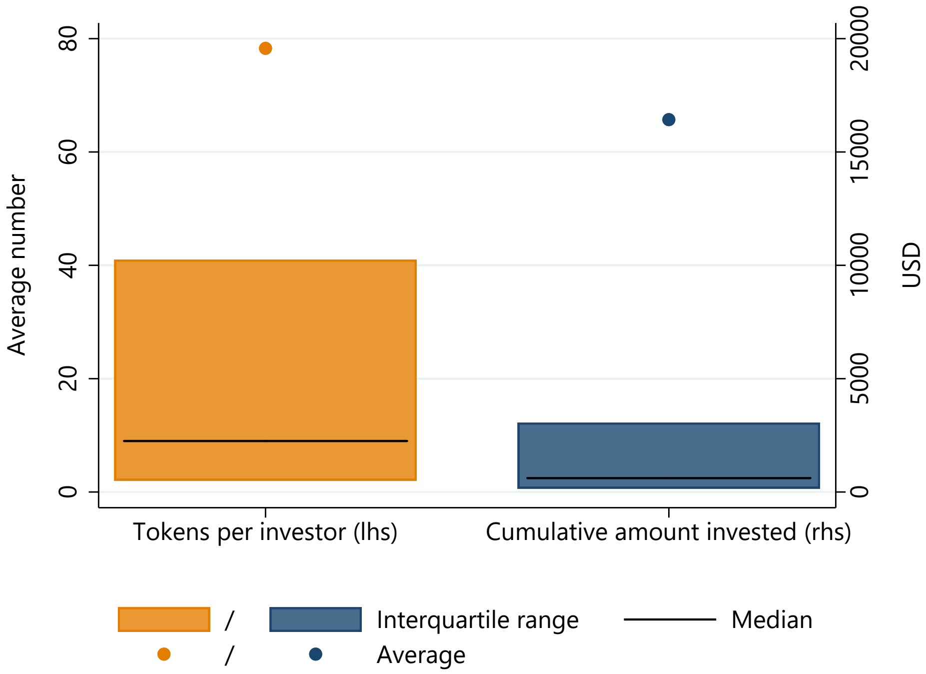
(a) Property fractionalisation

(b) Investor base diversification and liquidity



Note: The figure shows features for the average token of tokenised real estate properties in the US across three platforms. Panel (a) shows the average fractionalisation, calculated as one over the total number of tokens and the average minimum investment per property in USD. Panel (b) shows the average number of investors and the average number of transfers per token. Sources: Blockscout; Blocksquare; LoftyAI; RealT; author's calculations.

Figure 6: **Real estate tokenisation: investors' characteristics**



Note: The figure shows the interquartile range, average and median of the number of tokens held by investors and the cumulative amount invested in tokenised real estate properties in the US in one prominent platform over the period from July 2019 to February 2025. Sources: Blockscout; Etherscan; Gnosisscan; RealT; author's calculations.

3 Variable construction and descriptive statistics

Data on tokenised properties. I hand-collect data on the properties tokenised by Blocksquare, LoftyAI and RealT, three of the most prominent firms active in real estate tokenisation, which issue tokens representing fractional ownership of individual properties.[10]

Overall I track 841 properties in 183 zone improvement plan (ZIP) codes, from 71 counties and 28 states over the period July 2019–February 2025. De-

[10]Real estate tokenisation remains in its early stages and information about the size of the market is scarce. There are few market-wide estimates, let alone any official statistics. To the best of my knowledge, these three platforms are representative of the global market and account for a significant share of the "property-level tokenisation" market in the United States. Other platforms, such as Roofstock onChain, operate under the "tokenisation service only" business model. Similarly, platforms like RedSwan CRE and Republic adopt a hybrid approach, combining elements of the "portfolio-based" and "property-level tokenisation" business models. These platforms are not included in the sample, as this analysis focuses exclusively on those operating under the "property-level tokenisation" business model.

spite the lack of standardised reporting across platforms, I am able to collect detailed data for each property. This includes the exact location of the property and the tokenisation value (comprising the purchase price and any renovation cost). I also obtain information about the tokens' trading activity either directly or through Blockchain explorers (ie Allo', Blockscout, Etherscan, GnosisScan). Additional data, available to a varying degree, include the fees levied at different stages of the process—such as sourcing, property management, administrative fees and platform fees—as well as information on running costs, maintenance expenditures and expected rental income.

Data on traditional real estate. Information on traditional real estate properties is sourced from Redfind. The dataset includes granular information at the ZIP code level on the median list price per square foot, the year-on-year median list price change, the total number of listed properties (ie inventory), the number of properties sold, the percentage of properties that go off market within the first two weeks since the listing date, the average sale-to-list price ratio (which measures the discount or premium relative to the list price) and the number of new listings. These indicators are measured monthly over 90-day periods and are available for residential properties. They are also broken down by property type, such as single-family homes and condos. Data on rental prices of traditional real estate properties come from Zillow. Specifically, I compute the year-on-year change in the Zillow Observed Rent Index (ZORI) which tracks developments in asking rents over time, controlling for changes in the quality of rental properties.

Data on REITs. Information on REITs comes from S&P Capital IQ Pro. I collect data on individual properties in the portfolio of the top 100 residential, office and industrial US focused REITs by market capitalisation (subject to data availability).[11] The data contain the acquisition date, location and acquisition price of the property.

Additional data. I complement the dataset with indicators on the number of bank branches (both brick and mortar (ie physical) and other types such as online branches) at the ZIP code level that I source from the FDIC *Summary of Deposits*. I use loan-level data collected under the Home Mortgage Disclosure Act (HMDA) on the number of loan originations and refinancings at the

[11] For more details on the specific REITs included in the sample see Popular Stock List - Industry Lists

county-year level for the period $2018-2023$. Based on these data, I assess the degree of concentration in mortgage lending activity across counties and years by calculating two standard measure of competition used in the literature (e.g., Buchak and Jørring 2024; Scharfstein and Sunderam 2016; Doerr and Fuster 2025): the Herfindahl-Hirschman Index (HHI) and the concentration ratio of the top four lenders (CR4). Let $share_{l,c,t}$ denote the market share of lender l among all lenders L in the number of loans originated in county c in year t. Then

$$HHI_{c,t} = \sum_{l \in L} share^2_{l,c,t} \tag{1}$$

$$CR4_{c,t} = \sum_{l \in L^4} share_{l,c,t} \tag{2}$$

Based on these measures, I construct two indicator variables, $HHI^{high-concentration}$ and $CR4^{high-concentration}$, which take the value of one when the HHI exceeds 0.15 or when CR4 surpasses 60%, respectively, to identify counties with highly concentrated mortgage markets.[12] County-year level data on personal income per capita come from the Bureau of Economic Analysis (BEA). I source the ZIP code population data from the 2020 Decennial Census. These data are only available for 2020, as the US Census at this level of granularity is conducted only once every ten years. Finally, I collect data on natural disasters from the Federal Emergency Management Agency (FEMA) Individuals and Households Program – Valid Registrations dataset. This dataset collects applicant-level data of all major disasters and includes only registrants who meet the eligibility criteria for assistance related to the respective declared disasters.[13]

Descriptive statistics. The final ZIP code-month level dataset contains information on 142,376 ZIP code-month observations, from July 2019 to February 2025. I winsorise the data on the median list price per square foot, the year-on-year list price growth, rental prices, income per capita, number of bank branches, number of brick and mortar bank branches and the number of lenders per thousands people at the 1st and 99th percentile.

Table 2 provides summary statistics for the indicators and the sample used in the empirical analysis.

[12] A market is typically "unconcentrated" if the HHI is lower than 0.15. Above this threshold the market is considered to be "moderately to highly concentrated".

[13] These criteria include applying in a declared county, within the registration period, having damage due to the incident and within the incident period.

Table 2: Descriptive statistics

	No Obs	Mean	St Dev	Min	Max
Panel (a): drivers' analysis					
Cumulative tokenised real estate properties$_{z,c,t}$	142,376	0.01	0.07	0.00	1.41
Cumulative tokenised real estate value$_{z,c,t}$	142,376	3.74	35.42	0.00	1249.96
Median price per sqft$_{z,c,t}$	141,797	237.26	171.98	36.35	960.36
Median price, % change$_{z,c,t:t-12}$	140,938	0.10	0.22	-0.60	1.99
Properties sold, % of inventory$_{z,c,t}$	137,588	1.58	1.32	0.01	58.00
% properties sold quickly$_{z,c,t}$	142,063	0.44	0.20	0.00	1.00
Sale-to-list price ratio$_{z,c,t}$	136,617	0.99	0.04	0.50	1.79
New listings, % of inventory$_{z,c,t}$	137,303	1.72	1.10	0.05	37.50
Population$^{2020}_{z,t}$	142,376	26,684	18,844	194.00	128,180
Income per capita$_{c,t}$	142,376	66,144	12,504	34,228	127,302
Cumulative traditional real estate properties$_{z,c,t}$	142,376	308.08	246.69	18.80	5,307.69
Cumulative single-family properties$_{z,c,t}$	142,376	234.28	220.08	0.00	5,307.69
Cumulative condo properties$^{'000people}_{z,c,t}$	142,376	44.99	106.58	0.00	1,279.86
Cumulative townhouse properties$_{z,c,t}$	142,376	20.16	44.21	0.00	654.12
Cumulative REIT properties$_{z,c,t}$	142,376	0.01	0.05	0.00	1.15
Cumulative residential REIT properties$_{z,c,t}$	142,376	0.00	0.01	0.00	0.26
Cumulative office REIT properties$_{z,c,t}$	142,376	0.00	0.01	0.00	0.28
Cumulative industrial REIT properties$_{z,c,t}$	142,376	0.01	0.05	0.00	1.15
Bank branches$_{z,c,t}$	120,128	0.27	0.29	0.03	2.55
Brick and mortar branches$_{z,c,t}$	118,088	0.26	0.28	0.03	2.50
Number of lenders$_{c,t}$	113,056	0.41	0.44	0.07	5.53
HHI$^{high-concentration}_{c,t}$	113,056	0.003	0.055	0.00	1.00
CR4$^{high-concentration}_{c,t}$	113,056	0.003	0.055	0.00	1.00
Rental price, % change$_{z,c,t:t-12}$	51,096	0.06	0.06	-0.18	0.44
Panel (b): staggered difference-in-difference analysis					
Transactions$_{z,c,n,t,t^*}$	4,496	22.15	83.85	0.00	1,979
$\ln(\text{Transactions}_{z,c,n,t,t^*})$	4,496	1.65	1.56	0.00	7.59

NOTES: The table reports the descriptive statistics for the sample of analysis. Based on data for 2,143 ZIP codes in 56 counties across 27 states in the United States for the period July 2019–February 2025. z denotes ZIP codes, c denotes counties and t denotes time (ie month-year). The variables cumulative tokenised real estate properties, cumulative tokenised real estate value, cumulative traditional real estate properties, cumulative single-family properties, cumulative condo properties, cumulative townhouse properties, cumulative REIT properties, cumulative residential REIT properties, cumulative office REIT properties, cumulative industrial REIT properties, bank branches, brick and mortar branches and number of lenders are expressed per thousands people.

4 Empirical analysis

4.1 The drivers of real estate tokenisation

In this section I study the factors that explain the growth of tokenised real estate properties and explore the relationship between these drivers and traditional real estate properties, as well as REIT portfolios. Additionally, I investigate whether access to traditional credit influences the growth of real estate tokenisation.

4.1.1 Empirical strategy

I use the total number of tokenised real estate properties as an outcome variable to capture the development of real estate tokenisation. To account for the count like nature of this outcome variable, I estimate Poisson Pseudo Maximum Likelihood regressions (Chen and Roth, 2024; Mullahy and Norton, 2022). Furthermore, Poisson regressions address the issue of zeros in the dependent variable.[14] Specifically, I fit the following specification for ZIP code z, county c, month-year t level:

$$y_{z,c,t} = \exp\Big(\beta_1\, pricing_{z,c,t-6} + \beta_2\, demand_{z,c,t-6} + \beta_3\, liquidity_{z,c,t-6} \\ + \beta_4\, supply_{z,c,t-6} + \gamma\, X_{z,c,t-6} + \alpha_c + \theta_t + \varepsilon_{i,t}\Big) \tag{3}$$

The dependent variable $y_{z,c,t}$ is the cumulative number of tokenised properties in ZIP code z, county c from the beginning of the observation window up to month-year t. Taking the number of properties that are being tokenised in a given ZIP code as the dependent variable means estimating the effect on the average number of tokenised properties. Since I am interested in estimating the effect on the total number of properties moving to the digital space and not the average number of properties, I take the cumulative number of tokenised real estate properties as the dependent variable for the analysis (as done for the cumulative number of commercial software releases by Beraja et al. 2023). The vector $pricing_{z,c,t-6}$ contains traditional real estate pricing indicators such as the price per square foot and the year-on-year (yoy) price growth. The variable $demand_{z,c,t-6}$ measures the demand for traditional real estate properties and is proxied by the ratio of the number of houses sold to

[14]The number of observations included in the regressions is smaller than the total number available in the dataset. This reflects the fact that estimates from Poisson maximum likelihood regressions may not exist due to the problem of "statistical separation", determined by a lack of convergence. By detecting and dropping separated observations the separation issue is reduced to a collinearity problem, which typically is solved by dropping one of the two collinear regressors. Therefore, the results are obtained on nearly 143,000 observations that are not perfectly predicted by the fixed effects included in the specification from Equation 3. These represent 2,143 ZIP codes in 56 counties across 47 MSAs and 27 states. For a comprehensive discussion see Primer on statistical separation in Poisson models.

the total inventory of properties. The vector $liquidity_{z,c,t-6}$ contains traditional real estate liquidity indicators such as the percentage of homes that sold in less than two weeks and the sale-to-list price ratio. The variable $supply_{z,c,t-6}$ measures the supply of traditional real estate properties and is proxied by the ratio of new listings to the total inventory of properties. The vector of controls $X_{z,c,t-6}$ includes population at the ZIP code level from the 2020 Decennial Census and personal income per capita at the county level. α_c are county fixed effects to control for time-invariant unobservable characteristics at the county level and θ_t are time dummies that control for time-specific trends that are common to all ZIP codes, like overall trends in equity or crypto currency prices.[15] All the independent variables are taken with a six-month lag to account for the fact that, on average, the decision to purchase a property and the actual purchase date are not contemporaneous. Six-months is a typical time lag between these events.[16] I cluster standard errors at the county level to account for serial correlation within the same county over time.

Identification and endogeneity. My empirical approach exploits the variation in characteristics of local traditional real estate markets for similar properties at the same time in the same ZIP code by controlling for a vector of ZIP code- and county-level controls, $X_{z,c,t-6}$ as well as county and time fixed effects, α_c and θ_t. The coefficients derived from estimating this specification indicate whether, conditional on deciding to operate within a county, real estate tokenisation platforms are more likely to target "hot" or "cold" ZIP codes within that county. There are two potential concerns in interpreting the results of the following analysis causally: omitted variable bias and reverse causality.

With respect to the first, factors like a higher share of young (and tech-savvy) population in a specific county could drive the supply of tokenised real estate properties as well as the demand for conventional properties. To alleviate these concerns, Equation 3 controls for time-invariant county fixed effects. By including county fixed effects I compare the number of tokenised properties in ZIP codes in the same county. Time (month-year) fixed effects control for the existence of a trend. In addition, to further alleviate concerns of omitted variable bias, in the robustness section, I estimate Equation 3 re-

[15] Table A1 in Appendix A presents the results from estimating Equation 3, substituting county fixed effects with Metropolitan Statistical Area (MSA) fixed effects. The findings remain consistent with those of the baseline specification, supporting the robustness of the results.

[16] See Jordan 2021 for anecdotal evidence.

placing county and time fixed effects with county*time fixed effects. Effectively, this model controls for time-varying unobservable characteristics at the county level (see Table 10). An unobservable factor would then need to systematically affect one of the independent variables in the same county to a different extent.

Second, there could be reverse causality at play. In this scenario, an increased supply of tokenised real estate could influence the price per square foot or the rate of price growth in traditional real estate markets. However, it seems highly unlikely that such a small number (and total value) of tokenised properties could impact the traditional real estate market six months prior.

4.1.2 Results

Drivers from the traditional real estate market. Results from Table 3 provide evidence on the real estate market drivers of tokenisation. Coefficients from column 1 suggest that a lower price per square-foot and a higher year-on-year (yoy) price growth are associated with more tokenised properties on a per capita basis. The effects are economically and statistically significant. A one standard deviation increase in the price per square foot is associated with a 90% drop in the number of tokenised properties, while a one standard deviation increase in the yoy price change is linked to a 10% increase in the same figure. Relative to the mean, these translate into about 9 less and 1 more properties per million people, respectively. These results suggest that tokenised properties tend to develop more in areas with lower price levels but stronger price dynamics. Such characteristics are more consistent with investment-oriented behaviour than with owner-occupation. Moreover, they suggest that real estate tokenisation tends to offer opportunities to target capital gains through investments in undervalued areas with strong growth potential, rather than value preservation through exposure to established residential markets.

Column 2 sheds light on the link between tokenisation and the demand for properties. Specifically, *properties sold, % of inventory* measures the percentage of properties sold relative to the overall number of properties (ie inventory) in a specific ZIP code and is negatively associated with the development of tokenised properties. This result is statistically significant at the 1% level and the associated magnitude is economically meaningful. A one standard deviation increase in this indicator is associated with a 70% decrease in the total number of tokenised properties per capita. This result is consistent with real estate tokenisation focusing on areas with lower demand.

Column 3 presents the results on indicators capturing market liquidity. I augment the specification including *% properties sold quickly*, a variable measuring the percentage of properties that sold within two weeks from the listing date and the *sale-to-list price ratio* which captures the average discount or premium on a real estate transaction in the specific ZIP code. The results suggest that real estate tokenisation is negatively associated with both measures. These relationships are statistically significant and economically meaningful. A one standard deviation increase in the percentage of homes selling quickly is associated with a 27% decrease in tokenised properties. Similarly, an increase of one standard deviation in the average sale-to-list price ratio is linked to a decrease in tokenisation of nearly 30%. The magnitude of these effects corresponds to an increase of about 13 tokenised properties per capita, relative to the average. Taken together, these findings suggest that real estate tokenisation tends to target areas where properties take longer to sell and typically trade at a discount to their list prices. These patterns are consistent with tokenisation focusing on less liquid property markets, thereby offering greater potential to enhance local market liquidity.

Column 4 offers evidence on the link between tokenisation and measures of the supply of properties. Specifically, I include in the specification *new listings, % of inventory*, a variable measuring the new properties coming to the market in a month as a share of the overall inventory for each of the ZIP codes. Notably, the number of tokenised properties per capita is negatively associated with the overall supply of new properties in the same area. A one standard deviation increase in the latter is associated with an 70% decrease in the former. Relative to the average number of tokenised real estate properties per capita, this translates into 7 less tokenised properties per million inhabitants. This result is consistent with tokenisation targeting areas with price appreciation potential, insofar as a shortage of properties on the market can lead to upward pressure on prices, which may, in turn, spill over into higher rents.

Finally, column 5 includes measures of demand, market liquidity and supply all together in a horse race model. Reassuringly, the signs and the point estimates remain stable, with the only exception of the percentage of properties that sold quickly, which keeps its sign but becomes statistically not significant. Overall, the results suggest that tokenisation of real estate grows more where there is lower demand, where the market is less liquid and where there is a lower supply of properties.

Table 3: The market determinants of tokenised real estate supply

	Cumulative tokenised real estate properties$_{z,c,t}$				
	(1)	(2)	(3)	(4)	(5)
Median price per sqft$_{z,c,t-6}$	-0.013*	-0.008**	-0.010*	-0.009*	-0.008**
	(0.008)	(0.004)	(0.005)	(0.005)	(0.004)
Median price, % change$_{z,c,t-6:t-18}$	0.451***	0.288***	0.363***	0.297***	0.271***
	(0.047)	(0.033)	(0.045)	(0.029)	(0.033)
Properties sold, % of inventory$_{z,c,t-6}$		-1.014***			-0.652***
		(0.242)			(0.137)
% properties sold quickly$_{z,c,t-6}$			-1.601**		0.153
			(0.717)		(0.476)
Sale-to-list price ratio$_{z,c,t-6}$			-6.980***		-3.891***
			(1.055)		(0.863)
New listings, % of inventory$_{z,c,t-6}$				-1.093***	-0.420**
				(0.260)	(0.195)
County FEs	✓	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓
Observations	142,376	137,819	136,502	137,819	135,982
Pseudo R-squared	0.17	0.18	0.18	0.18	0.19

NOTES: The results are obtained from the Poisson regression in equation 3. Based on data for 2,143 ZIP codes in 56 counties across 27 states in the United States for the period July 2019–February 2025. z denotes ZIP codes, c denotes counties and t denotes time (ie month-year). The dependent variable, *cumulative tokenised real estate properties*$_{z,c,t}$, denotes the cumulative number of tokenised properties per capita. *% properties sold quickly*$_{z,c,t-6}$, corresponds to the percentage of properties that went off market within two weeks of the respective listing date. Regressions additionally control for population at the ZIP code level for 2020 and personal income per capita at the county-year level. Standard errors clustered by county in parentheses.

Comparison with the traditional real estate market. An important question is whether these variables drive the development of traditional real estate properties in the same way. To answer this question I re-run the baseline specification from Equation 3, replacing the dependent variable with traditional real estate properties. The results reported in Table 4 column 1 correspond to the same results as in Table 3 column 5 to simplify the comparison. The dependent variable in columns 2–6 is the cumulative number of new traditional real estate properties that go on the market (ie new listings) per capita. Specifically, columns 2 and 3 includes all residential properties, while columns 4–6 focus on single-family houses, condos and townhouses, respectively, which are the most represented property types in the tokenised real estate sample.

The results from Table 4 offer two interesting insights. First, for most drivers, the relationship reverses in sign, suggesting that tokenised and traditional real estate properties are distinct and likely cater to different types of investors. Second, the predictive power of the regressions decreases significantly, from nearly 20% when tokenised properties are the dependent variable to about 5% for regressions involving all residential properties, or single-family houses, which are the most represented category in the tokenized real estate sample.

These differences could be due to the different geographical coverage of the two samples. To control for this, columns 2 and 3 follow the same specification, but while the former includes a larger sample of ZIP codes, the latter uses the same set as Column 1. Interestingly and reassuringly, the point estimates remain stable and very similar. Specifically, the results from column 3 suggest that traditional real estate properties are more frequently transacted where the price per square foot is higher (about a 30% increase for one-standard deviation increase) and price growth is lower (2% decrease for a one standard deviation increase). Traditional real estate properties are also higher where demand is higher (2% increase for a one standard deviation increase, even though not statistically significant), where properties sell less quickly (8% drop for a one standard deviation increase) and at a higher price relative to the list price (3.5% increase for a one standard deviation increase) and where there is a lower supply (3% decrease for a one standard deviation increase). These findings for traditional real estate properties are indicative of an investor base that prioritises value preservation by focusing on established residential markets, which are characterised by elevated price levels, transaction prices that consistently include a premium over the list price and a scarcer supply of properties.

The results in columns 4–6 for individual property types are consistent and similar. This suggests that the findings are not driven by a specific type of real estate but are broadly applicable.

Table 4: Comparison of market determinants of traditional real estate supply

	Cumulative real estate properties$_{z,c,t}$					
	Tokenised	Traditional				
		All residential	All residential	Single-family	Condo	Townhouse
	(1)	(2)	(3)	(4)	(5)	(6)
Median price per sqft$_{z,c,t-6}$	-0.008**	0.002***	0.002***	0.000	0.005***	0.002***
	(0.004)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Median price, % change$_{z,c,t-6:t-18}$	0.271***	-0.101***	-0.111***	-0.032	-0.523***	-0.194**
	(0.033)	(0.007)	(0.017)	(0.020)	(0.056)	(0.082)
Properties sold, % of inventory$_{z,c,t-6}$	-0.652***	0.003*	0.015	0.036***	-0.032	0.036
	(0.137)	(0.002)	(0.011)	(0.013)	(0.024)	(0.026)
% properties sold quickly$_{z,c,t-6}$	0.153	-0.108***	-0.442**	-0.298	-1.017**	0.106
	(0.476)	(0.022)	(0.178)	(0.220)	(0.466)	(0.393)
Sale-to-list price ratio$_{z,c,t-6}$	-3.891***	0.173**	0.967**	1.639***	0.610	3.489*
	(0.863)	(0.083)	(0.478)	(0.428)	(1.975)	(1.811)
New listings, % of inventory$_{z,c,t-6}$	-0.420**	-0.018***	-0.026*	-0.042**	-0.006	-0.050
	(0.195)	(0.003)	(0.015)	(0.016)	(0.044)	(0.034)
County FEs	✓	✓	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓	✓
Observations	135,982	1,123,715	122,372	122,372	122,112	121,845
Pseudo R-squared	0.19	0.06	0.04	0.04	0.17	0.15

NOTES: The results are obtained from a Poisson regression. Results in columns 1 and 3 are based on data for 2,143 ZIP codes in 56 counties across 27 states in the United States for the period July 2019–February 2025. Results in column 2 are based on data for 18,811 ZIP codes in 1,774 counties across 51 states in the United States for the period July 2019–February 2025. z denotes ZIP codes, c denotes counties and t denotes time (ie month-year). The dependent variable in column 1 denotes the cumulative number of tokenised properties per capita. The dependent variable in columns 2–6 denotes the cumulative number of new listings of traditional properties per capita. *% properties sold quickly*$_{z,c,t-6}$, corresponds to the percentage of properties that went off market within two weeks of the respective listing date. Regressions additionally control for the same set of controls as column 5 of Table 3. Standard errors clustered by county in parentheses.

Comparison with REITs. As previously discussed, REITs are arguably the most comparable traditional financial product to real estate tokens. However, while REITs provide investors with diversified portfolios of real estate properties, real estate tokens allow investors to directly select and hold individual properties in their portfolios. Thus, it is worth considering whether the factors driving the development of tokenised properties have a similar influence on the selection of properties within REIT portfolios. In this section, I re-estimate Equation 3, replacing the dependent variable with properties in REIT portfolios in ZIP code z at each point in time.

The results reported in Table 5 column 1 are the same results as in Table 3 column 5 to simplify the comparison. The dependent variable in columns 2–6 is the cumulative number of properties in REIT portfolios per capita. Specifically, columns 2 and 3 includes all REITs, while columns 4–6 focus on residential, office and industrial REITs, respectively.

The results from Table 5 show three interesting features. First, in the aggregate, liquidity is the only common driver between tokenised and REIT properties. The coefficient for the sale-to-list price ratio in column 3 is the only one that is statistically significant and of similar magnitude and sign relative to column 1. Second, residential REITs behave similarly to traditional residential real estate properties, as evidenced by the coefficients in column 4 reversing in sign relative to those in Column 1. Office and industrial REITs share certain commonalities with tokenised properties – such as demand drivers for the former and pricing drivers for the latter – but also exhibit differences, as observed with residential REITs.

Third, the predictive power of the regressions decreases significantly, dropping from nearly 20% when tokenised properties are the dependent variable to approximately 5% in regressions involving REIT properties. Columns 2 and 3 follow the same specification; however, the former includes a larger sample of ZIP codes, while the latter uses the same set as Column 1. Interestingly and reassuringly, the point estimates remain stable and very similar for almost all the independent variables. Specifically, the results from column 3 suggest that REIT properties are more represented where properties sell more quickly (22% increase for a one standard deviation increase) and at a lower price relative to the list price (13% drop for a one standard deviation increase). Overall, this evidence suggests that tokenised properties and REIT properties are distinct, likely catering to different types of investors, yet sharing similar preferences for market liquidity.[17]

[17] In an unreported regression analysis, I test whether REIT penetration influences the penetration of real estate tokenisation by augmenting the specification from Equation 3 with the six-month lag of four variables (one at a time) measuring the cumulative number of REIT properties per capita. The results indicate that the coefficients associated with REIT penetration are statistically not significant. This suggests that REIT penetration does not have a significant impact on the penetration of tokenised properties, supporting the thesis that these investment vehicles likely cater to different types of investors.

Table 5: Comparison of market determinants of REIT supply

	Cumulative real estate properties$_{z,c,t}$					
	Tokenised	REIT				
		All	All	Residential	Office	Industrial
	(1)	(2)	(3)	(4)	(5)	(6)
Median price per sqft$_{z,c,t-6}$	-0.008**	0.000	-0.000	0.004***	0.005***	-0.003***
	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Median price, % change$_{z,c,t-6:t-18}$	0.271***	-0.058	-0.066	-0.260*	-0.442***	0.017
	(0.033)	(0.045)	(0.059)	(0.157)	(0.160)	(0.059)
Properties sold, % of inventory$_{z,c,t-6}$	-0.652***	-0.059***	-0.042	0.048	-0.198**	-0.012
	(0.137)	(0.016)	(0.050)	(0.042)	(0.085)	(0.050)
% properties sold quickly$_{z,c,t-6}$	0.153	-0.060	0.983**	-0.115	-0.966	1.850***
	(0.476)	(0.298)	(0.433)	(0.384)	(0.908)	(0.310)
Sale-to-list price ratio$_{z,c,t-6}$	-3.891***	-3.073*	-3.928*	-0.514	-4.585	-3.502
	(0.863)	(1.667)	(2.315)	(1.809)	(2.817)	(2.985)
New listings, % of inventory$_{z,c,t-6}$	-0.420**	0.096***	0.095	-0.108*	0.039	0.122***
	(0.195)	(0.022)	(0.059)	(0.059)	(0.140)	(0.046)
County FEs	✓	✓	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓	✓
Observations	135,982	645,585	115,246	90,775	87,214	109,897
Pseudo R-squared	0.19	0.05	0.02	0.06	0.08	0.04

NOTES: The results are obtained from a Poisson regression. Results in columns 1 and 3 are based on data for 2,143 ZIP codes in 56 counties across 27 states in the United States for the period July 2019–February 2025. Results in column 2 are based on data for 9,998 ZIP codes in 451 counties across 45 states in the United States for the period July 2019–February 2025. z denotes ZIP codes, c denotes counties and t denotes time (ie month-year). The dependent variable in column 1 denotes the cumulative number of tokenised properties per capita. The dependent variable in columns 2–6 denotes the cumulative number of REIT properties per capita. *% properties sold quickly*$_{z,c,t-6}$, corresponds to the percentage of properties that went off market within two weeks of the respective listing date. Regressions additionally control for the same set of controls as column 5 of Table 3. Standard errors clustered by county in parentheses.

Credit access. Access to credit is a key enabler of real estate transactions. In the banking literature, distance is a well established indicator for access to local information and it is widely documented how it affects the ability of lenders to collect soft/private information about the borrowers (see eg Sussman and Zeira 1995; Almazan 2002; Degryse and Ongena 2005; Alessandrini et al. 2009; Agarwal and Hauswald 2010; Knyazeva and Knyazeva 2012; Hollander and Verriest 2016). Specifically, Eichholtz et al. 2023 show that bank-lender geographic distance has an impact on commercial mortgage backed securities (CMBS) pricing. Therefore, the presence of bank branches in the area likely influence the ease with which banks raise information about lenders and grants traditional mortgages to prospective home buyers. However, banks are not the sole lenders in the mortgage market, as non-bank lenders also play a significant role in providing credit. Real estate tokenisation may emerge more prominently in areas with a weaker presence of credit intermediaries and underserved property financing needs, offering an alternative channel for gaining exposure to the real estate asset class.

I test for this channel in Table 6. In column 1, I include in the specification a variable counting the number of bank branches per thousand people (ie *Bank branches*). The negative and statistically significant coefficient suggests that tokenised real estate properties are more present where there are fewer bank branches. The magnitude is economically meaningful: a one standard deviation increase in bank branches per thousand people is associated with a nearly 40% reduction in tokenised real estate, which corresponds to 4 fewer properties per million people relative to the average. These results are consistent with tokenisation targeting areas where there is potentially an unmet demand stemming from lower bank presence. Notably, if I replace the number of bank branches per thousand people with the number of brick and mortar branches per thousand people – as those are involved in customer facing activities such as collecting information to grant mortgages – this results in a larger point estimate (in absolute value) (column 2).

Extending the universe of lenders to banks and non-banks yields consistent results. The coefficient associated to the number of lenders per thousand people (ie *Number of lenders*) is negative and statistically significant (column 3). This result suggest that real estate tokenisation develops more in those areas with fewer lenders active in the mortgage market.

Columns 4 and 5 report evidence on the impact of lenders' concentration on the development of tokenised real estate properties. The variables that capture the high-concentration of the mortgage market in a certain area are $HHI_{c,t}^{high-concentration}$ and $CR4_{c,t}^{high-concentration}$. The positive and statistically significant coefficient for $HHI_{c,t}^{high-concentration}$ suggests that higher lender concentration is associated with more tokenised properties. Results are similar when measuring concentration with $CR4$ – the supply of tokenised real estate is about one-third higher in areas with high lender concentration. These results are consistent with those in the first three columns, insofar as higher concentration is linked to higher rates and more expensive credit.[18]

Finally, column 6 reports the results for a model that includes these measures at the same time. Specifically, in addition to the variables included in column 5 of Table 3, I augment the specification to include the number of lenders and CR4.[19] Overall, the results remain similar.

[18]Scharfstein and Sunderam 2013 document that the effect of lower yields on mortgage-backed securities (MBS), is dampened in counties with concentrated mortgage markets. Corvoisier and Gropp 2002 find that increasing concentration may result in less competitive pricing on loans.

[19]I don't include both the number of bank branches and the HHI in the same specification,

Table 6: Bank credit access and tokenised real estate supply

	Cumulative tokenised real estate properties$_{z,c,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Bank branches$_{z,c,t-6}$	-1.856***					
	(0.519)					
Brick and mortar branches$_{z,c,t-6}$		-2.036***				
		(0.536)				
Number of lenders$_{c,t-6}$			-0.408**			-0.409**
			(0.191)			(0.191)
HHI$^{high-concentration}_{c,t-6}$				0.289**		
				(0.120)		
CR4$^{high-concentration}_{c,t-6}$					0.289**	0.332**
					(0.120)	(0.144)
County FEs	✓	✓	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓	✓
Observations	112,873	109,624	108,054	108,054	108,054	108,054
Pseudo R-squared	0.21	0.21	0.19	0.19	0.19	0.19

NOTES: The results are obtained from a Poisson regression. Based on data for 2,143 ZIP codes in 56 counties across 27 states in the United States for the period July 2019–February 2025. z denotes ZIP codes, c denotes counties and t denotes time (ie month-year). The dependent variable, *cumulative tokenised real estate properties*$_{z,c,t}$, denotes the cumulative number of tokenised properties per capita. Number of lenders$_{c,t-6}$ corresponds to the number of lenders that originated or refinanced a loan in a county in a given year and is expressed per thousands people. $HHI^{high-concentration}_{c,t-6}$ corresponds to an indicator variable taking value one when the Herfindahl-Hirschman index, calculated based on the number of mortgage loans at the county-year level, exceeds 0.15 and captures the concentration of lending activity in a given county. $CR4^{high-concentration}_{c,t-6}$ corresponds to an indicator variable taking value one when the share of the top four lenders, calculated based on the number of mortgage loans at the county-year level, exceeds 60% and captures the concentration of lending activity in a given county. Regressions additionally control for the same set of variables as column 5 of Table 3, as well as population at the ZIP code level for 2020 and personal income per capita at the county-year level. Standard errors clustered by county in parentheses.

In sum, these results are consistent with tokenisation tapping unmet demand by traditional financial intermediaries.

4.2 Trading activity around natural disasters

In this section, I examine whether tokenisation can ameliorate the liquidity gaps inherent in traditional real estate markets. I document the effect of a natural disaster on the trading activity of tokens representing fractional ownership of (tokenised) real estate properties. For identification, I exploit natural disasters since these are exogenous shocks to real estate trading activity, which

to avoid multicollinearity issues.

I proxy with the number of transactions of tokens associated with properties based in a specific ZIP code.

To assess the effect of a natural disaster on trading in tokenised properties, I first estimate an event study regression around disaster dates (Davydiuk et al., 2024). I identify disaster dates specific to each ZIP code as the earliest day of a registration for an individual assistance program with the FEMA in that specific ZIP code. A registration for a FEMA individual assistance program is the first step for a property owner to claim financial aid from FEMA in the aftermath of a disaster. Specifically, I estimate the following regression:

$$ln(Transactions_{z,c,n,t,t^*}) = \beta_h \mathbb{1}\{t \geq t^*_{z,n}\} + \alpha_{c,n} + \zeta_z + \theta_t + \varepsilon_{z,c,n,t,t^*} \tag{4}$$

where $ln(\text{Transactions}_{z,c,n,t,t^*})$ denotes the natural logarithm of one plus the number of transactions for tokens representing fractional ownership of tokenised properties in ZIP code z with disaster date $t^*_{z,n}$.[20] $\mathbb{1}\{t \geq t^*_{z,n}\}$ is an indicator variable equal to one for days following a natural disaster in ZIP code z and zero elsewhere. For each ZIP code, I include ten days prior to a natural disaster as the pre-shock period. The specification includes granular fixed effects to control for the heterogenous effect of a natural disaster on different counties (ie county x natural disaster fixed effect, $\alpha_{c,n}$), time-invariant characteristics at the ZIP code-level (ie ZIP code fixed effects, ζ_z) and common trends in ZIP code features (ie time fixed effects, θ_t). [21]

Results from Table 7 suggest that when a natural disaster occurs in a specific ZIP code, trading of tokenised real estate tokens in that area increases. This finding is consistent with investors seeking to liquidate their investments in areas affected by natural calamities, which typically represent a negative shock to real estate valuations and market liquidity. On the day of the disaster, trading in tokenised properties soars more than twofold relative to the ten pre-disaster days. The effect is sizeable and correspond to nearly 25 more transactions relative to the average. Furthermore I find that in the days after the disaster, transactions are 20%−60% higher relative to the ten days before the disaster date. The effect peaks on the day of the disaster (ie column (1),

[20] In unreported regression analyses, I test the robustness of the results by using the inverse hyperbolic sine of the number of transactions instead of the natural logarithm of one plus the number of transactions. The results remain consistent with those presented in Table 7.

[21] As a robustness check, Table A2 reports the results estimating Equation 4 with a Poisson regression. Reassuringly, results are similar and consistent with the ones from Table 7.

h $=$ 0) and then decreases in magnitude and persists up to 30 days after the disaster.

Table 7: Trading activity around natural disasters: event-study analysis

	Trading activity					
	h = 0	h = 5	h = 10	h = 20	h = 30	Placebo
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}\{t \geq t^*_{z,n}\}$	0.750***	0.479**	0.478**	0.246**	0.184*	
	(0.219)	(0.178)	(0.174)	(0.118)	(0.097)	
$\mathbb{1}\{t \geq t^*_{z,n} - 90\}$						0.059
						(0.082)
County x natural disaster FEs	✓	✓	✓	✓	✓	✓
Zip code FEs	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Observations	1,223	1,785	2,350	3,474	4,496	3,102
Adjusted R-squared	0.68	0.69	0.68	0.65	0.65	0.60

NOTES: The results are obtained from the panel OLS regression in equation 4. Based on data for 68 ZIP codes in 16 counties across 11 states in the United States and 15 natural disasters for the period July 20192025. The dependent variable is the natural logarithm of one plus the number of transactions in day t of tokens representing fractional ownership of properties located in ZIP code z that was affected by natural disaster on day t^*. $\mathbb{1}\{t \geq t^*_{z,n}\}$ is an indicator variable equal to one for days following a natural disaster in ZIP code z and zero elsewhere. The date t^* in which a natural disaster n affects ZIP code z corresponds to the earliest day of a registration for an individual assistance program with the FEMA in that specific ZIP code. In columns (1) $-$ (5), the sample includes ten days prior to the natural disaster and $h \in \{0, 5, 10, 20, 30\}$ days after the natural disaster hit ZIP code z. In column (6) (Placebo), the specification is similar to one in column (4) h $=$ 20 with the sample period and the natural disaster date shifted prior by 90 days. Standard errors clustered by county x natural disaster in parentheses.

One concern with these results may be that trading may be driven by some idiosyncratic factor rather then the natural disaster itself. To address this concern, I implement a placebo test by shifting the disaster date by 90 days backwards. Column (6) reports the corresponding results for h $=$ 20. Reassuringly, the coefficient is not statistically significant indicating the absence of any significant effect. [22]

Ideally, I would be comparing the transactions of tokens associated with properties based in two identical ZIP codes following the exogenous shock, where one ZIP code is hit by the natural disaster and the other is not. I exploit the tokenised properties in ZIP codes that were never hit by a natural disaster as well as ZIP codes prior to being exposed to the exogenous shock to build a control group. I estimate a difference-in-difference (DiD) regression

[22] Table A3 reports the results of the same placebo test for all the horizons considered in Table 7 ($h \in \{0, 5, 10, 20, 30\}$). The coefficients are all not statistically significant. These results suggest that increased trading activity is linked to the occurrence of natural disasters, further confirming the robustness of the findings.

with staggered treatment following the methodology of Borusyak et al. 2024. Specifically, I compare trading in tokenised properties based in ZIP codes that were hit by natural disasters relative to trading in tokenised properties in ZIP codes that were either never hit or were not yet hit by the exogenous shock. The model that I estimate corresponds to:

$$ln(Transactions_{z,c,n,t,t^*}) = \sum_{k=-4}^{k=5} \beta_k \mathbb{1}\{t - t^*_{z,n} = k\} + \alpha_{c,n} + \zeta_z + \theta_m + \varepsilon_{z,c,n,t,t^*} \tag{5}$$

where $ln(\text{Transactions}_{z,c,n,t,t^*})$ is the natural logarithm of one plus the number of transactions for tokens representing fractional ownership of properties located in ZIP code z, $t^*_{z,n}$ is the natural disaster date in ZIP code z, θ_m are month-year fixed effects.[23] The variable k is the number of days relative to the disaster date. Thus, $k < 0$ denotes days before the natural disaster , while $k \geq 0$ denotes days after the natural disaster hit ZIP code z. The indicator variables $\mathbb{1}\{t - t^*_{z,n} = k\}$ correspond to leads and lags of the specific natural disaster date and, thereby, these β_k coefficients capture the dynamic effect of interest.

The estimation results from Table 8 confirm the findings from Table 7. Notably, coefficients from column 1 suggest that there are 23% more transactions at the date in which the ZIP code is hit by the natural disaster and 11% more in the following day. These effects are economically large and correspond to roughly 2 and 0.7 more transactions relative to the mean (ie 4), respectively. The effect is also present three, four and five days after the disaster date. Importantly, with the only exception of two days prior to the natural disaster date, I do not find any significant pre-disaster trends in trading activity –the coefficients at $k \in \{-4, -3, -1\}$ are not statistically significant.

[23] In unreported regression analyses, I test the robustness of the results by using the inverse hyperbolic sine of the number of transactions instead of the natural logarithm of one plus the number of transactions. The results remain consistent with those presented in Table 8.

Table 8: Trading activity around natural disasters: staggered diff-in-diff analysis

	Trading activity		
	All platforms	With buy back features	No buy back features
	(1)	(2)	(3)
$\mathbb{1}\{t - t^*_{z,n} = -4\}$	-0.097	-0.180	0.062
	(0.152)	(0.206)	(0.096)
$\mathbb{1}\{t - t^*_{z,n} = -3\}$	0.208**	0.316***	0.033
	(0.102)	(0.122)	(0.112)
$\mathbb{1}\{t - t^*_{z,n} = -2\}$	-0.135	-0.138	-0.082
	(0.103)	(0.152)	(0.100)
$\mathbb{1}\{t - t^*_{z,n} = -1\}$	0.045	0.160	-0.109
	(0.177)	(0.235)	(0.101)
$\mathbb{1}\{t - t^*_{z,n} = 0\}$	0.232***	0.432***	-0.044***
	(0.023)	(0.023)	(0.009)
$\mathbb{1}\{t - t^*_{z,n} = 1\}$	0.112**	0.241***	-0.065**
	(0.024)	(0.020)	(0.030)
$\mathbb{1}\{t - t^*_{z,n} = 2\}$	-0.018	0.084***	-0.133***
	(0.020)	(0.017)	(0.029)
$\mathbb{1}\{t - t^*_{z,n} = 3\}$	0.102***	0.308***	-0.142***
	(0.021)	(0.025)	(0.021)
$\mathbb{1}\{t - t^*_{z,n} = 4\}$	0.141***	0.365***	-0.181***
	(0.024)	(0.028)	(0.034)
$\mathbb{1}\{t - t^*_{z,n} = 5\}$	0.182***	0.332***	-0.017
	(0.023)	(0.037)	(0.033)
County x natural disaster FEs	✓	✓	✓
Zip code FEs	✓	✓	✓
Month-year FE	✓	✓	✓
Observations	4,769	2,658	2,430

NOTES: The entries results are obtained from the panel OLS regression in equation 5. Based on data for 73 ZIP codes in 20 counties across 14 states in the United States and 18 natural disasters for the period July 2019–February 2025. The dependent variable is the natural logarithm of one plus the number of transactions in day t of tokens representing fractional ownership of properties located in ZIP code z that was affected by natural disaster on day t^*. Column 1 includes all platforms, whereas column 2 includes only properties tokenised by platforms that do not allow buybacks by management companies. $\mathbb{1}\{t - t^*_{z,n} = k\}$ are an indicator variables equal to one for the respective leads and lags of the date of a natural disaster in ZIP code z and zero elsewhere. The date t^* in which a natural disaster n affects ZIP code z corresponds to the earliest day of a registration for an individual assistance program with the FEMA in that specific ZIP code. Standard errors clustered by county x natural disaster in parentheses.

The benefits of higher liquidity enabled by tokenisation seem to vanish in absence of a "centralised" agent, such as the platform itself, which guarantees to buy back a limited number of tokens (typically per week) at the property's last appraisal value within a few days. Column 2 presents the results from estimating the same regressions on transactions of properties tokenised by platforms that provide this feature, whereas column 3 presents the results for platforms that do not offer this feature. Notably, while trading activity for tokens on platforms with a buyback feature increases after a natural disaster, it declines on platforms without this feature, both on the event date and in the following five days. This likely happens because holders of tokens from platforms offering a buyback feature can sell a portion of their holdings back to the platform at the pre-disaster appraisal price. Conversely, holders of tokens on platforms without buyback features can only trade at market prices, which reflect the most recent developments.

Drawing a parallel with traditional financial instruments, tokens with buyback features are akin to money market funds (MMFs) with a limited but compulsory sponsor support. When sponsor support is present, the value of MMF shares remains constant for investors, irrespective of the underlying value of the fund's assets. In this way, sponsor support insulates investors from losses in the fund's asset portfolio – the fund's net asset value (NAV) does not "break the buck" (Parlatore 2016). In contrast, tokens without buyback features resemble equity-like instruments, which rely on a counterparty for transactions and are typically traded at prices reflecting the current value of the underlying asset.

Importantly, I find no evidence of significant pre-disaster trends in trading activity – the coefficients in columns 2 and 3 at $k \in \{-4, -3, -2, -1\}$ are not statistically significant in (almost) all cases. It is important to note that the results from column 3 should be interpreted with caution, as they may be influenced by the smaller sample size, given that these platforms operate in fewer ZIP codes.

In sum, these results on trading activity around natural disasters suggest that investors in tokenised real estate properties pay a spread to invest in tokenised properties for harnessing the higher liquidity provided by these platforms. In other words, these results suggest that tokenisation appears to enhance liquidity in a market traditionally characterised by lengthy transaction times, particularly during periods when liquidity typically dries up. However, these benefits only materialise if the market is supported by a "centralised" agent, contingent on the agent's solvency. Consequently, the higher liquidity for investors may come at the cost of increased insolvency risk for platforms, a fragility that could be further exacerbated during housing crises.

4.3 Robustness tests

4.3.1 Using amounts as dependent variable

To test the robustness of the findings, I examine whether the results hold when the dependent variable is replaced with the cumulative value of tokenised properties. As a first robustness test, I re-estimate the regressions in Tables 3 changing the dependent variable accordingly.

The estimation results are reported in Table 9 and show that the signs of the coefficients remain consistent with the baseline analysis (ie Table 3). Moreover, the point estimates remain consistent, albeit being slightly smaller in magnitude and exhibiting a marginally weaker statistical significance. While the median price per square foot loses statistical significance, all other independent variables – namely, the year-over-year change in the median list price (ie, pricing), the number of properties sold (ie, demand), the sale-to-list price ratio (i.e., liquidity) and the number of new listings (ie, supply)– remain statistically significant.

Table 9: The market determinants of tokenised real estate supply

	Cumulative value of tokenised real estate properties$_{z,c,t}$				
	(1)	(2)	(3)	(4)	(5)
Median price per sqft$_{z,c,t}$	-0.007	-0.004	-0.005	-0.004	-0.003
	(0.011)	(0.007)	(0.008)	(0.007)	(0.006)
Median price, % change$_{z,c,t-6:t-18}$	0.326***	0.170**	0.231*	0.191**	0.151*
	(0.115)	(0.083)	(0.124)	(0.082)	(0.079)
Properties sold, % of inventory$_{z,c,t-6}$		-1.085***			-0.669***
		(0.334)			(0.192)
% properties sold quickly$_{z,c,t-6}$			-1.472		0.656
			(1.205)		(0.751)
Sale-to-list price ratio$_{z,c,t-6}$			-6.327***		-2.762***
			(1.108)		(0.994)
New listings, % of inventory$_{z,c,t-6}$				-1.186***	-0.712***
				(0.369)	(0.210)
County FEs	✓	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓
Observations	141,741	137,196	135,870	137,196	135,362
Pseudo R-squared	0.46	0.52	0.49	0.51	0.54

NOTES: The results are obtained from a Poisson regression. Based on data for 2,143 ZIP codes in 56 counties across 27 states in the United States for the period July 2019–February 2025. z denotes ZIP codes, c denotes counties and t denotes time (ie month-year). The dependent variable, *cumulative value of tokenised real estate properties*$_{z,c,t}$, denotes to the cumulative value of tokenised properties per capita. *% properties sold quickly*$_{z,c,t-6}$, corresponds to the percentage of properties that went off market within two weeks of the respective listing date. Regressions additionally control for population at the ZIP code level for 2020 and personal income per capita at the county-year level. Standard errors clustered by county in parentheses.

In sum, the evidence presented in Tables 9 supports that pricing, demand, liquidity and supply factors in traditional real estate markets drive the development of the tokenised counterpart.

4.3.2 Controlling for time-varying county characteristics

One concern with the results presented in Table 3 is that these could be confounded by unobservable time-varying characteristics at the county level such as, for instance, local labour market dynamics. In such instance, coefficients would be affected by omitted variable bias. To address this concern I re-estimate Equation 3 replacing the county and time fixed effects with more granular county x time fixed effects. The results reported in Table 10 are similar and consistent with those in Table 3. Notably the point estimates are similar, confirming the robustness of the baseline findings.

Table 10: The market determinants of tokenised real estate supply: controlling for time-varying county level characteristics

	Cumulative tokenised real estate properties$_{z,c,t}$				
	(1)	(2)	(3)	(4)	(5)
Median price per sqft$_{z,c,t-6}$	-0.018*	-0.011*	-0.013*	-0.012*	-0.010
	(0.009)	(0.007)	(0.008)	(0.007)	(0.006)
Median price, % change$_{z,c,t-6:t-18}$	0.432***	0.288***	0.362***	0.308***	0.278***
	(0.060)	(0.047)	(0.040)	(0.055)	(0.050)
Properties sold, % of inventory$_{z,c,t-6}$		-1.031***			-0.634***
		(0.238)			(0.127)
% properties sold quickly$_{z,c,t-6}$			-1.962***		-0.050
			(0.667)		(0.659)
Sale-to-list price ratio$_{z,c,t-6}$			-5.531***		-3.056***
			(1.959)		(1.128)
New listings, % of inventory$_{z,c,t-6}$				-1.150***	-0.486**
				(0.262)	(0.201)
County× time FEs	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓
Observations	142,341	137,774	136,313	137,774	135,783
Pseudo R-squared	0.17	0.19	0.18	0.19	0.19

NOTES: The results are obtained from a Poisson regression. Based on data for 2,143 ZIP codes in 56 counties across 27 states in the United States for the period July 2019–February 2025. z denotes ZIP codes, c denotes counties and t denotes time (ie month-year). The dependent variable, *cumulative tokenised real estate properties*$_{z,c,t}$, denotes the cumulative number of tokenised properties per capita. *% properties sold quickly*$_{z,c,t-6}$, corresponds to the percentage of properties that went off market within two weeks of the respective listing date. Regressions additionally control for population at the ZIP code level for 2020. Standard errors clustered by county in parentheses.

4.3.3 Double clustering standard errors at the county time level

In the baseline specification I cluster standard errors at the county level to account for serial correlation within the same county over time. However, since some of the independent variables in our regressions are monthly time-series measured on overlapping three-month periods, one reasonable concern would be that the standard errors obtained are impacted by this specific feature of the data. To address this concern I replicate the baseline analysis by clustering standard errors at the county and time level. Results from Table A4 in Appendix A are similar and consistent with those in Table 3 suggesting the robustness of the baseline results.

4.3.4 The investment yield driver: controlling for rental price growth

Results from Table 3 are consistent with investors buying tokenised properties located in areas where the traditional real estate market is relatively weak (ie lower prices, lower demand and lower liquidity). This raises a reasonable question: why would prospective investors be interested in such properties at all? One possible explanation is that, while the demand to purchase properties in these areas is weak, the demand for rental properties may be strong. Under this hypothesis, tokenised properties are more likely to develop in areas where it is financially attractive to purchase a property in anticipation of strong rental income. To test this hypothesis, I augment the specification in Equation 3 including the yoy rental price growth in ZIP code z.

Table 11: The investment yield driver: controlling for rental price growth

	Cumulative tokenised real estate properties$_{z,c,t}$				
	(1)	(2)	(3)	(4)	(5)
Median price per sqft$_{z,c,t-6}$	-0.018***	-0.012***	-0.012**	-0.012***	-0.011**
	(0.006)	(0.004)	(0.005)	(0.004)	(0.004)
Median price, % change$_{z,c,t-6:t-18}$	0.338***	0.611***	0.489***	0.630***	0.595***
	(0.102)	(0.112)	(0.176)	(0.121)	(0.142)
Rental price, % change$_{z,c,t-6:t-18}$	2.611***	3.966***	4.104***	4.015***	4.388***
	(0.671)	(0.826)	(0.965)	(0.883)	(0.974)
Properties sold, % of inventory$_{z,c,t-6}$		-0.960***			-0.610***
		(0.212)			(0.165)
% properties sold quickly$_{z,c,t-6}$			-3.220***		-1.632***
			(0.503)		(0.632)
Sale-to-list price ratio$_{z,c,t-6}$			-8.038***		-5.927***
			(2.396)		(2.006)
New listings, % of inventory$_{z,c,t-6}$				-1.066***	-0.050
				(0.220)	(0.261)
County FEs	✓	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓
Observations	42,188	41,220	41,024	41,220	41,021
Pseudo R-squared	0.17	0.19	0.19	0.19	0.19

NOTES: The entries results are obtained from a Poisson regression. Based on data for 1,109 ZIP codes in 41 counties across 22 states in the United States for the period July 2019–February 2025. z denotes ZIP codes, c denotes counties and t denotes time (ie month-year). The dependent variable, *cumulative tokenised real estate properties*$_{z,c,t}$, denotes the cumulative number of tokenised properties per capita. *rental price, % change*$_{z,c,t-6:t-18}$ corresponds to the year-on-year change in the Zillow Observed Rent Index (ZORI). *% properties sold quickly*$_{z,c,t-6}$, corresponds to the percentage of properties that went off market within two weeks of the respective listing date. Regressions additionally control for population at the ZIP code level for 2020 and personal income per capita at the county-year level. Standard errors clustered by county in parentheses.

Despite the smaller sample size, the results from Table 11 remain similar to the ones from Table 3. The coefficient associated with rental price growth is positive and significant. From an economic perspective the magnitude is large – looking at column 1, a one standard deviation increase in rental price growth is linked to a nearly 20% increase in the availability of tokenised properties.[24]

5 Conclusions

Tokenisation is rapidly gaining traction across various areas of traditional financial markets, purportedly due to its promise to enhance accessibility, transparency, and liquidity across a wide range of asset classes. This paper provides a comprehensive analysis of the development and dynamics of tokenised real estate properties, offering novel insights into the drivers, implications and unique characteristics of this growing market.

I find three main results. First, I identify key traditional real estate market forces – pricing, demand, liquidity and supply – that influence the development of tokenised properties. These drivers operate differently than for traditional real estate properties and REIT portfolios, highlighting the distinct nature of tokenised real estate as a financial product. For instance, tokenisation appears to thrive in markets with lower demand, less liquidity and limited supply, underscoring its potential to address inefficiencies in traditional real estate markets.

Second, the study demonstrates the importance of access to credit in shaping the growth of tokenised real estate. Areas with fewer physical bank branches or higher banking market concentration tend to exhibit greater adoption of tokenisation. This suggests that tokenised real estate may serve as an alternative in regions where traditional financial intermediaries are less accessible. This finding underscores the role of tokenisation in bridging gaps in access to certain asset classes, thereby facilitating portfolio diversification.

Third, the paper examines trading activity around natural disasters as an exogenous shock to market liquidity. The results reveal that trading in tokenised properties increases significantly in the immediate aftermath of such events, reflecting investors' ability to trade in response to adverse shocks. However, the evidence also suggests that the higher liquidity offered by to-

[24]The data on rental price growth is available for fewer ZIP codes. Therefore, given the smaller sample size determined by the inclusion of the rental prices in the specification, I omit this variable from the baseline specification.

kenisation is contingent on platforms guaranteeing buyback features enabling holders to sell back tokens at a price based on the last appraisal value, which pre-dates the occurrence of the disaster. Thus, this feature comes at the cost of higher insolvency risk for the platform.

While tokenisation offers promising benefits such as enhanced market liquidity, broader access to investment opportunities and the potential to serve as a complement to traditional real estate markets, these advantages, in some cases, rely on the presence of centralised and trustworthy agents. This underscores the critical role of institutional design and backstops in unlocking its full potential.

This study opens several avenues for future research. First, while this paper provides early evidence on tokenised real estate, sustained growth warrants further exploration of its long-term implications for price stability and market volatility in traditional real estate markets. Second, an analysis of the interconnections with DeFi lending pools or Decentralised Exchanges (DEXs) could provide insights into the degree of leverage accumulation within the tokenised real estate market. Finally, future studies could assess the broader social and economic impacts of tokenisation, including its potential to democratise access to "capital-intensive" asset classes and its implications for wealth distribution.

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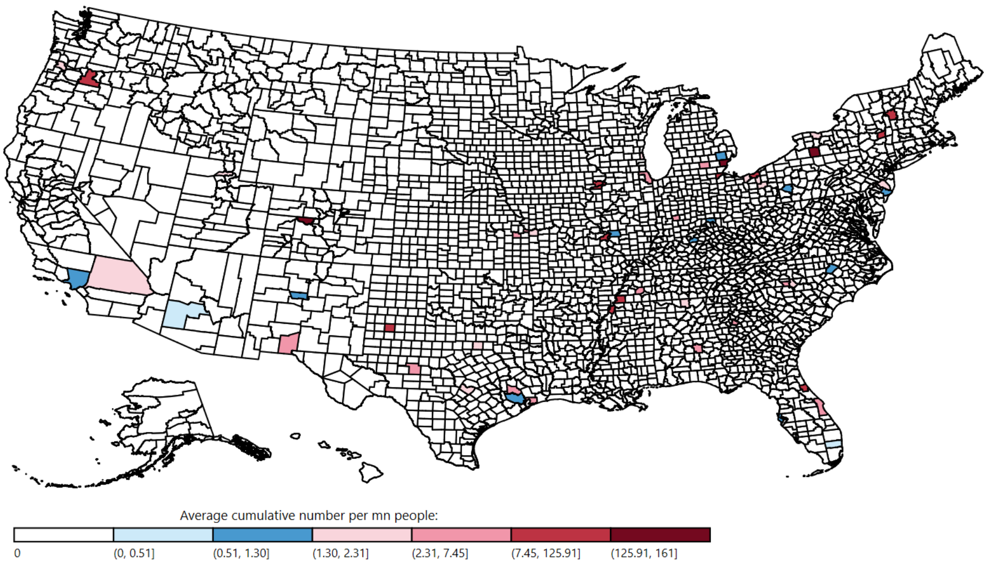
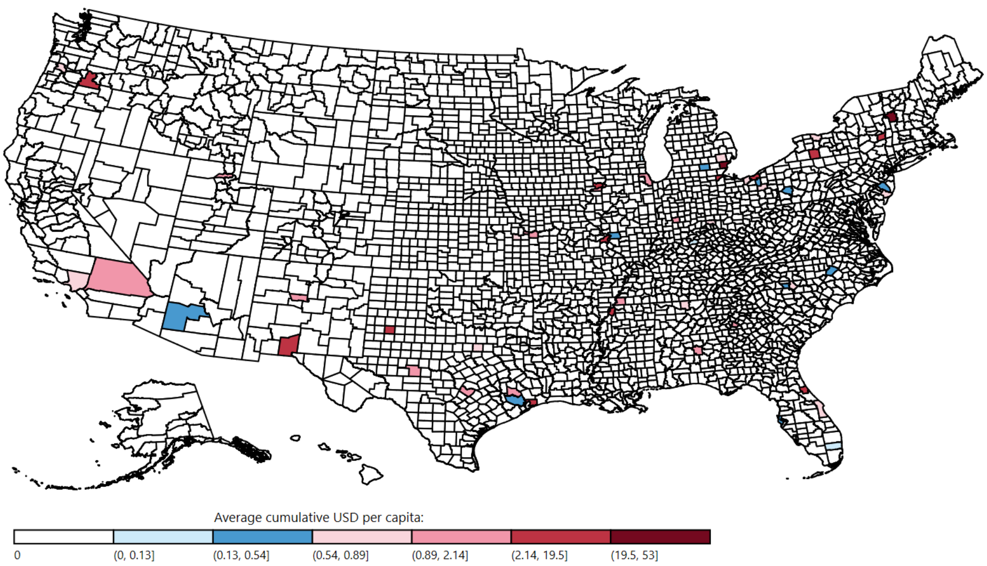
Appendix A: additional analyses

Figure A1: **Real estate tokenisation**

(a) Number of tokenised real estate properties

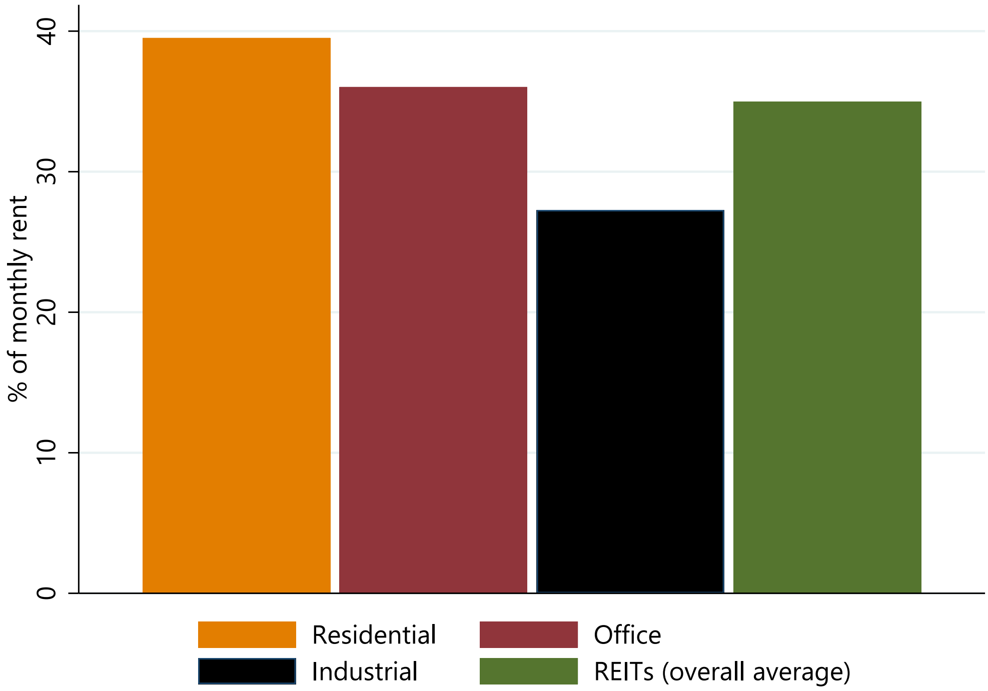


(b) Value of tokenised real estate properties



Note: The figure shows the distribution of tokenised real estate properties across counties in the US as of March 2025. Panel (a) shows the breakdown by cumulative number (per million people) of properties. Panel (b) shows the breakdown by cumulative value (per capita) of these properties. The use of this map does not constitute, and should not be construed as constituting, an expression of a position by the BIS or the author regarding the legal status of, or sovereignty of any territory or its authorities, to the delimitation of international frontiers and boundaries and/or to the name and designation of any territory, city or area. Sources: Blocksquare; LoftyAI; RealT; author's calculations.

Figure A2: **REITs property portfolio: monthly property running costs**



Note: The figure shows the average ratio of the total expense resulting from operating and maintaining all real estate assets to the total rental revenue for the top 100 (subject to data availability) residential, office and industrial US focussed REITs by market capitalisation for the period 2019–2024. Sources: S&P Capital IQ; author's calculations.

Table A1: The market determinants of tokenised real estate supply: MSA fixed effects

	Cumulative tokenised real estate properties$_{z,c,t}$				
	(1)	(2)	(3)	(4)	(5)
Median price per sqft$_{z,c,t-6}$	-0.015	-0.008	-0.009	-0.009	-0.007
	(0.015)	(0.008)	(0.011)	(0.009)	(0.006)
Median price, % change$_{z,c,t-6:t-18}$	0.711***	0.443***	0.507***	0.478***	0.393***
	(0.165)	(0.070)	(0.098)	(0.073)	(0.068)
Properties sold, % of inventory$_{z,c,t-6}$		-1.668***			-1.025***
		(0.444)			(0.214)
% properties sold quickly$_{z,c,t-6}$			-2.396***		-0.168
			(0.913)		(0.521)
Sale-to-list price ratio$_{z,c,t-6}$			-10.960***		-7.280***
			(3.314)		(1.796)
New listings, % of inventory$_{z,c,t-6}$				-1.758***	-0.607**
				(0.472)	(0.243)
MSA FEs	✓	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓
Observations	332,496	318,800	318,666	318,800	316,140
Pseudo R-squared	0.16	0.19	0.18	0.18	0.19

NOTES: The results are obtained from the Poisson regression in equation 3. Based on data for 2,143 ZIP codes in 47 MSAs across 27 states in the United States for the period July 2019–February 2025. z denotes ZIP codes, c denotes counties and t denotes time (ie month-year). The dependent variable, *cumulative tokenised real estate properties*$_{z,c,t}$, denotes the cumulative number of tokenised properties per capita. *% properties sold quickly*$_{z,c,t-6}$, corresponds to the percentage of properties that went off market within two weeks of the respective listing date. Regressions additionally control for population at the ZIP code level for 2020 and personal income per capita at the county-year level. Standard errors clustered by county in parentheses.

Table A2: Trading activity around natural disasters: event-study analysis

	h = 0	h = 5	h = 10	h = 20	h = 30	Placebo
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}\{t \geq t^*_{z,n}\}$	0.873**	1.133*	1.512*	1.547***	0.747**	
	(0.357)	(0.587)	(0.813)	(0.290)	(0.381)	
$\mathbb{1}\{t \geq t^*_{z,n} - 90\}$						-0.010
						(0.121)
County x natural disaster FEs	✓	✓	✓	✓	✓	✓
Zip code FEs	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Observations	1,183	1,726	2,275	3,404	4,406	3,072
Pseudo R-squared	0.73	0.75	0.73	0.66	0.65	0.66

NOTES: The results are obtained from the panel Poisson regression in equation 4. Based on data for 68 ZIP codes in 16 counties across 11 states in the United States and 15 natural disasters for the period July 20192025. The dependent variable is the number of transactions in day t of tokens representing fractional ownership of properties located in ZIP code z that was affected by natural disaster on day t^*. $\mathbb{1}\{t \geq t^*_{z,n}\}$ is an indicator variable equal to one for days following a natural disaster in ZIP code z and zero elsewhere. The date t^* in which a natural disaster n affects ZIP code z corresponds to the earliest day of a registration for an individual assistance program with the FEMA in that specific ZIP code. In columns $(1) - (5)$, the sample includes ten days prior to the natural disaster and $h \in \{0, 5, 10, 20, 30\}$ days after the natural disaster hit ZIP code z. In column (6) (Placebo), the specification is similar to one in column (4) h = 20 with the sample period and the natural disaster date shifted prior by 90 days. Standard errors clustered by County x natural disaster in parentheses.

Table A3: Trading activity around natural disasters: placebo test

	Trading activity				
	h = 0	h = 5	h = 10	h = 20	h = 30
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}\{t \geq t^*_{z,n}\}$	-0.530	-0.343	-0.158	0.059	0.059
	(0.313)	(0.226)	(0.132)	(0.082)	(0.097)
County x natural disaster FEs	✓	✓	✓	✓	✓
Zip code FEs	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓
Observations	1,095	1,598	2,099	3,102	3,956
Adjusted R-squared	0.56	0.59	0.60	0.60	0.59

NOTES: The results are obtained from the panel OLS regression in equation 4. Based on data for 68 ZIP codes in 16 counties across 11 states in the United States and 15 natural disasters for the period July 20192025. The dependent variable is the natural logarithm of one plus the number of transactions in day t of tokens representing fractional ownership of properties located in ZIP code z that was affected by natural disaster on day t^*. $\mathbb{1}\{t \geq t^*_{z,n}\}$ is an indicator variable equal to one for days following a natural disaster in ZIP code z and zero elsewhere. The date t^* in which a natural disaster n affects ZIP code z corresponds to the earliest day of a registration for an individual assistance program with the FEMA in that specific ZIP code. The sample includes ten days prior to the natural disaster and $h \in \{0, 5, 10, 20, 30\}$ days after the natural disaster hit ZIP code z, shifted prior by 90 days. Standard errors clustered by county x natural disaster in parentheses.

Table A4: The market determinants of tokenised real estate supply: double clustering standard errors

	Cumulative tokenised real estate properties$_{z,c,t}$				
	(1)	(2)	(3)	(4)	(5)
Median price per sqft$_{z,c,t-6}$	-0.013*	-0.008**	-0.010*	-0.009*	-0.008**
	(0.008)	(0.004)	(0.005)	(0.005)	(0.004)
Median price, % change$_{z,c,t-6:t-18}$	0.451***	0.288***	0.363***	0.297***	0.271***
	(0.055)	(0.040)	(0.050)	(0.039)	(0.039)
Properties sold, % of inventory$_{z,c,t-6}$		-1.014***			-0.652***
		(0.243)			(0.139)
% properties sold quickly$_{z,c,t-6}$			-1.601**		0.153
			(0.713)		(0.473)
Sale-to-list price ratio$_{z,c,t-6}$			-6.980***		-3.891***
			(1.061)		(0.852)
New listings, % of inventory$_{z,c,t-6}$				-1.093***	-0.420**
				(0.259)	(0.192)
County FEs	✓	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓
Observations	142,376	137,819	136,502	137,819	135,982
Pseudo R-squared	0.17	0.18	0.18	0.18	0.19

NOTES: The results are obtained from a Poisson regression. Based on data for 2,143 ZIP codes in 56 counties across 27 states in the United States for the period July 2019–February 2025. z denotes ZIP codes, c denotes counties and t denotes time (ie month-year). The dependent variable, *cumulative tokenised real estate properties*$_{z,c,t}$, denotes the cumulative number of tokenised properties per capita. *% properties sold quickly*$_{z,c,t-6}$, corresponds to the percentage of properties that went off market within two weeks of the respective listing date. Regressions additionally control for population at the ZIP code level for 2020. Standard errors clustered by county and time in parentheses.

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