Mortgage Rates and Rents: Evidence from Local Mortgage Lock-In Effects

Jorge De la Roca* USC

Marco Giacoletti† USC

Lizhong Liu‡ USC

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Abstract

Using new comprehensive micro-data covering the Los Angeles County rental market, we study how mortgage rate changes influence rents through their effects on local sales markets. A one-standard-deviation increase in average mortgage lock-in for homes within a narrow radius of a rental listing raises rents by 4.5% and shortens time-on-market. These estimates are not confounded by differences in property characteristics, sub-market trends, or migration. Instead, they are driven by spillovers from reduced sales volume and higher prices onto rents. Spillovers are stronger in lower-socioeconomic status areas, and for multi-family buildings, which are segmented from for-sale supply. This variation contributes to diverging patterns in local rent inflation.

Keywords: Mortgage Rates, Housing Rents, Rent Inflation, Lock-In

*University of Southern California, Sol Price School of Public Policy, Phone: +1 (213) 621-4659, Email: jdelaroc@usc.edu

†University of Southern California, Marshall School of Business, Phone: +1 (650) 475-6410, Email: mgiacole@marshall.usc.edu

‡University of Southern California, Sol Price School of Public Policy, Phone: +1 (213) 245-3787, Email: lizhongl@usc.edu

1 Introduction

An increasing body of work is exploring the interplay between the sales and rental market in housing[1]. However, still relatively little is known about how these markets jointly respond to external economic shocks, such as changes in interest rates and mortgage market conditions. Understanding how these shocks affect rental market outcomes is important, since rent is a prominent component of the consumer price index and the main driver of living costs of many US households (Adams et al., 2024). Existing studies mainly focus on how higher mortgage costs or stricter underwriting standards affect the collateral constraints faced by first-time home-buyers, delaying access to homeownership and reallocating demand from the sales to the rental market. Given that housing inventory cannot easily transition between the two markets, higher interest rates or lower mortgage supply can result in *lower* house prices, and, at least in the short run, *higher* rents (Greenwald, 2018, Gete and Reher, 2018, Dias and Duarte, 2019, and Greenwald and Guren, 2024).

In this paper, we study an alternative mechanism, which, as emerges from our analysis, also has significant effects on rental demand and rents. We show that higher mortgage rates affect the rental market by impacting the inventory of sales listings and sales prices through mortgage lock-in effects. Approximately one third of the effect of mortgage lock-in on sales prices spills over onto rents. Through this channel, higher mortgage rates lead to both *higher* sales prices and *higher* rents, increasing housing cost for all households searching for a new residence. Based on data from Los Angeles County, our estimates reveal that a 1% increase in the gap between the monthly payment based on current market rates and the payment per dollar of principal locked in by local owners translates into 0.35% higher rents. Equivalently, a one standard deviation increase in monthly payments leads to an increase in rents of 4.5% or $130 per month, given monthly average rents of $2,825.

We also show that the extent of co-movement between prices and rents induced by mortgage rates crucially depends on the characteristics of local demand and supply. Spillovers are larger in lower socioeconomic status neighborhoods, due to less elastic local rental demand. The magnitude of the spillovers also varies substantially across rental property types. They are

[1] See, for example, Han et al., 2023, and Badarinza et al., 2024.

the smallest for single-family rentals and are the largest for properties that are managed by professional investors and for large multi-family buildings (with 10 or more units), which have the highest degree of segmentation from the for-sale housing stock.

This paper also contributes to a growing body of empirical and theoretical work on mortgage lock-in effects. In the US, most residential mortgages have fixed rates and are not portable. Thus, increases in rates create a gap between the rate most owners have locked-in on their loans and the rate they would receive if they were to sell and move to a new house. This gap reduces mobility (Fonseca and Liu, 2023 and Liebersohn and Rothstein, 2024) and can have broader effects across the housing ladder (Fonseca et al., 2024). Our findings provide new empirical evidence of the spillovers of lock-in effects on the rental market. Through this mechanism, tightening monetary policy can lead to rent inflation, thus counteracting its main goal. Moreover, given the heterogeneous effects that we document in this paper, tightening policy and higher rates can lead to diverging patterns in rent inflation across neighborhoods, potentially increasing cost of living the most in areas with low incomes and high density of multi-family buildings.

We focus our analysis on Los Angeles County to take advantage of comprehensive and geographically granular data on rental listings from Renthub.[2] These data cover a representative share of the rental market, which come from online listings published by large developers, property management companies, and mom-and-pop landlords. The study period ranges from 2014 to 2023, when a total of 3.7 million listings and 1.3 million rental units are observed. Los Angeles County is the second-largest housing market in the country and has shown sustained rental growth despite a declining population after the COVID-19 pandemic (see Figure 1). The inflationary effects of mortgage lock-in can be one of the contributing factors to this sustained rent inflation.

We use CoreLogic data on housing transactions and mortgages from deeds and tax registry files to construct exposure measures to mortgage lock-in for individual rental listings. Our central thesis is that lock-in creates spillovers from sales to the rental market. Thus, when

[2]Renthub is a rental consulting company that web-scrapes online rental listings from various online listing platforms and property management companies. The data are collected every other week since 2014, with lower coverage in 2017 and 2018. Each wave of data is a snapshot of all listings in the market.

constructing lock-in measures, we restrict the sample to "starter homes," i.e., those more likely to be in the choice set of tenants interested in homeownership (smaller than 1,800 square feet and with three or fewer bedrooms).

To construct our local lock-in measure, we find all "starter home" primary residences within a 0.5 miles radius of each rental listings, with a fixed rate mortgage (FRM) that originated in the previous 15 years (either a new purchase loan or a refinancing). We then recover the prevailing monthly mortgage market rate for every starter home at the time of mortgage origination and calculate the average origination rate within the radius. Local mortgage lock-in is a function of the difference between the current monthly mortgage market rate and the historical locked-in rates in the 0.5-mile radius. Following a similar approach to Fonseca et al. (2024), we use prevailing market rates instead of individual contract rates since the former are unaffected by local households' creditworthiness and other neighborhood conditions. Therefore, US market-wide rate fluctuations and the timing of origination of the last mortgages solely determine the spatial and temporal variation in the lock-in measure.

Our preferred lock-in measure is the mortgage payment gap between current market conditions and existing mortgages in the 0.5-mile radius (Liebersohn and Rothstein, 2024). Specifically, we calculate monthly mortgage principal payments per dollar based on current market and historical origination rates and obtain the percentage difference in payments. Our payment gap measure underwent substantial fluctuations between 2014 and 2023 along with the evolution of mortgage market rates. A notable spike appeared in 2022-2023, when payment per new dollar borrowed increased by 40% compared to the existing payments (Figure 2). We choose this measure for several reasons. First, existing work shows that monthly payments are highly salient for households and are used as a benchmark for financial decision-making due to liquidity constraints or reference-dependence (see for example, Fuster and Willin, 2017; Argyle et al., 2020; and Giacoletti and Parsons, 2022). Second, the ratio of monthly payments to income (debt-to-income ratio) is one of the critical underwriting standards in lenders' mortgage origination decisions (Greenwald, 2018; Ringo, 2024).

A reasonable concern with our estimation approach is that the mortgage payment gap can correlate with time-invariant and time-varying characteristics of a local market. For instance, residents in more affluent neighborhoods might be better at timing purchase and refinancing decisions than residents in less advantaged neighborhoods.[3] Furthermore, substantial migration flows across and within metropolitan areas occurred in the wake of the COVID pandemic, impacting local sales and rental markets in the latter part of our sample (Gupta et al., 2022; Ramani and Bloom, 2022; and Mondragon and Wieland, 2022). These migration patterns may have increased local rents due to higher demand for housing, leading to higher house sales volume. House sales prompt the resetting of mortgage rates, affecting local mortgage lock-in. Consequently, migration may create spurious correlations between rents and lock-in.

We address these concerns with multiple empirical strategies. First, we include a rich set of property characteristics and census tract fixed effects to control for time-invariant differences across rental properties and locations. Our data further allow us to identify listings from multi-family buildings with ten or more units, which exhibit higher tenant turnover than single-family residences and smaller properties. We construct a subsample of listings from multi-family buildings and include building fixed effects to mitigate any bias from unobserved landlord and property characteristics.

Second, we show that the local payment gap measure does not positively correlate with zip code-level contemporaneous or lagged population inflows (measured using USPS change of address data made available by Ramani and Bloom, 2022). Hence, the positive relation between local lock-in effects and rents is not conflated with migration waves across the county. Third, along with census tract fixed effects, we include time-by-location fixed effects to account for diverging trends in housing markets within the county. Specifically, we interact year-month indicators with neighborhoods (see Figure A.2), using neighborhood definitions obtained from the Los Angeles Times. While comparable to zip codes, these neighborhoods are specifically designed to encompass areas with common civic characteristics, and are based on historical demarcations and current consensus.[4] We believe that these time by location fixed effects are helpful in greatly reducing the potential impact of omitted factors on our results. Indeed, any

[3] Kermani and Wong (2024) show consistent evidence for such purchase timing. Further, there is extensive literature on refinancing inertia and how it relates to household characteristics (Andersen et al., 2020, Keys et al., 2016, and Agarwal et al., 2016)

[4] The LA Times defines 272 distinct neighborhoods in Los Angeles County, and 114 neighborhoods in Los Angeles City. For more details see also: https://www.latimes.com/travel/story/2023-10-19/los-angeles-neighborhood-city-guides.

omitted local factor driving the lock-in payment gap would create positive spatial autocorrelation and clustering in the variable, even after accounting for regression controls. We show that the residual spatial autocorrelation (measured by Moran's I, see Figure 5) of the lock-in gap after including census tract and time by neighborhood fixed effects shrinks to approximately zero.

Third, we employ an event-study design to further address concerns about confounding effects, especially in the post-COVID sample. We examine the diverging evolution of rents between census tracts with high and low payment gap. If our effects are confounded by diverging trends that began during COVID or earlier, such as suburban migration or the decline of city centers, then rents in the tracts with above-median payment gaps should start diverging before the recent interest rate hikes. We demonstrate that, when sorting tracts based on their 2021 lock-in level, rents in tracts with high lock-in move parallel to rents in the rest of the county until 2022, when the Federal Reserve started to increase rates. Subsequently, rents in tracts with high payment gaps grow faster as mortgage rates increase. The results remain unchanged if we sort tracts based on their average lock-in level in late 2022 and early 2023.

Fourth, we show that the effects of the local payment gap on rents are attenuated for rental listings that are located in close proximity to new multi-family developments. This is consistent with the effects of the payment gap being driven by demand spillovers from the sales market, which are more easily absorbed in micro-locations with new rental supply.

After establishing our key findings on rents, we also show that higher values of the payment gap lead to *shorter* time-on-market, consistent with a demand-side explanation. In the absence of a positive demand shock, landlords could raise rents in neighborhoods with a higher exposure to lock-in properties but would face a lower matching probability and thus experience *longer* time-on-market (Andersen et al., 2022).[5]

We then turn to providing direct evidence of the spillovers from the sales market to the rental market. First, we show that at the census tract and year-quarter level higher values of

[5]Landlords' payment effects are unlikely to drive our findings. Landlords benchmarking rents against mortgage payments may face higher costs due to adjustable-rate mortgages or forced refinancings and may raise rents. However, this effect would depend on the current rental mortgage contracts and not on the local payment gap for the surrounding owner-occupied properties. Moreover, a rent increase driven by landlords' financial conditions should lead to longer time-on-market in the absence of a positive housing demand shock.

the lock-in payment gap predict an increase in the number of units rented out, and a decrease in sales volume. Then, we show that the local payment gap in the 0.5-mile radius surrounding a rental listing has a positive and statistically significant relation with sales prices within the radius. Homeowners who secured low rates and payments are willing to move only in exchange for higher sales prices. Combined, these findings are consistent with higher prices in the sales market being driven by supply-side pressure, and leading to a shift in demand to the rental market. We then estimate a two-stage-least-squares specification in which we regress rents on local sales prices (within a 0.5-mile radius), instrumented using the payment gap, and find that rents increase by between 0.2 and 0.35% in response to a 1% increase in local prices (driven by the payment gap). Thus, up to 35% of the price effects of local lock-in on sales prices spill over onto rents.

Finally, we examine heterogeneous effects based on local rental demand and supply characteristics. Lock-in effects are larger in census tracts with a higher poverty rate, lower education, and higher unemployment. Tenants in these neighborhoods are likely to be less sophisticated in their housing search, and may be constrained to a limited set of local markets within the county due to lower credit scores or financial hardship (see Bergman et al., 2014 and Bezy et al., 2024). Thus, local demand shocks have steeper effects on rents in these lower socioeconomic status areas due to lower demand elasticity.

On the supply side, we focus on the characteristics of rental listings. Here we formulate two competing hypothesis. On one hand, we may expect larger effects on single-family residences and condos, since these are the rental units most similar to owner-occupied housing, and thus most likely to be cross-searched by households transitioning from the rental to the ownership market. On the other hand, the effects might be larger for larger multi-family buildings and corporate landlords. This could be for two reasons. First, corporate landlords and managers of large buildings are more sophisticated, and likely have better information on local demand pressure. Second, large multi-family buildings are highly segmented from the for-sale stock, and thus are less exposed to competition from properties transitioning from the for-sale to the rental market.

We find that lock-in effects on rentals are the weakest for single-family properties and strongest for large multi-family buildings. Moreover, the effects are stronger for corporate landlords rather than for mom-and-pop landlords. The difference in the magnitude of spillovers between single-family and large multi-family is substantial, and exceeds 60% in relative terms. These results are not confounded by the demand-side effects discussed above, since they hold also when we limit the sample to neighborhoods with poverty rate below the median.

While these differences could be driven by sophistication, we find that higher values of the payment gap also lead to an increase in the supply of single-family properties listed as rentals. This response is likely driven by locked-in owners who are able to move without using their home-equity, and decide to rent out their old residence rather than sell it and forego the associated below-market mortgage rate. The fact that local lock-in leads to an increase in the supply of single-family rentals can explain why these properties experience the smallest spillovers on rents.

The rest of the paper proceeds as follows. Section 2 describes the data sets used for our analysis. Section 3 describes the measurement of local mortgage lock-in. The primary evidence of the effects on rentals is in Section 4. Section 5 provides evidence of spillovers from the local sales market onto the local rental market. Section 6 explores heterogeneous effects. Section 7 concludes.

2 Data

To assess the impact of mortgage lock-in on rental housing markets, we employ various sources of proprietary data on residential rental listings, property sales, and new purchase mortgages and refinancings.

Our first data set is from Renthub, which provides residential rental listings across Los Angeles County from January 2014 to December 2023. The data contain information on asking rent, date listed, exact geolocation (latitude and longitude), number of bedrooms and bathrooms, square footage, and property amenities (e.g., pool, gym, garage) for each listing. The top panel of Table 1 shows the summary statistics of the sample of rental listings. The data reveal the substantial increase in housing costs that the county experienced over time. The median rent over the study period is \$2,350, while in recent years (2021-2023) is almost \$2,860. The median unit size is approximately 1,000 square feet, and the median number of bedrooms is two. The sample has ample coverage, with nearly 3.7 million listings from 1.3 million rental units.

Since this is a new data set in the literature, we examine whether the Renthub listings are representative of the Los Angeles County rental housing market by comparing them against other data sources. Panel (a) of Figure 1 plots the median quarterly rent for Renthub listings in Los Angeles County from Q1 2014 to Q1 2023, the Zillow Observed Rent Index (ZORI) for the county, and the median rent of American Community Survey (ACS) one-year estimates across the county. While the Renthub rent series is much higher than the median contract rent reported in ACS, its level is slightly above the ZORI series. Further, the Renthub rent series is more volatile, given its ample coverage and periodicity.

Two reasons may contribute to the higher rents in the Renthub series. First, Renthub (similar to ZORI) records rents for new rental listings, while ACS reports rents paid by all tenants, including new and existing rent contracts. Previous work has shown that the gap between rents paid by new and existing tenants can generate marked disparities across the main rental indices (Adams et al., 2024). This gap amplifies in metropolitan areas with rent stabilization policies, such as Los Angeles County. One of the prevalent policies in the county and many of its consolidated cities is vacancy decontrol, which allows the landlord to reset the rent to market levels when the rental unit vacates and the landlord searches for a new tenant. Second, Renthub data do not contain subsidized rental units, while ACS surveys a representative sample that includes subsidized units. In the presence of a subsidy, the household reports the actual rent paid instead of the total rent for the unit. New listing rents for non-rent-controlled units are most sensitive to current market conditions, and since our analysis focuses on the demand effects of the current lock-in phenomenon, the Renthub data provide an ideal sample for the study.

We study the cross-sectional differences between Renthub and the ACS for additional validation. We compute median rents for each census tract for 2014-2018 and 2019-2022.[6] We then regress these rents on the median contract rents from 2018 and 2022 ACS five-year esti-

[6]It is worth noting that Renthub changed data sources since 2019, and the most recent sample exhibits better amenities, as a larger share of listings had a garage, laundry in the unit, granite countertops, and stainless steel appliances in the kitchen. We include controls for these traits in all our estimations.

mates, respectively (Figure A.1). After adjusting for the level difference, Renthub data track the ACS rents reasonably well in both periods, and ACS data explain over 50% of the variations in Renthub median rents across neighborhoods.

It is interesting to note the consistent growth path of rents throughout our analysis period, especially in the Renthub and ZORI data in panel (a) of Figure 1. Rent growth is highest in the first years of the sample when it is close to 8% per year, and in the last three years, when it reaches almost 10% annually. Panel (b) plots the annual population growth of the county between 2014 and 2023. While strong rent growth coincides with population growth in the first part of the sample, in 2021 and 2022, despite solid rent growth, Los Angeles County lost 1.5% and 2% of its population. Such an unexpected pattern is consistent with the premise of our study, which is that rent growth is also driven by factors that are not directly related to population growth.

One potential concern with the Renthub data is that they report asking rents instead of actual contractual (closing) rents. This is a typical challenge empirical work faces due to the lack of centralized registries for rental contracts in the US. This limitation would be quantitatively relevant if there were large gaps between asking and contractual rents. However, during our study period, Los Angeles is a hot rental market, and thus tenants have limited bargaining power to bring contractual rents below listing rents. We validate this fact using Multiple Listing Services (MLS) data from CoreLogic, covering Los Angeles County, between January 2015 and December 2020.[7] Table A.1 reports summary statistics of the percentage difference between the contractual rent and the last listing rent of each listed unit, both for the entire sample and each two-year subsample. Overall, asking rents track MLS contractual rents quite well. On average, the contractual rents are roughly 0.5% below listing rents. However, the median is zero, and for 70% of units there is no difference between listing and contractual rents.

Our second data set is from CoreLogic, which collects data on housing transactions and mortgages from deeds and tax registry files of Los Angeles County. These data allow us to track the sequence of new purchase mortgages and refinancing for each residential property

[7]The MLS data cover some rental contracts, even though they are less comprehensive than the Renthub data (e.g., institutional investors operating multi-family buildings and small landlords seldom use MLS agents). However, the subset of rental units covered by MLS contains both listing and contractual rents.

from January 1995 to April 2023. For each mortgage, we observe its closing date, lien, contract maturity, and whether it was a conventional loan, a Fixed Rate Mortgage (FRM), or an Adjustable Rate Mortgage (ARM). The data also contain information on sales prices and property characteristics, including size, number of bathrooms and bedrooms, geolocation, year built, garage, pool, fireplace, air conditioning, and heating system availability.

We exploit the spatial coordinates in Renthub data to assign all listings to land parcels using the Southern California Association of Governments (SCAG) 2019 Annual Land Use shapefile. Since properties in CoreLogic contain rich parcel characteristics, we can determine property types for rental listings, e.g., whether a listing is a single-family unit or belongs to a multi-family building.

Subsequently, we merge the data with LA county "neighborhoods" following the Los Angeles Times neighborhood delineations. The LA Times identifies 114 neighborhoods within the city of Los Angeles by combining census tracts (Figure A.2 Panel b). However, in some instances, some city blocks are reassigned to other census tracts when the tract delineation does not correspond to the historical and socioeconomic configurations of local communities. For the rest of the county, the LA Times primarily uses the Census Bureau's boundaries of 88 cities and 43 census-designated places. The remaining neighborhoods largely correspond to unincorporated areas within the county (Figure A.2 Panel a). The 272 resulting neighborhoods correspond to granular sub-markets within the county.[8]

Lastly, we match the Renthub data to 2012-2016, 2015-2019, and 2018-2022 American Community Survey (ACS) 5-year estimates to assemble tract-level demographics and socioeconomic characteristics (Manson et al., 2023).[9]

[8]Alternatively, we use the Census Bureau's Public Use Micro Areas (PUMAs) as spatial units to delineate sub-markets. PUMAs are geographic areas with at least 100,000 people, often aligning with city and census-designated place boundaries. However, the 69 PUMAs in LA County often miss the granularity and diversity of local sub-markets in dense areas such as the city of Los Angeles. Our empirical results are robust to this alternative specification of local markets.

[9]We choose these three ACS waves to minimize the overlaps across survey years.

3 Measuring Rental Listings Exposure to Local Mortgage Lock-In

We hypothesize that by impacting the for-sale inventory and prices in the sales market (Fonseca and Liu, 2023), mortgage lock-in generates a relative increase in the demand for rentals. Since rental supply is sticky at least in the short run, this demand shock would lead to an increase in rents in the short term.

We construct granular measures of mortgage lock-in across the Los Angeles County. First, we use data from CoreLogic to track mortgages for residential properties (single-family homes, townhouses, and condos) from January 2014 to April 2023. We focus on properties with conventional fixed-rate mortgages (FRMs) and exclude properties with investor loans or that were last purchased or refinanced more than 15 years before because these properties likely have paid back a large part of their principal. Given that we are interested in the spillover of mortgage lock-in on rentals, we further restrict our sample to "starter homes," which are most directly "connected" to the rental market since they may constitute the choice set for renters exploring transition into ownership. We define starter homes as properties below 1,800 square feet and with three or fewer bedrooms, approximately the mean square feet size and number of bedrooms of for-sale properties in Los Angeles County throughout our study (see Table 1). Such a characterization is consistent with definitions of starter homes used in the literature (D'Amico et al., 2024) and industry research.[10]

For each property i, we obtain the origination year-month $\tau(i)$ of the most recent mortgage, which is either the last new home purchase mortgage or the last refinancing, and the mortgage market rate $r^M_{\tau(i)}$ prevailing in that month. We measure this prevailing market rate using the 30-year mortgage rate national series published by the Federal Reserve Bank of St. Louis.[11] Panel (c) of Figure 1 plots the evolution of this series between Q1 2014 and Q1 2023. We prefer market rates to individual contract rates since the latter are driven by local market conditions and borrower characteristics, which are highly endogenous (Fonseca and Liu, 2023). The market-level series captures the aggregate level of rates in the US, which is arguably independent of the idiosyncrasies of neighborhoods.

[10] See, for example, this report by Zillow: https://www.zillow.com/learn/buying-starter-home/

[11] The series is available at https://fred.stlouisfed.org/series/MORTGAGE30US. It is based on weekly data collected by Freddie Mac across the US.

We construct a first measure of lock-in exposure for each rental listing j as follows:

$$LockRateGap_{j,t,Xml} = \frac{1}{|C_{Xml,j}|} \sum_{i \in C_{Xml,j}} \left(r_t^M - r_{i,\tau(i)}^M \right) = r_t^M - \overline{r}_{j,Xml}^M, \qquad (1)$$

where $C_{Xml,j}$ is the number of starter homes with active FRMs located within an X-mile (Xml) radius surrounding each rental listing j. In our preferred specification, we set $X = 0.5$ miles. r_t^M is the prevailing mortgage rate in the year-quarter when rental j is listed, and $r_{i,\tau(i)}^M$ was the prevailing mortgage rate when the last new purchase or refinancing mortgage was issued for property i.

A negative $LockRateGap$ indicates that the current market rate is lower than the average rate for the most recently originated mortgages within the radius. As such, if owners are considering moving, they are likely to obtain a lower mortgage rate by terminating the current contracts and purchasing a home with a new mortgage. On the contrary, when the $LockRateGap$ is positive, resetting mortgage rates through a new purchase will increase mortgage costs. As such, a higher (lower) value of $LockRateGap$ indicates a stronger (weaker) "lock-in" effect in the local housing market.

The study of local housing externalities typically focuses on small distances since the effects of an individual shock decay quickly in space (Rossi-Hansberg et al., 2010, Campbell et al., 2011, and Anenberg and Kung, 2014). Thus, we also use a small (X-mile) radius when evaluating the effects of local market-level lock-in on rentals. Choosing a high value for X increases the room for biases due to broader within-county concurring effects unrelated to lock-in. However, choosing a value of X that is too small may impede us from appropriately capturing the extent of lock-in in a neighborhood surrounding the listing. We choose 0.5-mile radius as a compromise that balances these opposing concerns and conduct several robustness tests to show that confounding effects do not drive our results.

Panel (a) in Figure 2 displays the evolution of $LockRateGap_{0.5ml}$ from Q1 2014 to Q1 2023. We report the mean and the 10^{th}, 25^{th}, 75^{th}, and 90^{th} quantiles of $LockRateGap_{0.5ml}$ in each quarter. The mean ranges between -0.5% and -1% in the early years of the sample when market mortgage rates slightly declined from 4.36% in 2014Q1 to 3.45% in 2016Q3 (see panel c of Figure 1). The $LockRateGap_{0.5ml}$ edged upward and turned positive in 2018 due to a rise in market rates, which reached 4.78% in 2018Q4. Market rates fell from 2019 to 2021, and $LockRateGap_{0.5ml}$ turned negative. Finally, in 2022, primarily due to the change in monetary policy stance, mortgage rates quickly hiked from 3% to 7.3%. This rise coincided with an increase in $LockRateGap_{0.5ml}$. At the beginning of 2023, the mean of $LockRateGap_{0.5ml}$ was close to 3%. Therefore, while the typical starting homeowner in a 0.5-mile vicinity of a rental listing would have benefited from a mortgage rate 50 to 100 basis points lower when terminating and purchasing a new mortgage from 2014 to 2016, the gap flipped markedly by 2023, and this starting homeowner had to incur in a mortgage that was 300 basis points higher than their existing mortgage.

While $LockRateGap$ directly measures the gap between current market rates and existing mortgage rates, the most salient effect of the difference in mortgage rates on households might be the resulting difference in recurring mortgage payments. This is because mortgage payments can be directly compared against the households' budget, and thus better capture liquidity constraints bounding the ability to meet higher monthly payments (Argyle et al., 2020) and anchoring effects, in which homeowners naively compare existing and market payments, without acknowledging the change in market conditions (see for example Giacoletti and Parsons, 2022).

We construct a second measure of local mortgage lock-in, which builds on equation (1):

$$LockPayGap_{j,t,Xml} = \frac{P(r_t^M)}{P(\bar{r}_{j,Xml}^M)} - 1, \tag{2}$$

where $P(r)$ is the monthly payment for a 30-year mortgage with rate r.[12] $LockPayGap$ is then the percentage difference between the monthly mortgage payment per dollar of principal based on the current market rate ($P(r_t^M)$) and the same monthly payment based on the average rate of existing mortgages within the X-mile radius ($P(\bar{r}_{j,Xml}^M)$). Panel (b) of Figure 2 displays the time series and the cross-sectional dispersion of $LockPayGap_{0.5ml}$. The series closely mirrors the evolution and dispersion of $LockRateGap_{0.5ml}$ in panel (a). An important aspect to highlight is the pronounced effect of changes in mortgage rates on payments due to capitalization effects

[12] This is the annuity operator. A 30-year FRM with constant payments, given r as the annual APR and monthly payments, equals $P(r) = \frac{r/12}{1-(1+r/12)^{-360}}$.

and the long duration of mortgage contracts. As discussed above, at the end of 2023, market rates are roughly 3% above existing mortgage rates. Consequently, payments per dollar of principal for new mortgages are 40% higher than those for existing mortgages.

Figure 3 displays the spatial distribution of the mean $LockPayGap_{0.5ml}$ on the census tract level in the fourth quarter of 2014, 2016, 2021, and 2022. There is substantial spatial heterogeneity in mortgage payment gaps across tracts, even between adjacent ones. However, in all four sample years, some parts of the county, such as the area between South Los Angeles and Compton, had relatively low values, indicating that residents having "bad" timing when locking-in their mortgage rates (i.e., their existing mortgage payments are high, lowering the ratio in equation (2)). This pattern is consistent with differences in attention to mortgage rates across locations and demographic groups (Andersen et al., 2020). We include granular location fixed effects in our estimations to absorb these time-invariant differences.

One potential concern is that our lock-in measures do not capture the composition of local mortgages. For instance, if the lock-in measures consistently show higher values in neighborhoods with a low prevalence of fixed-rate mortgages, they may imperfectly capture the actual share of lock-in exposure. Appendix B shows this is not the case because our lock-in measures are highly correlated with the share of lock-in mortgages in the neighborhood.

Specifically, we create an analogous lock-in measure that quantifies the share of properties within the X-mile radius around listing j whose owner would face a higher mortgage cost if she were to move ($LockShare_{Xml}$). Table $B.1$ confirms that $LockShare_{Xml}$ strongly relates to our lock-in measures. A 10 basis points rise in the average rate gap ($LockRateGap_{Xml}$) coincides with a 1.3% increase in the share of locked-in properties. For $LockPayGap_{Xml}$, a 1% increase in the payment gap is significantly associated with a roughly 1% increase in the locked-in share. Across all specifications, $LockRateGap_{Xml}$ or $LockPayGap_{Xml}$ alone explain more than 80% of the variation in $LockShare_{Xml}$.

We use $LockPayGap$ and $LockRateGap$ as the main variables in our analysis because the share of locked-in properties is more likely endogenous to local market characteristics and trends. For instance, adjustable rate mortgages in times of increasing rates may become more attractive in neighborhoods with more constrained households. On the other hand, variation in

$LockPayGap_{0.5ml}$ and $LockRateGap_{0.5ml}$ relies only on current changes in market-level rates and local variation in the precise timing of the last purchase or refinancing.

4 Effects on the Rental Market

4.1 Rents

We begin our empirical analysis by measuring the effects of the mortgage lock-in on residential rents. We estimate the following regression specification:

$$log(rent)_{j,t} = \alpha LockGap_{j,t,0.5ml} + BX_j + \Gamma G_{j,t} + \gamma_c + v_{j,t} \tag{3}$$

where $rent_{j,t}$ is the asking rent for listing j at time t. For our primary lock-in measure, we use $LockPayGap_{0.5ml}$, the mean monthly payment gap measure within a radius of 0.5 miles around each listing. We replace this payment gap measure with the corresponding mean rate gap, $LockRateGap_{0.5ml}$, to test the robustness of the results. We denote these two measures as $LockGap_{0.5ml}$ in our models. X_j is a vector of rental listing characteristics, including log square footage and a set of indicators for the number of bedrooms and bathrooms, and whether the unit is located in a multi-family building with at least five units, has specific amenities (i.e., granite countertops, stainless appliances, pool, gym, doorman, in-unit laundry, and garage), and is furnished. $G_{j,t}$ is a vector of time-varying characteristics, which in this specification includes lagged annual population growth in the Public Use Micro-Data Area (PUMA) of each rental listing. We double cluster standard errors by neighborhood (we discuss neighborhood definitions below) and year-quarter.

Table A.3 in the Appendix reports t-stats computed using bootstrapped standard errors, to account for local spatial autocorrelations that may not be captured by neighborhood-level clustering. The bootstrapped $t-$statistics are similar to $t-$statistics calculated based on clustered standard errors. Another potential econometric issue with our estimates is that OLS equally weights the effect of the mean lock-in gap across all rental listings. However, the effects of the gap should be larger when a larger share of the housing stock surrounding the listing is locked-in. To account for this effect, in Table A.4 we estimate Weighted Least Squares regressions

(WLS), with weights depending on the share of properties within half-mile of the listing that have an FRM that was closed at a time when mortgage rates were below current levels. As expected we find that the WLS estimates are larger and more significant than the OLS estimates. Since the OLS results are more conservative, we use them as our baseline in the analysis.

A confounding factor that may affect the interpretation of our estimates is that our lock-in measure may systematically correlate with the timing of the last purchase and refinancing in a local market. For instance, neighborhoods with a high share of financially savvy residents may refinance their mortgages in tandem when market rates are low. We include census tract fixed effects, γ_c, in equation (3) to control for local time-invariant characteristics and, thus, examine how rents and our lock-in measure vary over time within a neighborhood. Moreover, we can estimate a tighter regression specification and include building fixed effects, given the rich granularity and periodicity of Renthub data. Multi-family buildings with at least five units have much higher odds of having at least one unit listed in the market at any time. Hence, we can assess how rents and lock-in exposure vary over time within a building, mitigating any potential bias stemming from unobserved landlord and property characteristics.

Table 2 reports estimates from equation (3), where the lock-in measure is $LockPayGap_{0.5ml}$. Columns (1) and (2) display estimates over the entire sample period from January 2014 to April 2023. In column (1), the coefficient for $LockPayGap_{0.5ml}$ equals 0.6, implying that a 1% increase in payments translates into a 0.6% higher rent. Equivalently, a one standard deviation increase in payments of 13.7% (see Table 1) leads to an increase in rents of 8.2% or \$232 per month, given monthly average rents of \$2,825. We include building fixed effects in column (2) and obtain a similar coefficient: a 1% increase in the mortgage payment gap is associated with a 0.51% rise in asking rents. Thus, our results hold when we examine listings in multi-family buildings that cannot easily transition to ownership. Further, this finding indicates that unobserved landlord and property characteristics do not impact our estimates.

In columns (3) and (4), we focus on a later period from January 2021 to April 2023 with the steepest increase in $LockPayGap_{0.5ml}$ in Los Angeles County (see Figure 2). The increase was sudden and driven by the change in the monetary policy stance of the Federal Reserve. Point estimates reveal that a 1% rise in the lock-in measure is associated with an increase of 0.26% in rents for either all property types or only multi-family buildings. Analogously, a one standard deviation increase in payments of 20.3% results in a rent rise of 5.4% or $172 per month.[13]

Another concern for our estimations is time-varying factors that systematically influences local rent growth and lock-in measures across the county. For instance, during our study period, suburban migration and teleworking flattened the gradient of housing values and rents between city centers and suburbs in Los Angeles and many US metro areas (Ramani and Bloom, 2022; Gupta et al., 2022). Such an increase in housing demand would have jointly led to higher rents and home purchases by high-skilled households taking advantage of low market rates at the time, increasing the degree of local lock-in. We address this concern in multiple ways. First, we examine whether lock-in measures are higher in neighborhoods with large population inflows. Second, we analyze whether the residuals of lock-in measures from our estimations exhibit spatial autocorrelation. A high spatial autocorrelation would hint at other broad within-county factors affecting lock-in. Lastly, we extend equation (3) to control for within-county regional diverging trends and mitigate the impact of time-varying shocks.

We use the USPS zip code-level change of address data from Ramani and Bloom (2022) to analyze the relationship between lock-in exposure and the current or lagged local population inflows. Figure 4 reports binned scatter plots, visualizing the cross-sectional relation between the average $LockPayGap_{0.5ml}$ in the zip code and the corresponding population inflow. Both variables are normalized by removing the county-level mean in each year-quarter and dividing by their standard deviation. The four panels display the association between $LockPayGap_{0.5ml}$ and contemporaneous population inflows, and inflows lagged by one quarter, one year, and two years. The relation between population inflows and $LockPayGap_{0.5ml}$ is never positive, and at the two-year lag, both variables appear to be unrelated. Consequently, it is not the case that neighborhoods with higher lock-in during the study period had higher population growth.

We then extend equation (3) to incorporate year-month-neighborhood fixed effects, which, following our discussion above, will absorb suburban migration and related regional diverging

[13]Since our estimates in columns (3) and (4) rely on time series variation, one plausible driver is a population boom in LA after the COVID-19 pandemic. Nevertheless, the population decreased during this period, as shown in Figure 1, which rules out this potential explanation.

trends in rent growth across the county:

$$log(rent)_{j,t} = \beta LockGap_{j,t,0.5ml} + AX_j + \phi_c + \phi_{ym,N} + e_{j,t}, \tag{4}$$

where ϕ_c are census tract fixed effects and $\phi_{ym,N}$ are year-month-neighborhood fixed effects. The definition of neighborhoods comes from the Los Angeles Times (Los Angeles Times, 2016), which divides the county into 272 neighborhoods based on local civic characteristics, history, and social consensus. Standard errors are double-clustered by neighborhood and year-quarter. $T-$statistics based on bootstrapped and clustered standard errors have similar values (Table A.3).

We estimate equation (4) in column (5) of Table 2. The coefficient for $LockPayGap_{0.5ml}$ is 0.347, similar to estimates in columns (3) and (4). It thus confirms that landlord and property unobserved characteristics, as well as regional divergent trends, have a minor quantitative impact on the effect of local lock-in exposure on rents. Estimating the same model using WLS weighting with the share of locked-in properties surrounding the rental listings delivers larger estimates (Table A.4).

4.1.1 Addressing Confounding Mechanisms: Omitted Time-Varying Factors

Even with the rich set of fixed effects in equation (4), one may be concerned that the lock-in measure $LockPayGap_{0.5ml}$ may be driven by local time-varying unobservables that also determine higher rents. However, if this is the case, we should observe significant spatial autocorrelation in $LockPayGap_{0.5ml}$ after controlling for fixed effects. In Figure 5, we calculate the residuals of regressing $LockPayGap_{0.5ml}$ on year-month fixed effects. Then, we take the average of these residuals by census tract and semester from 2014 to 2023 and calculate the spatial (cross-sectional) autocorrelation of the average residuals using $Moran's\ I$.[14] The Moran's

[14] *Moran's I* is a measure of spatial autocorrelation introduced by Moran (1950) and computed as follows:

$$I = \frac{\sum_i \sum_j w_{i,j} (x_j - \bar{x})(x_i - \bar{x})}{\sum_i (x_i - \bar{x})^2},$$

where N is the number of observations, x_i is the value of the variable of interest for observation i, $\bar{x}$ is the sample mean of the variable of interest, and $w_{i,j}$ is a spatial weight, decreasing with the distance between i and j. We choose weights to be equal to zero if the distance between i and j ($d_{i,j}$) is greater than 15 miles, and equal to the inverse of distance, if the distance is smaller or equal than 15 miles. Therefore, the spatial weight takes the

I (solid line) hovered between 0.25 and 0.30 until 2020 (the index ranges from -1 to 1), after which the coefficient progressively decreases to 0.15. All these estimates are highly significant, suggesting substantial positive spatial autocorrelation, or in other words, clustering of values of $LockPayGap_{0.5ml}$ across tracts.

We then calculate residuals conditional on census tract fixed effects and year-month by neighborhood fixed effects. Moran's I drops to between 0.02 and zero (see the blue dashed line in Figure 5). Therefore, the combination of census tract and year-month by neighborhood fixed effects absorb the cross-sectional spatial autocorrelation in lock-in measures.

To further address concerns over local trends due to suburban migration, we interact the year-month-neighborhood fixed effects with quartiles of distance from each census tract's centroid to the closest central business districts (CBD) in the county. We follow the 1982 economic census' definition of CBDs, which is commonly used in other studies (e.g., Baum-Snow and Han, 2023; Ramani and Bloom, 2022). Figure A.3 demonstrates the location of CBDs in LA county and the distance quartile of each census tract. Column (1) of Table A.7 demonstrates the estimated β, which is virtually unchanged from Table 2.

Table A.2 reports the same set of regression estimates using $LockRateGap_{0.5ml}$. Qualitatively, the estimates align with the results in Table 2, with point estimates of the effects of mortgage lock-in on rents ranging from 3.5 to 7.7. These results reveal that a one standard deviation increase in the degree of lock-in (or 1.1%, see Table 1) leads to an increase in rents from 3.8% to 8.5% (or from \$105 to \$241 per month). Also in this case we estimate a version of equation (4) with year-month-neighborhood-quartiles of distance from the closest CBD fixed effects (see column 2 of Table A.7), and find no change in the estimate of the coefficient β.

4.1.2 Addressing Confounding Mechanisms: Event Study

We construct an event study to further address the concern that the association between the lock-in variable and rents might be spurious, especially in the latter part of the period, when the lock-in variable had the most notable increase and many large US metropolitan areas expe-

following values:

$$w_{i,j} = \begin{cases} d_{i,j}^{-1} / \sum_j d_{i,j}^{-1} & if \;\; d_{i,j} \leq 15 \, miles, \\ 0 & if \;\; d_{i,j} > 15 \, miles. \end{cases}$$

rienced substantial within-city migration. With the event study model, we show that diverging patterns in rent growth for high-lock-in areas occurred at the exact time of mortgage rate increases instead of confounded by pre-existing diverging trends in rents.

Specifically, we first calculate the average $LockPayGap$ for each census tract at a time T. We use two T for robustness. First is from the fourth quarter of 2022 to the first quarter of 2023, which reflects the spatial distribution of the lock-in degree at the end of the sample time period. The second is the year of 2021, which reflects the distribution before the increase in long term rates. We then estimate the following regression specification:

$$log(rent)_{j,t} = \sum_{\tau=1}^{T} \delta_\tau \left(I_\tau \times I(HighLockGap_{0.5ml,T,c})\right) + DX_j + \phi_c + \phi_{ym,N} + u_{j,t}$$

where τ is an index for every six months from 2018 to 2023, and $I(HighLockGap_{0.5ml,T,c})$ is an indicator equal to one in census tracts (c) that have above the median value of the lock-in measure in period T. The parameter of interest is δ_τ.

Figure 6 shows the results, where the reference point is the second half of 2021, immediately before the beginning of rate increases. Panel (a) reports results for the specification where T equals to the fourth quarter of 2022 to the first quarter of 2023, and panel (b) reports results for T set to 2021.

We find that rents rise at a faster pace in areas with either ex-ante or ex-post relatively higher levels of lock-in, but the divergence in trends only starts in the first half of 2022. There is no evidence of pre-trends in rents. High lock-in census tracts have on average 2.5-3% higher rents than low lock-in tracts by the end of the sample. Table A.5 reports the full model estimates.

Results based on the ex-ante or ex-post sorting of census tracts are remarkably aligned, because there were limited refinancing or new home purchase activities in 2022 and 2023, which would drive changes in the relative level of lock-in between tracts in the cross-section.

While we define the "treatment" status by the median value of payment gaps, such division is somewhat arbitrary. To further demonstrate the robustness of the event study results, we replace the dummy $I(HighLockGap_{0.5ml,T,c})$ with the continuous variable $\overline{LockGap}_{0.5ml,22:23,c}$, which is equal to the mean value of the payment gap in census tract c and period T. Appendix Figure

A.4 shows the resulting event study graphs. Consistently, we find that the gaps in rents related to local lock-in expand in the first half of 2022, and that there is no evidence of pre-trends.

4.1.3 Addressing Confounding Mechanisms: New Local Rental Supply

Finally, to show that the relation between local mortgage lock-in and rents is driven by excess demand rather than omitted time-varying local characteristics, we show that the presence of new local rental supply attenuates the lock-in effects.

To this end, we identify new construction of large multi-family buildings using parcel-level data from Corelogic, which are multi-family properties with 20 or more units with reported construction date between 2019 and 2022. Figure A.5 displays the locations of these sample buildings. These buildings scatter across the entire county with clusters in certain areas such as downtown. The locations of new constructions and local rent growth can both be driven by trends of neighborhood improvements and gentrification. This allows us to design a test that disentangles whether the mortgage lock-in variable is capturing gentrification, or just demand and supply imbalances in the market.

To measure the exposure of rental listings to new development, we set a narrow radius around each rental listing and count the number of new units in the large multi-family buildings completed in the two years before and after the listing enters the market. We use this time window to make sure that we capture units that have been recently completed, or that are under construction while the listing is on the market. We then define “highly exposed” rental listing as one located near at least 100 newly completed or under-construction units.

We then estimate a version of our main regression equation 4 augmented with an interaction term between a rental unit’s half-mile mortgage payment gap ($LockPayGap_{0.5ml}$) and a dummy equal to one for listings with high exposure to new development.

If our mortgage lock-in measure captures an imbalance between local supply and demand, the coefficient of the interaction term should be negative due to demand spillovers from the sales market. This is because new multi-family buildings that have been recently completed (or under construction) relax local supply constraints and reduce the impact of excess demand for rentals on rents. On the contrary, if the lock-in measure simply reflects local gentrification trends, we should expect the coefficient of the interaction term to be positive.

Table 3 reports our estimates. We report estimates in which exposure to new development is measured within a radius of 0.05, 0.10, and 0.25 miles around each listings. The estimates of the interaction coefficient are negative and significant for all radii. The largest point estimate (in absolute value) is for the narrowest radius of 0.05 miles, and is equal to -0.189, offsetting two-thirds the baseline effect of the lock-in payment gap (0.34). The smallest point estimate is for the widest radius of 0.25 miles. However, even this estimate is -0.095, offsetting a third of the baseline effect of the mortgage payment gap. These results are consistent with the hypothesis that the payment gap captures excess demand effects, which are attenuated by the presence of new supply in close proximity to a rental listing.

4.2 Time-On-Market

If mortgage lock-in affects rental markets by reducing for-sale market liquidity and, hence, increasing demand for rental, then we should also expect effects on the speed of rental units being leased out (or listings' time-on-market). In particular, if the demand effects are strong enough, landlords could ask for higher rents, and such higher asking rents would not result in a longer time-on-market. Consequently, we may witness both higher asking rents and *shorter* time-on-market for rental listings.

We estimate equations (3) and (4) on rental listings' time-on-market to test this hypothesis. To determine the time-on-market for a rental unit, we first construct a unique rental unit identifier for listings with the same unit characteristics in the same building. We thus obtain a unit-level panel data set that allows us to observe each rental unit's occurrence in the market. Next, we calculate the difference in days between every two listings for a rental unit. A potential limitation is that we do not observe the date when a rental unit is rented out. Hence, we cannot determine with certainty if a unit stays on the market between two listings in different periods. To address this issue, we establish that if the difference in days between two listings from the same rental unit is at least 90 days, then the unit is rented out during this period. This 90-day cutoff helps us identify the "rental cycle" for each unit.[15] We define the rented-out date within each rental cycle as seven days after the last listing date. Then, we can calculate time-on-market for a rental unit as the difference in days between the first date of listing and the date of rent-out within each rental cycle.

We compute three time-on-market measures as dependent variables to test the effects of mortgage lock-in: an indicator equals to one when a rental cycle for a sample unit is less than 15 days; an indicator equal to one for the rental cycle for a unit less than 45 days; and the log of number of days that a rental unit is on the market before leased out. Table 4 shows the estimates. Columns (1), (3), and (5) include census tract fixed effects, while columns (2), (4), and (6) add year-month by neighborhood fixed effects. Our findings show that a 1% increase in $LockPayGap_{0.5ml}$ increases the probability of the listing remaining on the market for less than 15 days by 0.45%-0.27% (the baseline is 49%), and increases the probability that the listing stays on the market less than 45 days by 0.2% (the baseline is 74%). Total days on the market are reduced by 1%-0.6%.

Appendix Table A.6 reports the results using the rate gap lock-in measure ($LockRateGap$). Consistent with the findings in Table 4, higher exposure to the mean rate gap within half a mile of a listing leads to *shorter* listings' time-on-market. These effects are highly significant and robust across specifications.

In Table A.7 we estimate time-on-market effects using a regression specification that includes year-month-neighborhood-quartiles of distance from the closest CBD fixed effects (columns 3 to 6). The results are virtually unchanged for both the payment gap and the rate gap.

5 Mechanism

In this section, we provide evidence of the mechanisms through which mortgage lock-in in the local sales market influences rentals. We first show that higher local mortgage lock-in coincides with lower transaction volume in the sales market and higher transaction volume in

[15] For example, if we observe a unit listed in January and February and observe it again listed in October, we assume the unit was rented out during that period. If a unit is continuously listed for several weeks and disappears for a month, it may be due to an unsuccessful match with a tenant that temporarily discontinues posting, or missing data for these weeks.

the rental market. We then provide direct evidence of price spillovers from the sales to the rental market.

5.1 Effects on Transaction Volume

Our hypothesis is that mortgage lock-in reduces the inventory of homes for sale, or raises prices, to the point of creating a shift in demand toward the local rental market. To provide supportive evidence of this effect, we study how local lock-in payment gaps affect transaction volume in the rental and sales market. For this analysis, we aggregate our data at the census tract by year-quarter level, since the frequency transactions on the tract level is relatively low. We then estimate the following regression specification:

$$Vol_{c,yq} = \gamma \overline{LockPayGap}_{c,yq} + \delta_c + \delta_{N,yq} + v_{c,yq}, \tag{5}$$

where $Vol_{c,yq}$ is either a measure of the number of properties rented out, or a measure of the number of sales, in census tract c and quarter yq. $\overline{LockPayGap}_{c,yq}$ is the average $LockPayGap$ in the census tract and quarter, while δ_c and $\delta_{N,yq}$ are census tract and neighborhood by year-quarter fixed effects. The coefficient of interest is γ, which under our hypothesis should be positive and significant in the rental market and negative and significant in the sales market.

Our estimates are reported in Table 5. Panel A reports results from OLS regressions in which the dependent variable is the log of the number of properties rented out or sold plus one. Panel B reports results from Poisson regressions in which the dependent variable is the number of transactions. The latter specifications avoid biases encountered when the dependent variable is a count number that can take the value of zero (Cohn et al., 2022). Results are consistent across the two models. When we only include census tract fixed effects, a 1% increase in census tract-level $LockPayGap$ increases the volume of rented properties by 6.4%, and reduces the volume of sold properties by 13.4%. With tract and year-quarter by neighborhood fixed effects, a 1% increase in $LockPayGap$ increases rental transactions by 5.3% and reduces sales by 3.1%. In the Poisson regressions, for a 1% increase in $LockPayGap$ increases rentals by 0.09 per census tract and year-quarter with no year-quarter-neighborhood fixed effects, and by 0.06 when fixed effects are included (the mean number of rented properties is approximately 8). However, the second estimates is not precise. In the sales market, we find decreases of sales by -0.16 and -0.036 (the mean number of sold properties is approximately 5).

These results are consistent with mortgage lock-in leading to a decrease in transaction volume in the sales market (as documented by previous research) and a corresponding increase in transaction volume in the rental market.

5.2 Sales Market Spillovers

We claim that the demand effect in the rental market is driven by a spillover from the sales market. The larger the lock-in gap measures in a local market, the more likely a seller would face higher payments per dollar borrowed if she were to sell her home and attain a new mortgage. Previous work has shown that mortgage lock-in reduces homeowners' mobility (Fonseca and Liu, 2023). The lower mobility translates into lower liquidity in the house sales market and potentially higher house prices.

An alternative interpretation of our findings could be that mortgage lock-in affects rental properties directly and not through spillovers. Extant research has shown that landlords benchmark asking rents against recurring payments on the property, such as debt cost (Giacoletti and Parsons, 2022). If landlords need to refinance their debt with higher market rates or hold adjustable rate mortgages, they may respond to the higher-rate environment by increasing rents. However, this is unlikely to drive our results. The lock-in variables are constructed to capture mortgage rate and payment gaps for primary residences, which are owner-occupied (we exclude investor or second-home loans). Hence, our lock-in variable does not reflect lock-in conditions in the rental market. Moreover, if landlords were trying to pass down their mortgage costs on tenants by demanding higher rents, we would expect an increase in time-on-market, which is the opposite of what we observe in our findings.

We provide direct evidence of spillovers from the sales market onto nearby rents. We first estimate the relationship between listing-level $LockPayGap$ and the sales prices in the area surrounding each sample listing:

$$log(P_{j,t,0.5ml}) = \psi LockPayGap_{j,t,0.5ml} + DX_j + \psi_c + \psi_{ym,N} + l_{j,t}, \tag{6}$$

where $log(P_{0.5ml,j})$ is the log average price across house sales in the 0.5-mile radius of rental listing j in the month when j is listed. Consistent with the lock-in measures calculation, we restrict the sample to likely starter homes (size below 1,800 square feet and three or fewer bedrooms).

Table 6 reports estimates for equation (6). We consider three different specifications of the dependent variable. First, we use the log of the average sale price in the 0.5-mile radius among all sales in the same quarter as the listing. Second, we use the log of the average sale price per square foot (again within the same radius and quarter as the listing). Third, we use the mean of the residual from a hedonic price regression of prices on property characteristics (following the same selection criteria as for the two other measures).[16] We estimate models both with and without year-month by neighborhood fixed effects ($\psi_{ym,N}$). The payment gap has a positive and significant relation with the local price measures, with a 1$\%$ increase in the gap leading to higher prices by 0.78$\%$. Including the year-month by neighborhood fixed effects leads to higher sales price effects by a factor of three. When using residuals of the hedonic regression as dependent variables, we find that a 1% increase in the gap leads to 2.6% higher prices. Overall, the results indicate that local lock-in is associated with higher sales prices.

We then estimate how local sales market conditions are associated with rents and exploit the lock-in measures to estimate spillovers to the rental market:

$$log(rent)_{j,t} = \omega log(P_{j,t,0.5ml}) + FX_j + \omega_c + \omega_{ym,N} + k_{j,t}, \quad (7)$$

$$log(rent)_{j,t} = \phi log(\widehat{P}_{j,t,0.5ml}) + GX_j + \phi_c + \phi_{ym,N} + h_{j,t}, \quad (8)$$

where $log(P_{j,t,0.5ml})$ is the sales prices in the 0.5-mile radius surrounding listing j, at time t. Thus, equation (7) establishes the association between volume and prices in the local sales

[16] We estimate the following regression equation:

$$log(P_{i,t}) = JX_i + a_{ym} + a_c + \epsilon_{i,t}$$

where $P_{i,t}$ is the transaction price for property i in month t, X_i is a vector of hedonic characteristics (including log size, property age, age-squared, dummies for number of bedrooms, bathrooms and stories, indicators for the number of bedrooms, bathrooms, and stories, indicators for different property types, indicators for properties with pool, fireplace, or garage), a_{ym} is a year-month fixed effect, and a_c is a census-tract fixed effect. We then collect the residuals $\hat{\epsilon}_{i,t}$, and using the geolocation and timing of each sale, we assign them to the 0.5-mile radius surrounding rental listings j. We then calculate $e^P_{j,t,0.5ml}$ as the average residual within the radius.

market and rents. Additionally, $log(\widehat{P}_{j,t,0.5ml})$ is the $log(P_{j,t,0.5ml})$ variable instrumented with $LockPayGap$. Equation (8) is the second stage of the two-stage least-squares (2SLS) estimator, while the first stage is equation (6). This 2SLS estimation captures the effects of lock-in on rentals through the sales market.

We report estimates for the OLS and 2SLS estimations in Table 7. For OLS estimates (equation (7)), we find that local average sales prices have a positive and significant association with rents (columns (1) to (3)). We again use three measures of sales price as dependent variables like in equation (6). These positive coefficients are consistent with demand spilling over to the rental market. However, the magnitude are economically small. A 1% increase in sales prices translates into a 0.02%-0.03% increase in rents. In interpreting these results, it is important to keep in mind that the regressions include both census tract and year-month by neighborhood fixed effects. The OLS coefficient in Table 7 are identified only by variation within tract over time that is not spanned by neighborhood trends. These estimates are likely attenuated by the fact that at this micro-location level, fluctuations in sales and rents are strongly affected by local market liquidity and idiosyncratic factors (Giacoletti, 2021).

The 2SLS estimates from equation (8) directly measure the spillovers from the lock-in channel. The coefficient for local prices, either for the average price, the average price per square foot (column 5), or the average hedonic residual (column 6), is positive, significant, and ranging between 0.18 and 0.36. Therefore, roughly 20%-35% of the sales price appreciation induced by local market-level lock-in effects spills onto the rental market. Such a large effect is consistent with contemporaneous evidence from the literature: Badarinza et al. (2024) use a shock to financing conditions in the United Kingdom to study spillovers on rental demand and find sizable effects on rental yields.

6 Heterogenous Effects

In this section, we study heterogeneity in the effects of local mortgage payment gaps on rents. Specifically, we estimate the following equation:

$$
\begin{aligned}
log(rent)_{j,t} = \beta_{Int,Z}\left(LockPayGap_{j,t,0.5ml} \times Z_{j,t}\right) + \beta LockPayGap_{j,t,0.5ml} + \beta_Z Z_{j,t} \\
+ AX_j + \phi_c + \phi_{ym,N} + e_{j,t}, \qquad (9)
\end{aligned}
$$

where $Z_{j,t}$ is a characteristic of listing j at time t, and all other variables have the same interpretation as in equation (4). The coefficient of interest is $\beta_{Int,Z}$, which captures the incremental effect of local mortgage lock-in on rents driven by characteristic $Z_{j,t}$. We choose $Z_{j,t}$ to be characteristics capturing the local demand for and the supply of rental units.

6.1 Demand-Side: Local Demographics

We first explore differences based on local demographic characteristics. Our hypothesis is that, since the effects are driven by demand-side pressure, landlords may be able to increase rents more in areas in which the demand for rental space is less elastic to rents. Higher income households are able to search over a broader set of local markets, can prolong their rental searches if needed, and are able to afford homeownership even when prices are higher because of mortgage lock-in. On the other hand, lower-income households are constrained and face barriers in exploring a large set of local markets (Bergman et al., 2014). This could be because these households are less sophisticated in their search, frequently face pressure to find accommodation quickly, or are unable to meet the screening criteria imposed by landlords in most neighborhoods (Bezy et al., 2024). Moreover, lower-income households that are cross-searching local markets for rental and homeownership are more likely to be forced to turn to rentals when local sales prices are inflated by lock-in effects.

Thus, we expect that spillovers on rents from local lock-in effects will be larger in less affluent neighborhoods. We test this hypothesis in Table 8. We estimate equation (4) interacting the mortgage payment gap and census tract characteristics, using data from the American Community Survey (Manson et al., 2023). We find that lock-in effects on the rental market are larger in tracts that have higher poverty share (column 1), lower share of household heads with bachelor education or higher (column 2), and higher share of unemployed household heads (column 3). The magnitude of these effects is large. A one standard deviation (10%) higher poverty share leads to an increase in the coefficient for $LockPayGap_{0.5ml}$ or 0.05, which is roughly a 15% relative increase compared to the baseline estimates presented in the previous sections.

We also find that poverty share, lower bachelor-education share, and higher unemployment, do not coincide with larger effects of the payment gap on time-on-market. Appendix Table A.8 reports estimates of equation (9) with dependent variable equal to a dummy for properties that were rented in less than 45 days. Point estimates of $\beta_{Int,Z}$ are not statistically significant and economically negligible. Thus, consistent with the fact that the heterogeneous effects of the lock-in gap are driven by inelastic demand, landlords are able to impose larger increases in rents in response to local lock-in, without facing penalties in terms of longer time-on-market.

6.2 Supply-Side: Rental Property Characteristics

We then study how property and landlord characteristics influence the magnitude of lock-in effects on rents. We test two competing hypothesis.

On the one hand, we may expect larger effects for listings that are most similar to for-sale properties (typically single-family residences). This is because first-time home buyers turned off by high prices in the sales market due to mortgage lock-in may mainly look for rental properties that are close substitutes to owner-occupied homes.

On the other hand, the effects could be larger for properties owned by professional investors and for larger buildings. Professionals and owners of larger buildings are more sophisticated and thus more aware of local demand shocks. Moreover, the supply of multi-family units is highly sticky, since the development of these large building is a lengthy process and these units are specifically designed for the rental market. As a result, multi-family rentals are strongly segmented from the sales market. Even if single-family units or condos were to transition from the sales to the rental market in response to higher rents and shorter time-on-market, they would be poor substitutes for multi-family units. Instead, these properties transitioning from the sales to the rental market would be directly competing with single-family rentals.

In column (1) of Table 9 we report estimates from equation (4) interacting the payment gap in the 0.5-mile radius surrounding the listing ($LockPayGap_{0.5ml}$) and a dummy equal to one if the listing is a single-family home. We restrict the sample to single-family homes and units in multi-family buildings, so that the interaction coefficients captures differences in the sensitivity to $LockPayGap_{0.5ml}$ for single-family with respect to multi-family units. We find that the sensitivity to the mortgage lock-in is smaller for single-family by 0.12, which is approximately a third of the baseline effect. In column (2), we find similar evidence when we test differences between condos and multi-family units. In columns (3) and (4) the sample is restricted to units in multi-family buildings, and we test heterogeneity based on building size, by interacting the lock payment gap with dummies for multi-family buildings with 10 or more and 20 or more units. We find that units in larger buildings are more sensitive to mortgage lock-in, with interaction coefficients equal to 0.07 (10 or more units) and 0.10 (20 or more units). Combining the evidence from column (1) and column (4), the sensitivity to the payment gap for single-family rental units is approximately 60% smaller than that of units in large multi-family buildings.

Finally, in column (5) we use the entire sample to estimate heterogeneous effects for corporate and non-corporate landlords. We find that the interaction coefficient for landlords that are legal entities is positive and statistically significant, with point estimate equal to 0.09.

In summary, we find that rents set by larger buildings and corporate landlords are more responsive to the lock mortgage lock-in. Appendix Table A.9 explores differences in time-on-market, by estimating regression specifications in which the dependent variable is a dummy equal to one if the property is rented within 45 days. Most estimates are statistically insignificant. The only significant interaction coefficient is for condos, but it is economically small.

A concern over the evidence in Table 9 is that the composition of local rental properties might be correlated with socioeconomic status. For instance, large multi-family buildings might be more frequent in higher poverty share tracts. To dispel this concern, we repeat the analysis in Table 9 after restricting the sample to only census tracts with poverty share below the median in the county. The estimates are reported in Table A.10 in the Appendix, and are virtually identical to those in Table 9.

Table A.11 in the Appendix further investigates whether differences in unit size have effects on the sensitivity of rental listings to local lock-in. While we find that the effects of the payment gap on rents are larger for listings with smaller size and number of bedrooms, these differences disappear once we exclude single-family residences from the data.

Overall, the results highlight that the characteristics of local rental supply can substantially attenuate or amplify the magnitude of lock-in spillover effects. The fact that the spillovers are smaller for single-family suggest that these differences are not driven by similarity between for sale and for rent properties. Rather, a potential explanation for the smaller effects for single-family listings is that mortgage lock-in not only induces an increase in rental demand but also an increase in supply of rentals for certain property types. Some owners of locked-in properties may be able to move to a new residence without having to liquidate their existing home equity. As such, these owners may hold onto their previous residence and the below-market mortgage rate, while re-listing it as a rental.

To test this channel, we estimate the following regression equation:

$$I(Type)_{j,t} = \delta LockPayGap_{j,t,0.5ml} + p_c + p_{ym,N} + e_{j,t}, \tag{10}$$

where $I(Type)_{j,t}$ is a dummy equal to one if the rental listing is a property of a specific type, and p_c and $p_{ym,N}$ are census tract and year-month by neighborhood fixed effects. Table 10 reports estimates of the coefficient δ, which captures the effects of changes in $LockPayGap_{0.5ml}$ on the likelihood that a listing if of a specific type. In column (1), the sample is restricted to multi-family and single-family listings only, and the dependent variable is a dummy equal to one for single-family rentals. In column (2), the sample is restricted to multi-family and condos. The dependent variable is a dummy equal to one if the property type is condo. We find that a 1% increase in the mortgage payment gap translates into an average of 0.6% higher likelihood of observing a single-family rental listing. A one standard deviation higher value of the payment gap translates into an almost 8% higher likelihood of observing a single-family rental. The point estimate of the same effect for condos is positive but not statistically significant.

This result is consistent with an increase in the supply of single-family rental units when the local payment gap is larger. The increase in single-family rentals supply is likely to absorb part of the local increase in demand for this type of rental properties, and attenuate the spillovers on rents, as we observe in Table 9.

Alternatively, the results in Table 9 could be explained by the fact that larger buildings are managed by more sophisticated landlords, who have better information on local demand. On the other hand, single-family rentals are more likely to be managed by mom-and-pop landlords, who are less likely to have complete information on local market conditions and may not always act as revenue maximizers. For instance, they may be willing to offer lower rents to tenants whom they find more reliable or more likely to renew their lease agreements at expiration.

7 Conclusion

The interactions between local sales and rental markets, as well as the effects of economic shocks on the interplay between these markets, are increasingly central to housing research. In this paper, using data covering the entire rental market of Los Angeles County over the period from 2014 to 2023, we study how mortgage rates indirectly affect rents through spillovers from reduced inventory and higher prices in the sales market.

We measure mortgage lock-in as the gap between mortgage payments based on prevailing market rates at the time the last mortgage on a property and payments based on current market rates. When the gap among properties in the 0.5-mile radius surrounding a rental listing is higher, the listing sets a higher rent. A one standard deviation higher payment gap translates to a 4.5% higher rent. Moreover, a larger local payment gap also translates into $shorter$ time-on-market for the rental.

We show that these effects are robust across different specifications. They are also unlikely to be explained by confounding factors related to neighborhood characteristics, diverging trends across local markets, or suburban migration.

We explain our results as spillovers from the sales market. Local lock-in increases prices for local for-sale inventory. This effect discourages households that are cross-searching the local sales and rental market and increases local demand for rental units. At the census tract level, a higher value of the payment gap reduces sales volume and increases the volume of properties rented out, consistent with a shift in demand from the sales to the rental market. We further show that the local payment gap leads to higher prices in the sales market and that a third of the lock-in-induced price increase in the local sales market spills over onto rents.

Finally, we show that lock-in effects are heterogenous by the characteristics of local demand (demographics) and supply (rental unit characteristics). The effects are larger in less affluent areas, where rental demand is less elastic. Moreover, the effects are larger for multi-family properties and, in particular, large multi-family buildings, and for landlords who are corporate entities. These findings are robust to restricting the sample to only areas with low poverty rates.

Most of the existing studies on the implications of higher mortgage rates and stricter mortgage market conditions for the rental market focuses on the direct effect on prospective homeowners, who face higher barriers to qualify for a mortgage. In this study, we show that mortgage rates can also indirectly affect rental demand via their impact on the for-sale inventory of homes. This generates local co-movement between prices and rents in response to rate changes, whose magnitudes strongly depend on local market characteristics. Our empirical findings are related to the effects of mortgage lock-in on the housing ladder explored in contemporaneous structural work.

Our results also contribute to the broader debate on the effects of tightening monetary policy on rents and on the broader economy. If higher rates generate higher rents through mortgage lock-in effects, then they could indirectly push up inflation and counteract the intended policy effects. Most importantly, our results suggest that the inflation effects of higher rates can generate diverging patterns across neighborhoods, potentially leading to higher rent growth in areas with lower incomes and a higher density of multi-family buildings.

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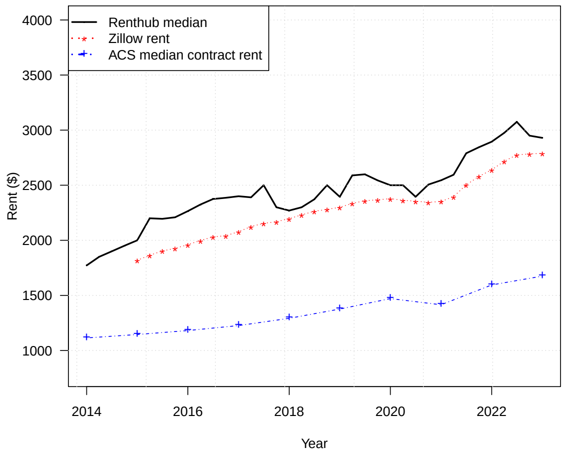
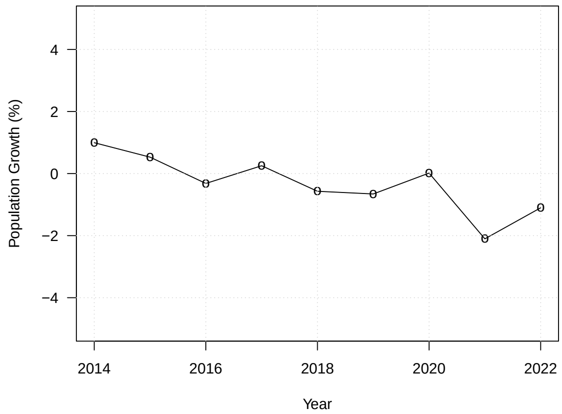
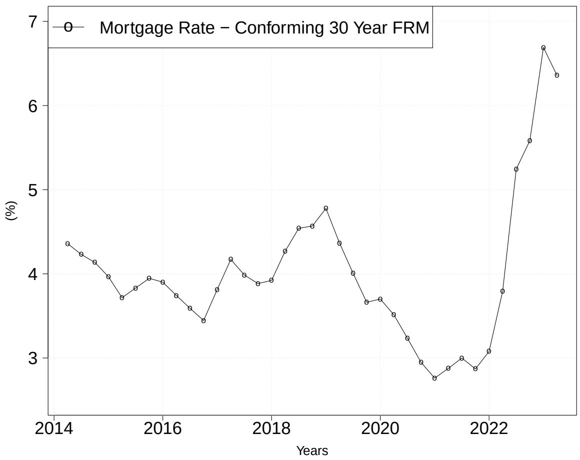
Figures and Tables



(a) Rents in Los Angeles County

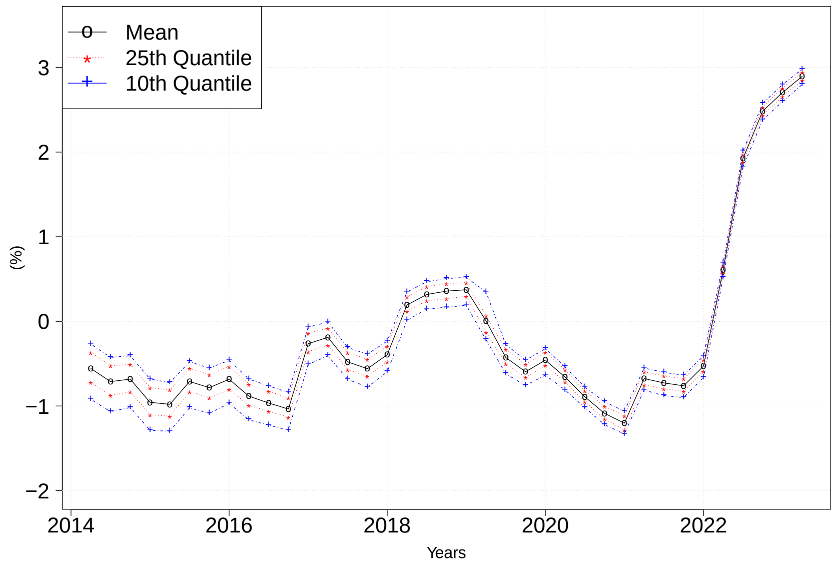


(b) Population Growth in Los Angeles County

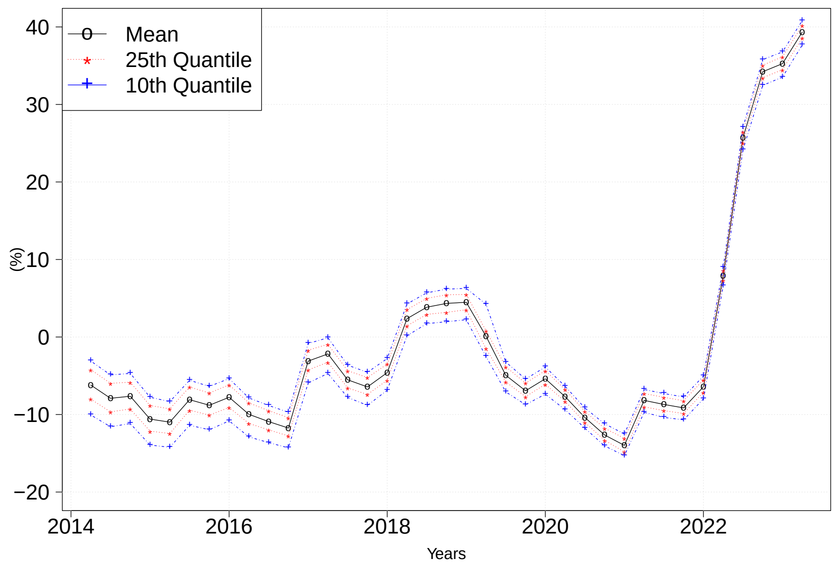


(c) Market Rate for 30-Yr FRM

Figure 1: Panel (a) of the Figure plots the quarterly median asking rent using Renthub data against the median contract rent from ACS one-year estimates and the quarterly Zillow Observed Rent Index (ZORI) for Los Angeles County. The ACS does not publish 2020 one-year estimate, so we use five-year estimate to proxy for the median rent in this year. Panel (b) shows the annual population growth rate for the county based on data from the American Community Survey. Panel (c) plots the evolution of the mortgage rate for conforming 30-year Fixed Rate Mortgages from 2014Q1 and 2023Q1.

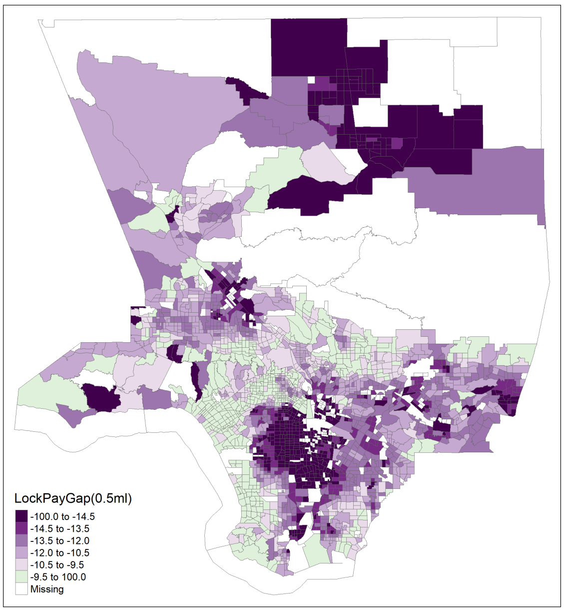


(a) $LockRateGap$

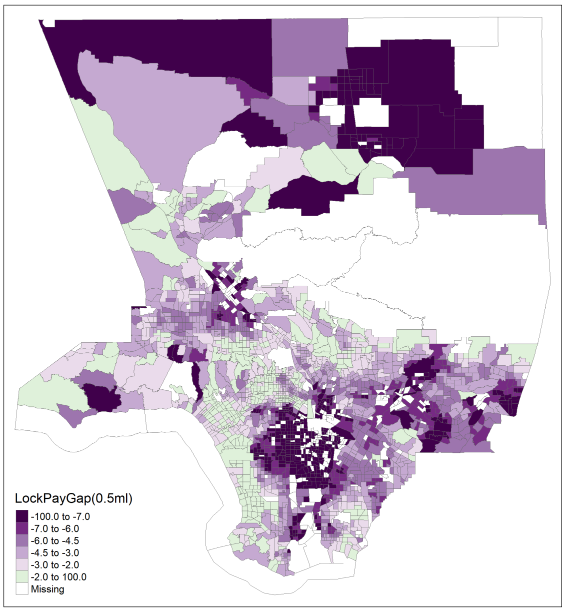


(b) $LockPayGap$

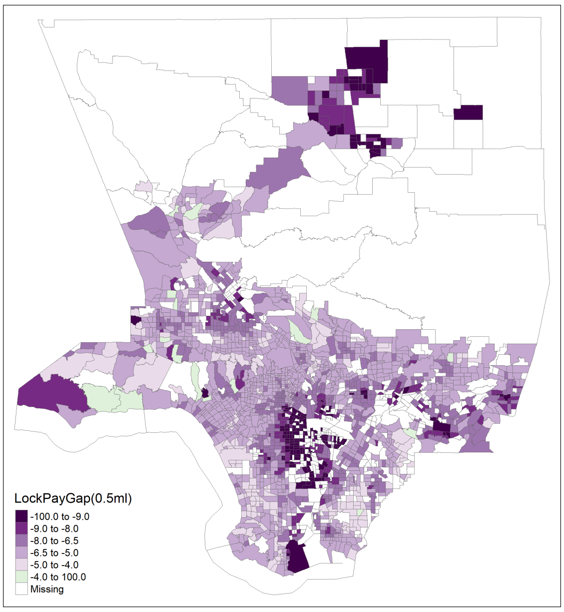
Figure 2: Panel (a) plots the mean and the 10th, 25th, 75th, 90th quantile of the distribution of the rate gap variable, $LockRateGap_{0.5ml}$ (see equation 1). Panel (b) plots the same statistics for the monthly payment gap variable, $LockPayeGap_{0.5ml}$ (see equation 2).



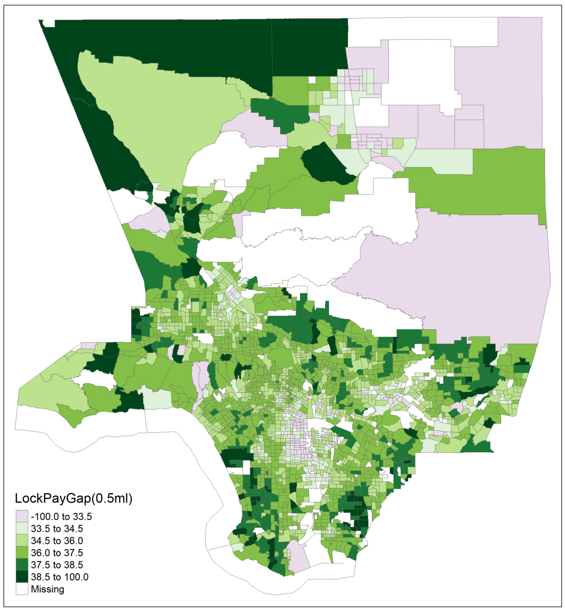
2014 Q4



2016 Q4

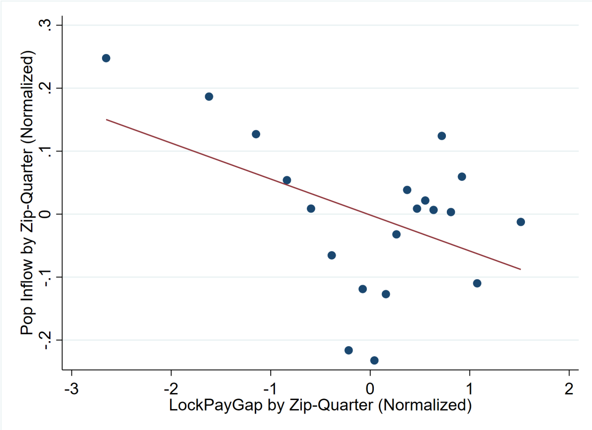


2021 Q4

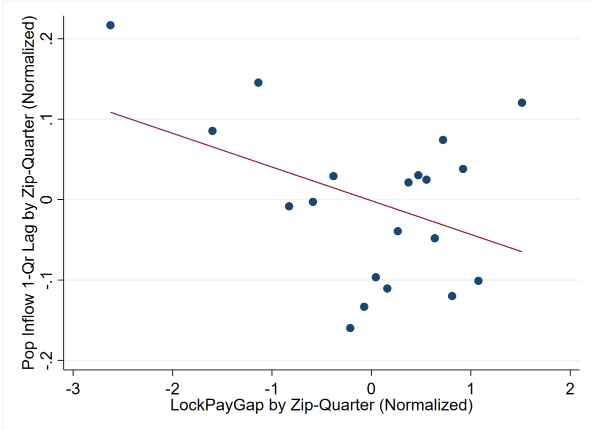


2022 Q4

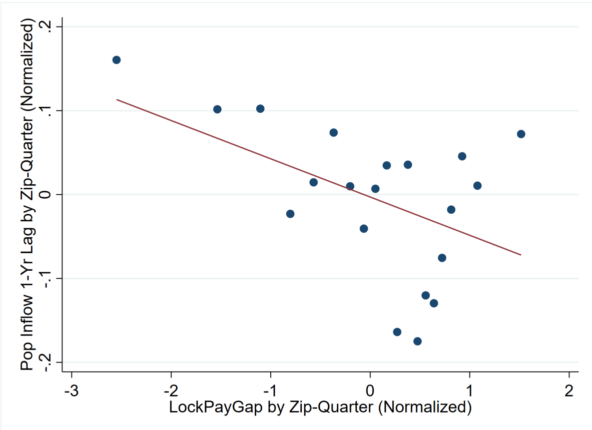
Figure 3: This figure shows the tract-level mortgage lock-in measure $LockPayGap_{0.5ml}$. Purples indicate negative values and shades of green indicate positive values. Darker purple marks a more negative $LockPayGap_{0.5ml}$, and darker green marks a larger positive $LockGap_{0.5ml}$.



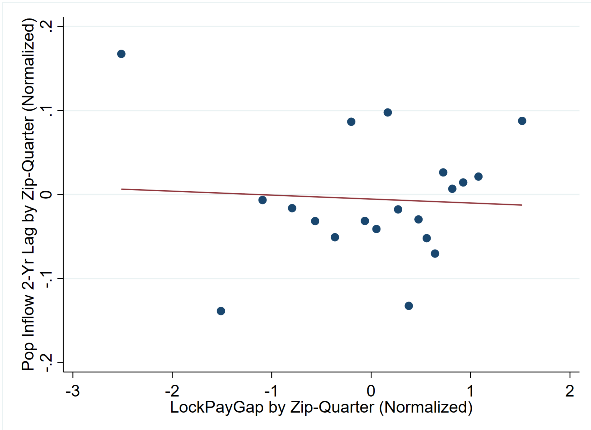
(a) $LockPayGap$ and Pop Inflow



(b) $LockPayGap$ and Pop Inflow 1-Qr Lag



(c) $LockPayGap$ and Pop Inflow 1-Yr Lag



(d) $LockPayGap$ and Pop Inflow 2-yr Lag

Figure 4: This Figure plots the relation between the average $LockPayGap$ per zip code and year-quarter and the total population inflow in the zip code, based on the USPS change of address data from Ramani and Bloom (2022), in the same quarter (panel a), one quarter ahead (panel b), one year ahead (panel c), two years ahead (panel d). The average of $LockPayGap$ and total population inflow are normalized by removing the mean (across the county) by year-quarter, and dividing by their standard deviation.

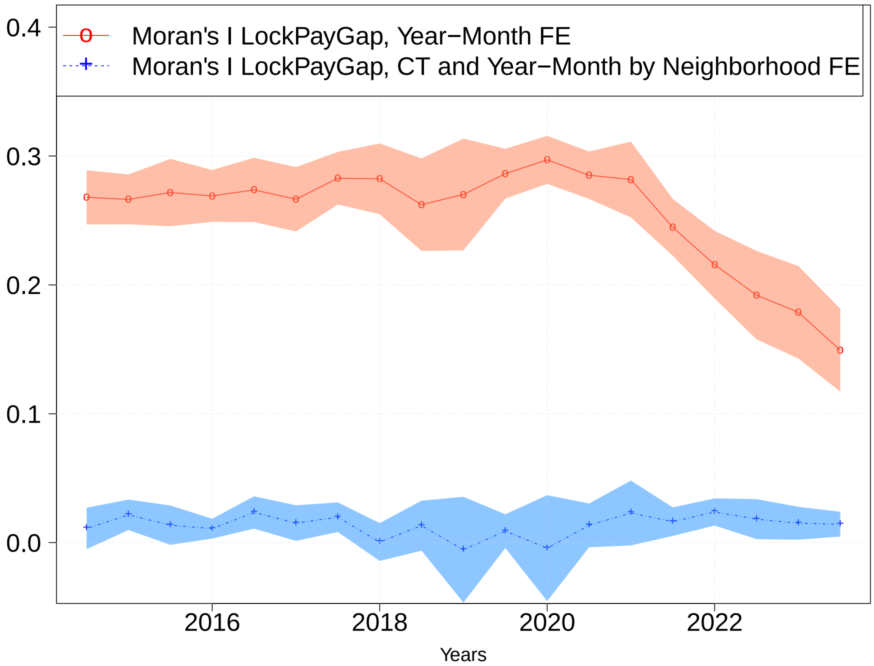
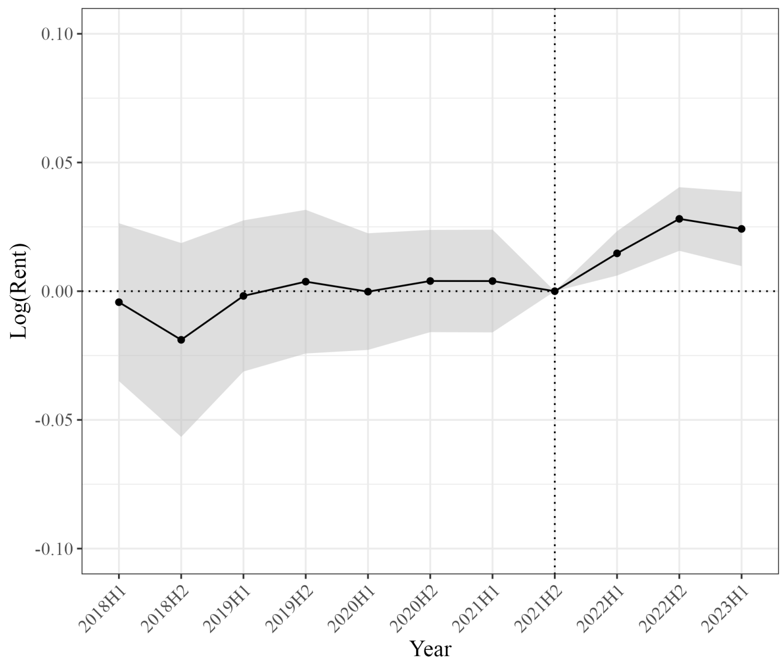
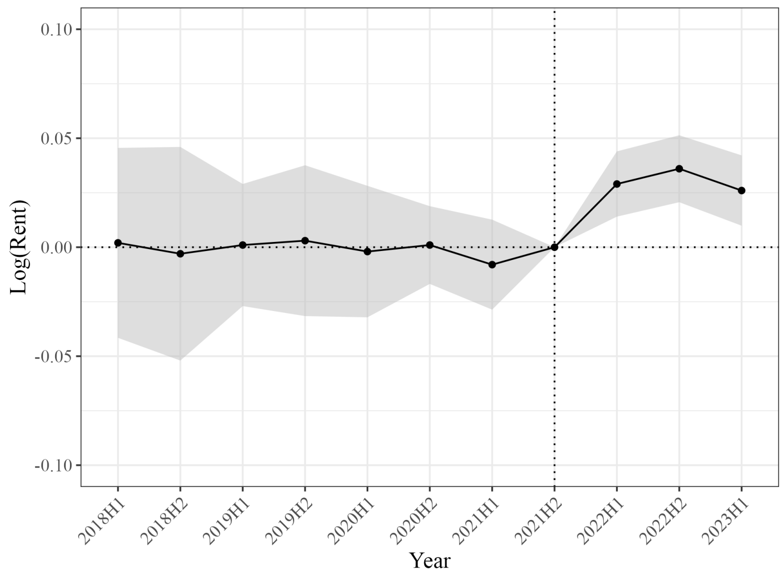


Figure 5: The Figure plots the spatial (cross-sectional) correlation and 95% confidence intervals (based on bootstrapped standard errors), measured with $Moran's\ I$ of the census tract-level means of the residuals from a regression of $LockGap_{0.5ml}$ on year-month fixed effects (in red) and on census tract fixed effects and year-month by neighborhood fixed effects (in blue).



(a) Event Study: $I(HighLockGap_{0.5ml,22:23})$



(b) Event Study: $I(HighLockGap_{0.5ml,21})$

Figure 6: The Figure shows the estimates from equation (4.1.2). Census tract-level exposures to lock-in are set to their Q4:2022-Q1:2023 values in panel (a), and their 2021 values in panel (b). The outcome variable is the log asking rents for sample rental listings in Los Angeles County. The gray ribbon surrounding the line shows 95% confidence intervals for each estimated value.

Table 1: Rental listing and for-sale property characteristics

	Rental listing characteristics					
	2014–2023			2021–2023		
Variables	mean	median	sd	mean	median	sd
Rent ($)	2,825	2,375	2,024	3,202	2,860	1,788
Square footage	1,143	1,000	661	1,132	1,017	577
# of bedrooms	1.8	2.0	1.1	1.9	2.0	1.2
# of bathrooms	1.6	1.5	0.8	1.6	1.5	0.7
Granite (%)	14.6	0.0	35.3	32.5	0.0	46.9
Stainless (%)	13.5	0.0	34.2	25.8	0.0	43.7
Pool (%)	37.0	0.0	48.3	33.8	0.0	47.3
Gym (%)	25.5	0.0	43.6	29.0	0.0	45.4
Doorman (%)	5.7	0.0	23.2	5.9	0.0	23.5
Furnished (%)	5.0	0.0	21.9	8.5	0.0	28.0
Laundry (%)	48.9	0.0	50.0	60.8	100	48.8
Garage (%)	19.5	0.0	39.6	41.3	0.0	49.2
Condo (%)	10.4	0.0	30.5	6.9	0.0	25.3
Single-family housing (%)	15.6	0.0	36.3	23.7	0.0	42.5
Multi-family $\geq$ 10 units (%)	61.7	1.0	48.6	56.0	1.0	50.0
Multi-family $\geq$ 20 units (%)	56.2	1.0	49.6	50.2	49.0	20.4
$LockPayGap_{0.5ml}$	-3.1	-7.5	13.7	17.1	25.5	20.3
$LockRateGap_{0.5ml}$	-0.3	-0.6	1.1	1.3	1.9	1.6
$LockShare_{0.5ml}$ (%)	20.5	16.1	15.7	39.6	48.0	20.8
$LockPayGap_{1ml}$	-3.0	-7.5	13.6	17.2	25.5	20.3
$LockRateGap_{1ml}$	-0.3	-0.6	1.1	1.3	1.9	1.5
$LockShare_{1ml}$ (%)	20.7	16.5	15.4	39.6	49.0	20.4
number of rental listings		3,696,933			697,444	
number of rental unit		1,281,420			362,342	

	For-sale property characteristics					
	2014-2023			2021-2023		
Variables	mean	median	sd	mean	median	sd
Year of built	1966	1962	26.5	1965	1962	25.8
number of bedrooms	3.0	3.0	1.1	3.0	3.0	1.1
number of bathrooms	2.4	2.0	1.2	2.3	2.0	1.1
square footage	1,756	1,501	1,097	1,733	1,486	1,255
condo (%)	25.4	0.0	43.5	26.0	0.0	43.9
townhouse (%)	1.2	0.0	11.0	1.2	0.0	11.1
single-family housing (%)	74.6	1.0	43.5	74.0	1.0	43.9
number of sales		425,038			95,880	
number of unique properties		355,296			91,181	

Table 2: Mortgage Lock-In ($LockPayGap_{0.5ml}$) Effects on Rents

	(1) 2014-2023	(2) 2014-2023 Multi-Family	(3) 2021-2023	(4) 2021-2023 Multi-Family	(5) 2014-2023
$LockPayGap_{0.5ml}$	0.599***	0.508***	0.263***	0.263***	0.347**
	(10.79)	(10.72)	(19.95)	(15.90)	(2.25)
PopGrowthPUMA	-0.128**	-0.114*	-0.005	0.003	
	(-2.09)	(-1.80)	(-0.20)	(0.12)	
log(size)	0.538***	0.383***	0.526***	0.471***	0.540***
	(30.34)	(16.69)	(25.06)	(10.10)	(30.64)
0 beds	-0.026***	-0.047***	-0.031***	-0.030*	-0.027***
	(-4.54)	(-6.59)	(-4.56)	(-1.86)	(-5.08)
2 beds	0.056***	0.082***	0.086***	0.098***	0.055***
	(8.05)	(7.54)	(15.21)	(6.48)	(8.50)
3 beds	0.174***	0.191***	0.188***	0.191***	0.167***
	(15.26)	(11.39)	(16.05)	(7.77)	(14.70)
≥4 beds	0.201***	0.345***	0.198***	0.255***	0.192***
	(10.52)	(7.59)	(9.44)	(6.00)	(10.12)
0 baths	-0.332***	-0.102***	0.073*	0.019	-0.319***
	(-15.07)	(-6.79)	(1.93)	(1.02)	(-16.30)
2 baths	0.013***	0.017	0.007	-0.015	0.016***
	(2.79)	(1.46)	(1.39)	(-1.41)	(3.85)
3 baths	0.080***	0.085***	0.081***	0.105***	0.086***
	(7.90)	(4.80)	(4.73)	(4.17)	(8.71)
≥4 baths	0.203***	0.071**	0.239***	0.231***	0.206***
	(13.19)	(2.37)	(9.28)	(7.41)	(15.62)
Multi	-0.095***		-0.087***		-0.098***
	(-7.50)		(-8.98)		(-7.97)
granite	0.031***	0.025***	-0.022***	-0.021***	-0.012**
	(3.33)	(3.43)	(-3.43)	(-3.07)	(-2.35)
stainless	0.044***	0.029***	0.009	0.008	0.025***
	(5.52)	(3.65)	(1.30)	(0.99)	(4.47)
pool	0.020**	0.005	0.023*	-0.005	0.018**
	(2.18)	(0.53)	(1.79)	(-0.55)	(2.49)
gym	0.040***	0.001	0.059***	-0.019*	0.032***
	(3.71)	(0.08)	(2.89)	(-1.78)	(3.18)
doorman	0.046***	-0.009	0.082***	0.038**	0.059***
	(3.69)	(-0.59)	(3.99)	(2.43)	(4.52)
furnished	0.065***	0.005	0.114***	0.006	0.062***
	(5.19)	(0.54)	(10.73)	(0.50)	(4.84)
laundry	0.002	0.018*	-0.022***	-0.020***	-0.003
	(0.20)	(1.94)	(-2.86)	(-3.10)	(-0.53)
garage	0.040***	0.023*	-0.015**	0.014*	-0.016**
	(3.01)	(1.70)	(-2.50)	(1.92)	(-2.53)
Census Tract FE	YES	NO	YES	NO	YES
Building FE	NO	YES	NO	YES	NO
YM × Neighbor FE	NO	NO	NO	NO	YES
Average Rent ($)	2,825	2,346	3,201	2,790	2,825
R-Square adj	0.824	0.915	0.817	0.919	0.857
N	3010270	876796	520553	127399	3118337

Notes: The Table shows coefficients estimates from different specifications of equations (3) in columns (1) to (4), and equation (4) in column (5). The dependent variable is log asking rent for a sample rental listing in Los Angeles County. $LockPayGap_{0.5ml}$ is the monthly payment gap in the 0.5-mile radius surrounding each listing. T-stats are reported in parentheses and are bases on standard errors clustered by neighborhood and year-quarter.

Table 3: Heterogeneous Effects of Mortgage Lock-In by Local Supply Changes

	(1) 2014-2023	(2) 2014-2023	(3) 2014-2023
$LockPayGap_{0.5ml} \times I^{100units}_{0.05ml}$	-0.189**		
	(-2.49)		
$LockPayGap_{0.5ml} \times I^{100units}_{0.10ml}$		-0.107*	
		(-1.70)	
$LockPayGap_{0.5ml} \times I^{100units}_{0.25ml}$			-0.095***
			(-3.79)
$LockPayGap_{0.5ml}$	0.342**	0.339**	0.332**
	(2.25)	(2.24)	(2.20)
$I^{100units}_{0.05ml}$	0.048***		
	(3.07)		
$I^{100units}_{0.10ml}$		0.055***	
		(4.92)	
$I^{100units}_{0.25ml}$			0.022
			(1.63)
Controls	YES	YES	YES
Census Tract FE	YES	YES	YES
YM $\times$ Neighbor FE	YES	YES	YES
R-Square adj	0.857	0.857	0.857
N	3115319	3115319	3115319

Notes: This Table reports estimates of equation (4) augmented with interactions that capture local changes in rental supply. $I^{100units}_{Xml}$ is a dummy equal to one for rental units that had at least 100 units from medium-large multifamily buildings being added within X-miles of their location, and over a 2-year window surrounding their listing date. $LockPayGap_{0.5ml}$ is the monthly payment gap in the 0.5-mile radius surrounding the listing. T-stats are reported in parentheses and are bases on standard errors clustered by neighborhood and year-quarter.

Table 4: Mortgage Lock-In Effects on Rental Listings' Time on Market

	(1) 2014-2023 $I(\tau \leq 15d)$	(2) 2014-2023 $I(\tau \leq 15d)$	(3) 2014-2023 $I(\tau \leq 45d)$	(4) 2014-2023 $I(\tau \leq 45d)$	(5) 2014-2023 $log(\tau)$	(6) 2014-2023 $log(\tau)$
$LockPayGap_{0.5ml}$	0.444***	0.273*	0.209***	0.217**	-1.008***	-0.629*
	(4.59)	(1.88)	(4.14)	(2.11)	(-4.72)	(-1.71)
Controls	YES	YES	YES	YES	YES	YES
Census Tract FE	YES	YES	YES	YES	YES	YES
YM $\times$ Neighbor FE	NO	YES	NO	YES	NO	YES
R-Square adj	0.109	0.211	0.100	0.181	0.162	0.282
N	496050	540330	496050	540330	496050	540330

Notes: The Table shows coefficients estimates from different specifications of equations (3) and (4), in which the dependent variable is a function of a listings' time-on-market. In columns (1) and (2) the dependent variable is a dummy equal to one if the listing was removed after 15 days. In columns (3) and (4) the dependent variable is a dummy equal to one if the listing was removed after 15 days.In columns (5) and (6) it is the log of the number of days between the first date in which the listing appears in the data and the date on which it is removed. $LockPayGap_{0.5ml}$ is the monthly payment gap in the 0.5-mile radius surrounding each listing. T-stats are reported in parentheses and are bases on standard errors clustered by neighborhood and year-quarter.

Table 5: Mortgage Lock-In Effects on Rentals and Sales Volume

	Panel A: OLS Regressions			
	(1)	(2)	(3)	(4)
	2014-2023	2014-2023	2014-2023	2014-2023
	$log(NRentals+1)$	$log(NRentals+1)$	$log(NSales+1)$	$log(NSales+1)$
$\overline{LockPayGap}$	6.424***	5.298*	-13.370***	-3.129*
	(29.85)	(1.88)	(-66.18)	(-1.71)
Census Tract FE	YES	YES	YES	YES
YQ $\times$ Neighbor FE	NO	YES	NO	YES
R-Square adj	0.504	0.721	0.727	0.766
N	63717	62425	63717	62425

	Panel B: Poisson Regressions			
	(1)	(2)	(3)	(4)
	2014-2023	2014-2023	2014-2023	2014-2023
	$NRentals$	$NRentals$	$NSales$	$NSales$
$\overline{LockPayGap}$	9.020***	6.465	-16.058***	-3.608*
	(29.80)	(1.63)	(-78.31)	(-1.83)
Census Tract FE	YES	YES	YES	YES
YQ $\times$ Neighbor FE	NO	YES	NO	YES
R-Square adj	-	-	-	-
N	63717	62425	62957	61493

Notes: The Table shows coefficients estimates from different specifications of equation (5), in which the dependent variable is a measure of the number of rented our, or sold, properties in a specific census tract and quarter. $\overline{LockPayGap}$ is the average $LockPayGap$ per census tract and quarter. In columns (1) and (2), the dependent variable is either the log number of properties rented out (plus one), or the number of properties rented out. In columns (3) and (4), the dependent variable is either the log number of properties sold (plus one), or the number of properties sold. T-stats are reported in parentheses and are bases on standard errors clustered by census tract.

Table 6: Mortgage Lock-In ($LockPayGap_{0.5ml}$) Effects on Housing Sales Prices

	Panel B: $LockPayGap$ and Local and Sales Prices				
	(1)	(2)	(3)	(4)	(5)
	2014-2023	2014-2023	2014-2023	2014-2023	2014-2023
	$log(P_{0.5ml})$		$log(Psqft_{0.5ml})$		$\epsilon^{p}_{0.5ml}$
$LockPayGap_{0.5ml}$	0.776***	2.615***	0.799***	1.297***	1.266***
	(6.79)	(5.16)	(7.36)	(2.82)	(3.24)
Controls	YES	YES	YES	YES	YES
Census Tract FE	YES	YES	YES	YES	YES
YM $\times$ Neighbor FE	NO	YES	NO	YES	YES
R-Square adj	0.749	0.860	0.759	0.874	0.634
N	2830616	2916607	2830616	2916607	2916478

Notes: The Table shows coefficients estimates from equation (6). In columns (1) and (2), the dependent variable is the log of the average sales price across sales within a 0.5-mile of each individual listing, and taking place in the same quarter. In columns (3) and (4), it is the log average sales price per square foot. In columns (5), the average of residuals from hedonic regressions of log prices on characteristics. $LockPayGap_{0.5ml}$ is the monthly payment gap in the 0.5-mile radius surrounding each listing. T-stats are reported in parentheses and are bases on standard errors clustered by neighborhood and year-quarter.

Table 7: Sales Market Spillover Effects on Rents

	(1) 2014-2023 OLS	(2) 2014-2023 OLS	(3) 2014-2023 OLS	(4) 2014-2023 2SLS	(5) 2014-2023 2SLS	(6) 2014-2023 2SLS
$log(P_{0.5ml})$	0.023***			0.176**		
	(3.08)			(2.06)		
$log(Psqft_{0.5ml})$		0.026***			0.354**	
		(3.25)			(2.22)	
$\epsilon^p_{0.5ml}$			0.027**			0.361**
			(2.71)			(2.28)
Controls	YES	YES	YES	YES	YES	YES
Census Tract FE	YES	YES	YES	YES	YES	YES
YM $\times$ Neighbor FE	YES	YES	YES	YES	YES	YES
F_{robust} (1st Stage)	-	-	-	26.619	7.964	10.516
R-Square adj	0.851	0.851	0.850	-	-	-
N	2916642	2916642	2916489	2916607	2916607	2916478

Notes: The Table reports estimates of equations (7) and (8). Columns (1), (2), and (3) report OLS regressions of log rents on local sales prices. $log(P_{0.5ml})$ is the log of the average price across sales in the 0.5-mile radius centered at the listing coordinate, and taking place in the same quarter as the listing. $log(Psqft_{0.5ml})$ is the log of the average price per square foot across sales. Finally, $\epsilon^p_{0.5ml}$ is the average price residual in the 0.5-mile square, from a regression of log prices on characteristics. Columns (4), (5), and (6), report 2SLS regressions in which sales volume and sales prices are instrumented using $LockPayGap_{0.5ml}$, which is the monthly payment gap in the 0.5-mile radius surrounding each listing. F_{robust} is the heteroskedasticity robust variant of the F-statistic for the first-stage regressions, calculated using the methodology by Kleibergen and Paap (2006). T-stats are reported in parentheses and are bases on standard errors clustered by neighborhood and year-quarter.

Table 8: Heterogeneous Effects of Mortgage Lock-In by Census Tract Characteristics

	(1) 2014-2023	(2) 2014-2023	(3) 2014-2023
$LockPayGap_{0.5ml} \times PovertySh$	0.486***		
	(3.68)		
$PovertySh$	-0.065		
	(-1.07)		
$LockPayGap_{0.5ml} \times BachelorEdSh$		-0.373***	
		(-5.38)	
$BachelorEdSh$		-0.048	
		(-1.08)	
$LockPayGap_{0.5ml} \times UnempSh$			0.547**
			(2.37)
$UnempSh$			-0.125
			(-1.63)
$LockPayGap_{0.5ml}$	0.272*	0.513***	0.297*
	(1.75)	(3.55)	(1.90)
Controls	YES	YES	YES
Census Tract FE	YES	YES	YES
YM $\times$ Neighbor FE	YES	YES	YES
R-Square adj	0.857	0.857	0.857
N	3113599	3113643	3114848

Notes: This Table reports estimates of equation (9), in which the interaction variable Z captures demographic characteristics of the census tract in which the listing is located. $PovertySh$, $BachelorEdSh$, and $UnempSh$ are the shares of households with income below the poverty rate, with household head with bachelor education or higher, and with unemployed household head in the census tract. These variables are constructed using data from the American Community Survey (ACS). More precisely, we use 5-year estimates from different vintages, matched by year to the rental listing data. For rental listings from 2016 and earlier, we use 2016 ACS estimates. For listings from 2017, 2018, and 2019, we use 2019 estimates, and for listings from 2020, 2021, 2022, and 2023, we use 2022 estimates.$LockPayGap_{0.5ml}$ is the monthly payment gap in the 0.5-mile radius surrounding the listing. T-stats are reported in parentheses and are bases on standard errors clustered by neighborhood and year-quarter.

Table 9: Heterogeneous Effects of Mortgage Lock-In by Property Type

	(1) 2014-2023 Only SFR&Multi	(2) 2014-2023 Only Condo&Multi	(3) 2014-2023 No SFR-Condo	(4) 2014-2023 No SFR-Condo	(5) 2014-2023 All
$LockPayGap_{0.5ml} \times I_{SFR}$	-0.122***				
	(-3.69)				
I_{SFR}	0.119***				
	(9.67)				
$LockPayGap_{0.5ml} \times I_{Condo}$		-0.140***			
		(-5.51)			
I_{Condo}		0.012			
		(0.87)			
$LockPayGap_{0.5ml} \times I_{\geq 10\ Multi}$			0.070**		
			(2.56)		
$I_{\geq 10\ Multi}$			0.024**		
			(2.07)		
$LockPayGap_{0.5ml} \times I_{\geq 20\ Multi}$				0.097***	
				(3.23)	
$I_{\geq 20\ Multi}$				0.045***	
				(3.59)	
$LockPayGap_{0.5ml} \times I_{Corp}$					0.089***
					(3.35)
I_{Corp}					0.016**
					(2.70)
$LockPayGap_{0.5ml}$	0.353**	0.543**	0.494*	0.485*	0.330*
	(2.19)	(2.23)	(1.92)	(1.89)	(1.95)
Controls	YES	YES	YES	YES	YES
Census Tract FE	YES	YES	YES	YES	YES
YM × Neighbor FE	YES	YES	YES	YES	YES
R-Square adj	0.866	0.849	0.850	0.850	0.859
N	2572187	2404078	2084235	2084235	2899232

Notes: This Table reports estimates of equation (9), in which the interaction variable Z captures characteristics of the property and landlord. I_{SFR} is a dummy equal to one if the rental listing is a single-family residence. I_{Condo} is a dummy equal to if the listing is a condo. $I_{\geq 10\ Multi}$ is a dummy equal to one if the rental listing is a unit in a multifamily building with 10 or more units. $I_{\geq 10\ Multi}$ is a dummy equal to one if the listing is a unit in a multifamily building with 20 or more units. I_{Corp} is a dummy equal to one when the landlord is a legal entity or corporation. $LockPayGap_{0.5ml}$ is the monthly payment gap in the 0.5-mile square surrounding the listing. The sample is restricted to single-family and multi-family units only in column 1, to condos and multi-family units in column 2, to units that are not single-family and condos in columns 3 and 4. T-stats are reported in parentheses and are bases on standard errors clustered by neighborhood year-quarter.

Table 10: Mortgage Lock-In Effects on Rental Listings' Property Types

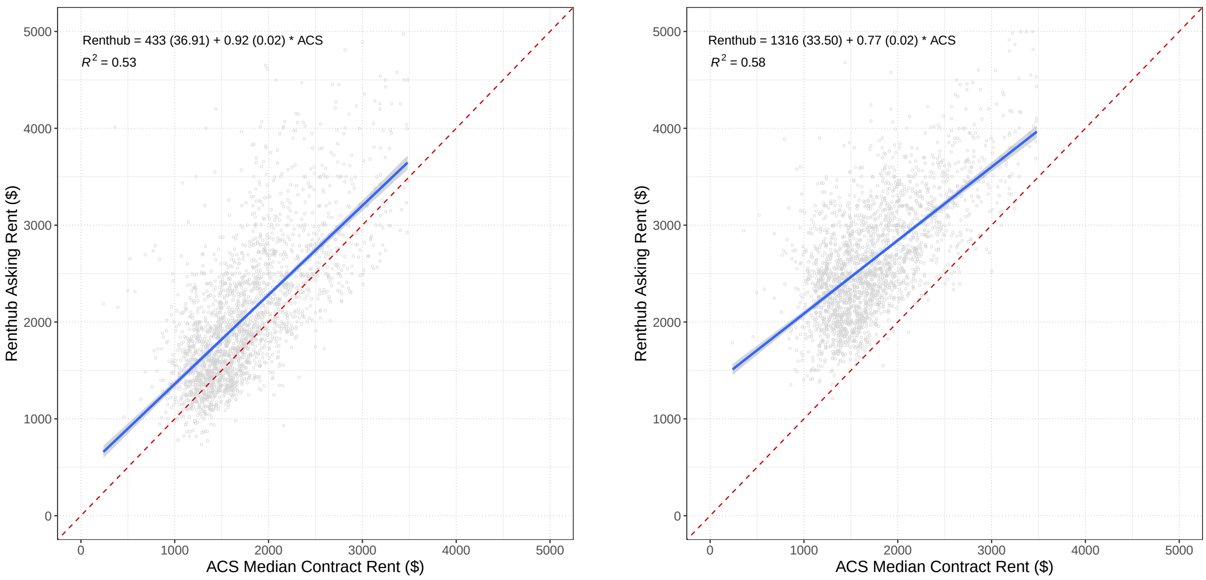
	(1) 2014-2023 Only SFR&Multi	(2) 2014-2023 Only Condo&Multi
$LockPayGap_{0.5ml}$	0.624***	0.161
	(3.26)	(0.73)
Census Tract FE	YES	YES
YM $\times$ Neighbor FE	YES	YES
R-Square adj	0.543	0.271
N	3060009	2878120

Notes: This Table reports estimates of equation (10). The dependent variable is a dummy equal one if the listing is a single-family residence in column (1), and a dummy equal to one if the listing is a condo in column (2). $LockPayGap_{0.5ml}$ is the monthly payment gap in the 0.5-mile square surrounding the listing. T-stats are reported in parentheses and are bases on standard errors clustered by neighborhood year-quarter.

Internet Appendix:

Mortgage Rates and Rents:
Evidence from Local Mortgage Lock-In Effects

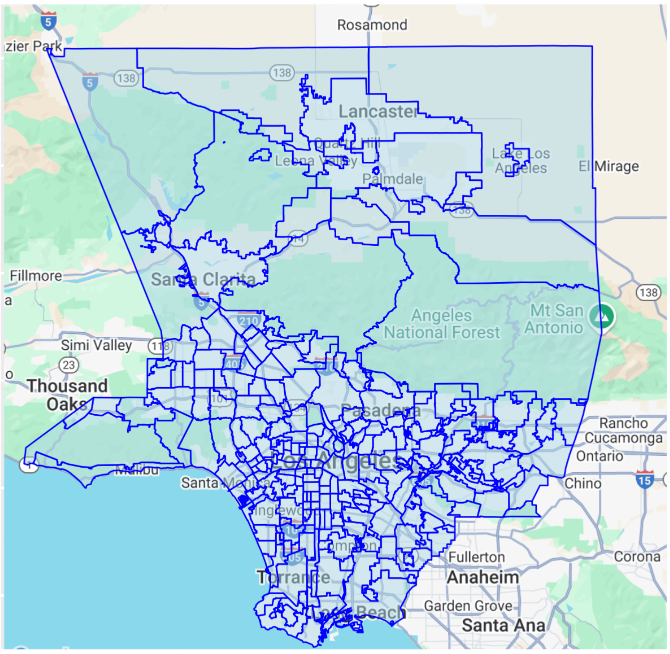
A Additional Figures and Tables



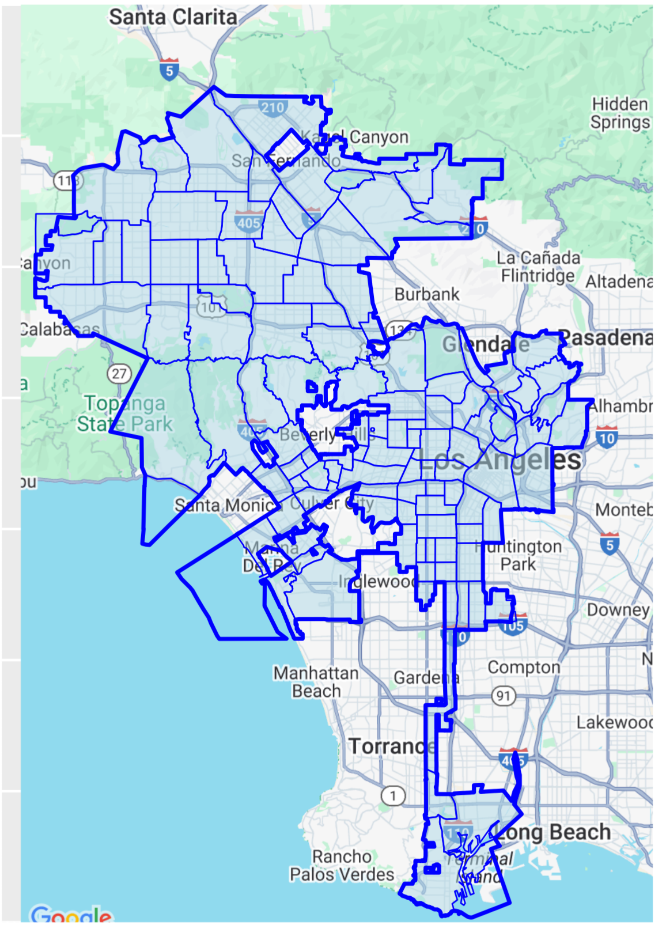
(a) 2014-2017

(b) 2019-2022

Figure A.1: This Figure shows the tract-level median Renthub rent from 2014 to 2017 and 2019 to 2022 against the median contract rents from ACS 2017 and 2022 five-year estimates, respectively. We choose to break the data in 2018 since there was a change in data source, and the sample size is small for 2018 due to a temporary discontinuity in data collection. To mimic the computation of ACS median contract rent, we first drop listings in the top 10 percentile of Renthub asking rents. We then calculate the mean asking rent for each sample property. Finally, we find the median rent for each census tract. We plot tract-level median asking rent from Renthub against the ACS median contract rent. Each point in the panels represents one census tract. ACS median contract rent is right censored, so we drop tracts with the censored rent at $3501. At the top left corner of each panel, we show the result of a Tobit regression where the dependent variable is Renthub rents and the independent variable is ACS median rents. The ACS median contract rents can explain 53% to 58% of the variation in median asking rents from Renthub. The red dotted reference line has a slope of 1.



(a) Neighborhoods in Los Angeles County



(b) Neighborhoods in Los Angeles City

Figure A.2: Panel (a) plots the neighborhoods boundaries for Los Angeles County, following the definition of Los Angeles Times. Panel (b) zooms into the 114 neighborhoods within Los Angeles City. Neighborhood boundary shapfiles come from Neighborhood Data for Social Change. The Basemap is sourced from Google Map API.

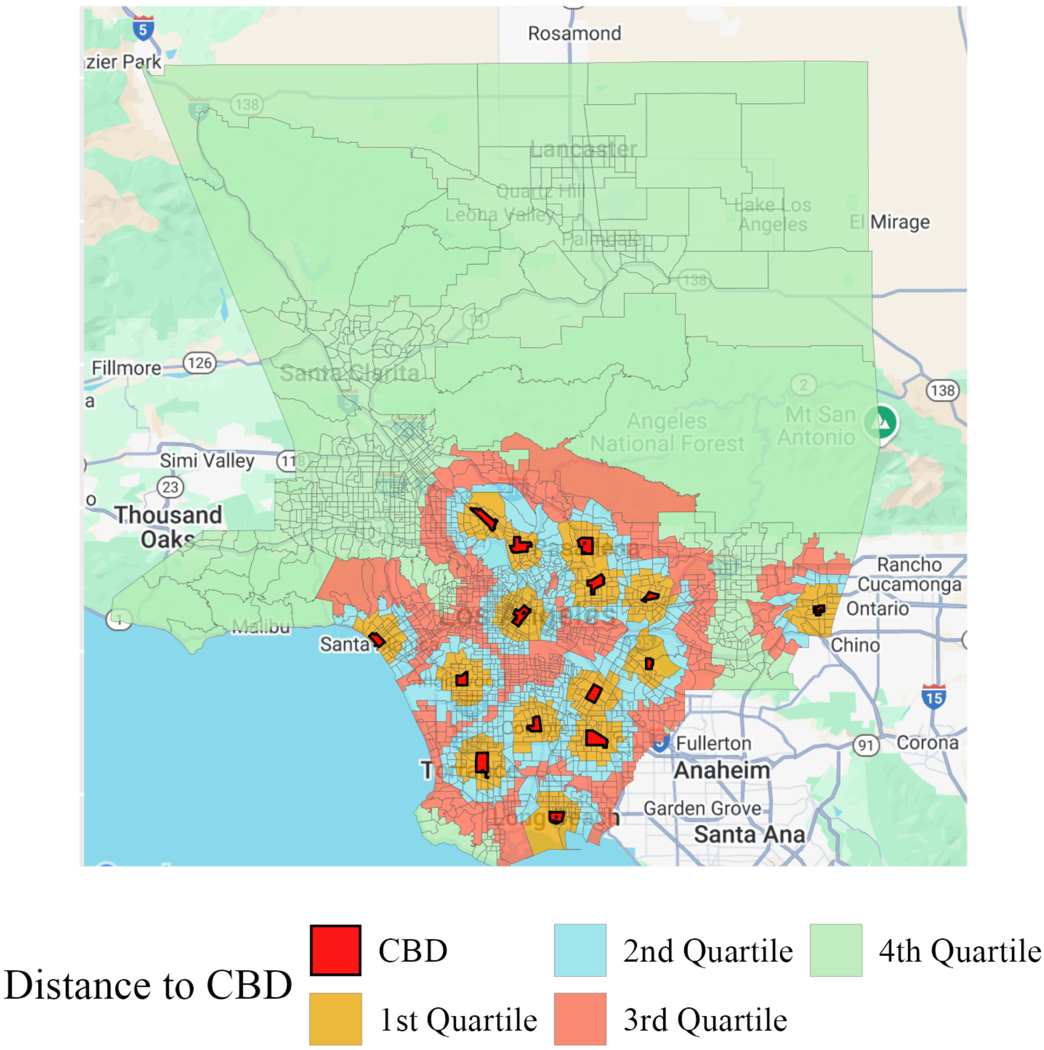
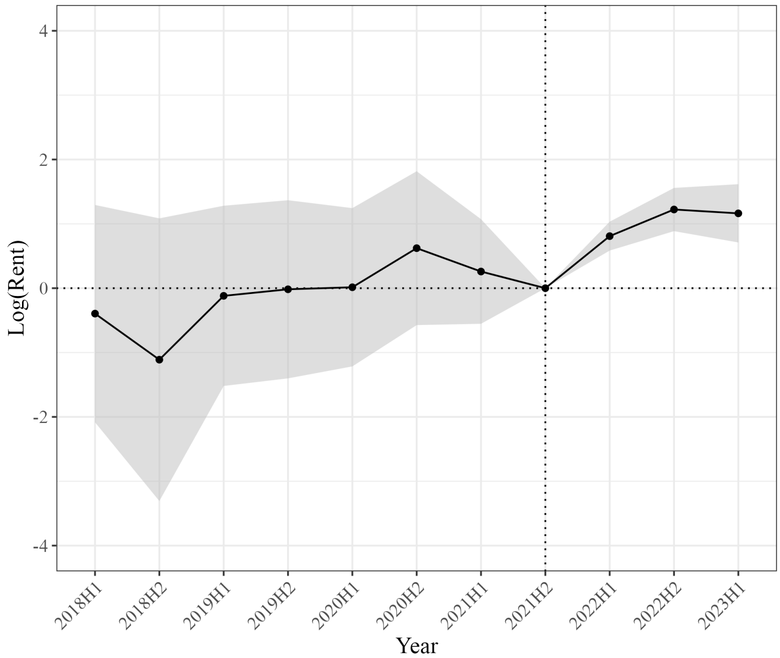
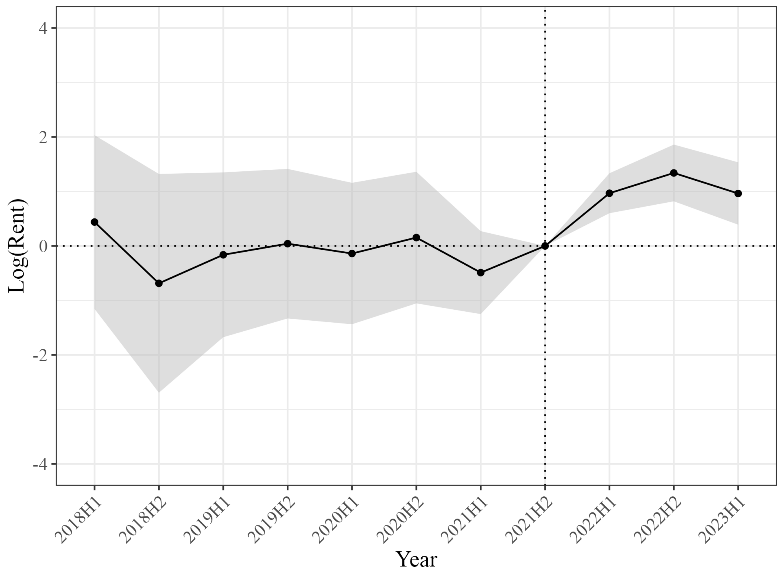


Figure A.3: The Figure plots the location of CBDs as defined in the 1982 Economic Census (Baum-Snow and Han, 2023, Ramani and Bloom, 2022) and the distance from each census tract's centroid to the closest CBD by quartile. The basemap is obtained from Google Map API.



(a) Event Study: $\overline{LockGap_{0.5ml,22:23}}$



(b) Event Study: $\overline{LockGap_{0.5ml,21}}$

Figure A.4: The Figure shows the estimates from equation (4.1.2). Census tract-level exposures to lock-in are set to their Q4:2022-Q1:2023 values in panel (a), and their 2021 values in panel (b). The outcome variable is the log asking rents for sample rental listings in Los Angeles County. The gray ribbon surrounding the line shows 95% confidence intervals for each estimated value.

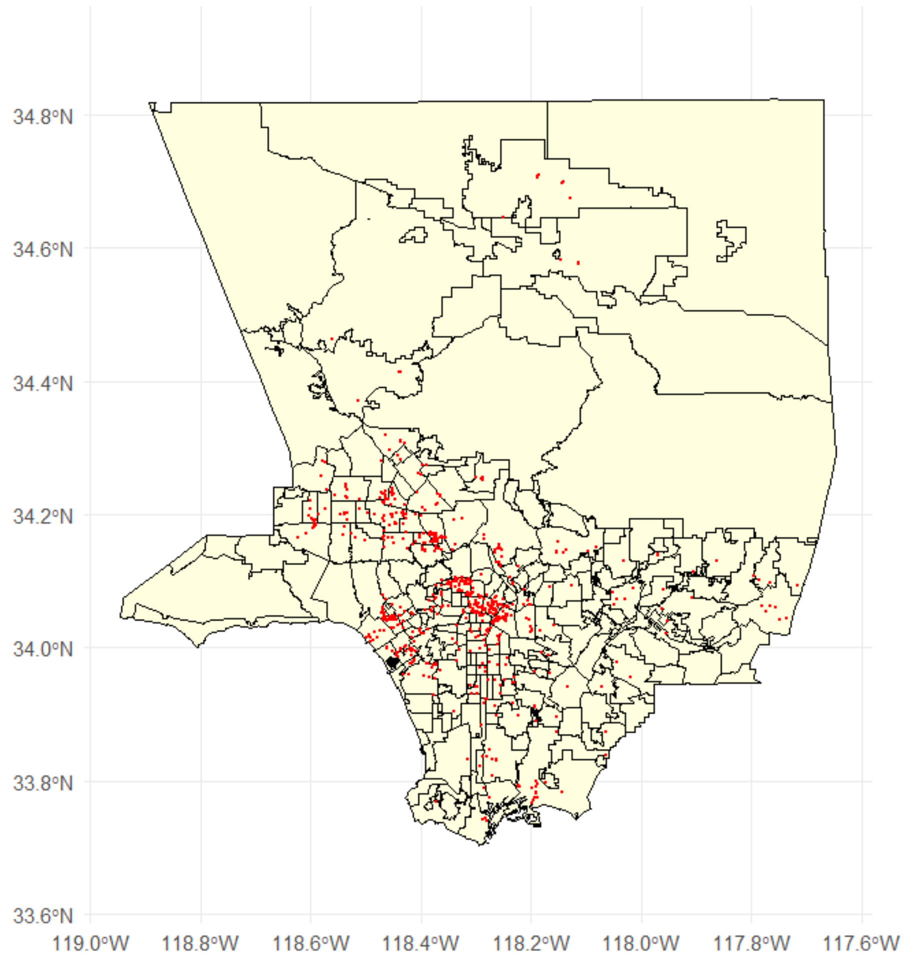


Figure A.5: The Figure locations of new large (with 20 or more units) multi-family buildings with completion date between 2009 and 2022.

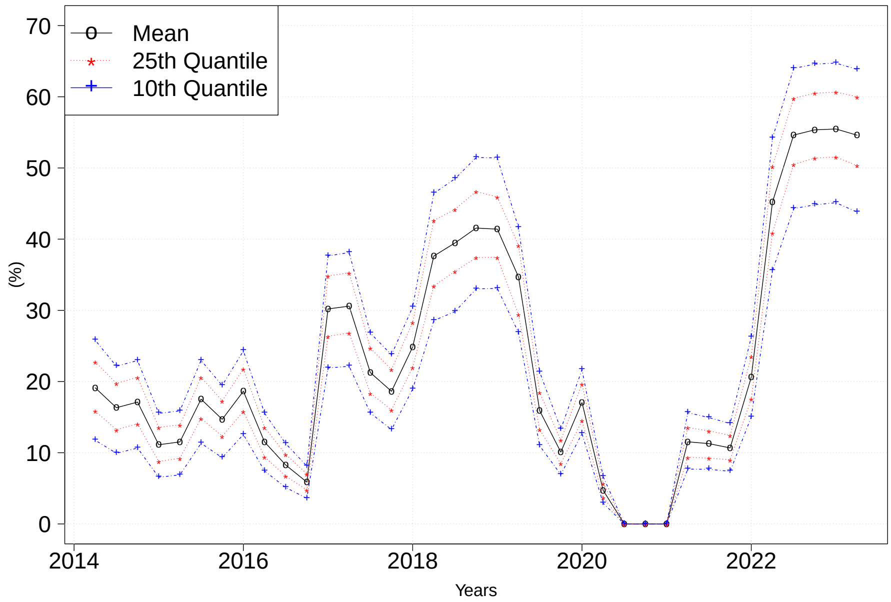


Figure A.6: The Figure plots the mean and the 10th, 25th, 75th, 90th quantile of the distribution of the lock-in variable, $LockShare_{0.5ml}$ (see equation B.1), across rental listings in each quarter from 2014Q1 to 2023Q1.

Table A.1: Renthub Listing Rents versus MLS Contractual Rents

	(1) 2015-2020	(2) 2015-2016	(3) 2017-2018	(4) 2019-2020
Mean % Price Diff Contractual/Listing	-0.49%	-0.47%	-0.53%	-0.46%
Median % Price Diff Contractual/Listing	0.00%	0.00%	0.00%	0.00%
Q10 % Price Diff Contractual/Listing	-4.00%	-4.05%	-4.08%	-3.85%
Q90 % Price Diff Contractual/Listing Price Diff	0.00%	0.00%	0.00%	0.00%
Share % Price Diff $=0$ Contractual/Listing	71.04%	69.99%	70.78%	71.84%
Share % Price Diff >0 Contractual/Listing Price Diff	9.31%	9.82%	9.06%	9.13%
Share % Price Diff <0 Contractual/Listing Price Diff	19.65%	20.19%	20.16%	19.023%
Number of Observations	456,041	107,485	193,145	147,314

Notes: The Table shows statistics of the percentage difference between contractual rents and listed rents in Los Angeles County. Results are based on information from MLS rental listings available from Corelogic, over the period from January 2015 to December 2020.

Table A.2: Mortgage Lock-In ($LockRateGap_{0.5ml}$) Effects on Rents

	(1) 2014-2023	(2) 2014-2023 Multi-Family	(3) 2021-2023	(4) 2021-2023 Multi-Family	(5) 2014-2023
$LockRateGap_{0.5ml}$	7.732***	6.526***	3.434***	3.449***	3.802**
	(11.12)	(10.82)	(19.64)	(16.00)	(2.16)
PopGrowthPUMA	-0.128**	-0.119*	-0.005	0.003	
	(-2.11)	(-1.89)	(-0.21)	(0.16)	
log(size)	0.538***	0.381***	0.526***	0.471***	0.540***
	(30.26)	(16.60)	(25.12)	(10.10)	(30.58)
0 beds	-0.027***	-0.048***	-0.031***	-0.030*	-0.027***
	(-4.60)	(-6.67)	(-4.54)	(-1.86)	(-5.08)
2 beds	0.056***	0.083***	0.086***	0.098***	0.055***
	(8.06)	(7.78)	(15.21)	(6.48)	(8.50)
3 beds	0.174***	0.192***	0.187***	0.191***	0.167***
	(15.27)	(11.60)	(16.07)	(7.77)	(14.70)
geq4 beds	0.202***	0.346***	0.198***	0.255***	0.193***
	(10.54)	(7.64)	(9.45)	(6.01)	(10.12)
0 baths	-0.330***	-0.102***	0.073*	0.018	-0.319***
	(-14.97)	(-6.78)	(1.93)	(1.00)	(-16.30)
2 baths	0.013***	0.016	0.007	-0.015	0.016***
	(2.82)	(1.50)	(1.42)	(-1.41)	(3.86)
3 baths	0.080***	0.085***	0.081***	0.105***	0.086***
	(7.92)	(4.82)	(4.73)	(4.17)	(8.70)
$\geq$4 baths	0.203***	0.072**	0.239***	0.231***	0.206***
	(13.25)	(2.38)	(9.29)	(7.41)	(15.61)
Multi	-0.095***		-0.087***		-0.098***
	(-7.49)		(-8.99)		(-7.96)
granite	0.030***	0.024***	-0.022***	-0.021***	-0.012**
	(3.28)	(3.37)	(-3.47)	(-3.08)	(-2.35)
stainless	0.044***	0.029***	0.008	0.008	0.025***
	(5.52)	(3.60)	(1.27)	(1.00)	(4.47)
pool	0.020**	0.005	0.023*	-0.005	0.018**
	(2.22)	(0.52)	(1.79)	(-0.54)	(2.48)
gym	0.040***	0.000	0.060***	-0.019*	0.032***
	(3.74)	(0.05)	(2.89)	(-1.77)	(3.19)
doorman	0.045***	-0.009	0.082***	0.038**	0.059***
	(3.67)	(-0.55)	(3.99)	(2.44)	(4.52)
furnished	0.065***	0.005	0.114***	0.006	0.062***
	(5.19)	(0.56)	(10.73)	(0.52)	(4.84)
laundry	0.001	0.018*	-0.022***	-0.020***	-0.003
	(0.20)	(1.96)	(-2.83)	(-3.07)	(-0.52)
garage	0.039***	0.023	-0.015**	0.013*	-0.016**
	(2.95)	(1.68)	(-2.48)	(1.89)	(-2.52)
Census Tract FE	YES	NO	YES	NO	YES
Building FE	NO	YES	NO	YES	NO
YM $\times$ Neighbor FE	NO	NO	NO	NO	YES
Average Rent ($)	2,825	2,346	3,201	2,790	2,825
R-Square adj	0.825	0.915	0.817	0.919	0.857
N	3010270	874820	520412	127396	3115319

Notes: The Table shows coefficients estimates from different specifications of equations (3) in columns (1) to (4), and equation (4) in column (5). The dependent variable is log asking rent for a specific rental listing in Los Angeles County. $LockRateGap_{0.5ml}$ is the mean rate gap in the 0.5-mile radius surrounding each listing. T-stats are reported in parentheses and are bases on standard errors clustered by neighborhood and year-quarter.

Table A.3: Mortgage Lock-In Effects on Rents (Bootstrap Standard Errors)

	Panel A: Effects of $LockPayGap_{0.5ml}$ on Rents				
	(1)	(2)	(3)	(4)	(5)
	2014-2023	2014-2023	2021-2023	2021-2023	2014-2023
		Multi-Family		Multi-Family	
$LockPayGap_{0.5ml}$	0.599***	0.508***	0.263***	0.263***	0.347**
	(10.79)	(10.71)	(19.94)	(15.90)	(2.18)
Controls	YES	YES	YES	YES	YES
Census Tract FE	YES	NO	YES	NO	YES
Building FE	NO	YES	NO	YES	NO
YM $\times$ Neighbor FE	NO	NO	NO	NO	YES
R-Square adj	0.824	0.915	0.817	0.919	0.857
N	3010270	876796	520553	127399	3118337

	Panel B: Effects of $LockRateGap_{0.5ml}$ on Rents				
	(1)	(2)	(3)	(4)	(5)
	2014-2023	2014-2023	2021-2023	2021-2023	2014-2023
		Multi-Family		Multi-Family	
$LockRateGap_{0.5ml}$	7.732***	6.526***	3.434***	3.449***	3.802**
	(11.13)	(10.83)	(19.64)	(16.00)	(2.10)
Controls	YES	YES	YES	YES	YES
Census Tract FE	YES	NO	YES	NO	YES
Building FE	NO	YES	NO	YES	NO
YM $\times$ Neighbor FE	NO	NO	NO	NO	YES
R-Square adj	0.824	0.915	0.817	0.919	0.857
N	3010270	876796	520553	127399	3118337

Notes: The Table shows coefficients estimates from different specifications of equations (3), in columns (1) to (4), and equation (4), in column (5). T-stats are based on bootstrapped standard errors, and can be compared against the corresponding estimates in Table 2 and Table A.2. Panel A uses $LockPayGap_{0.5ml}$ as the mortgage lock-in measure, which is the monthly payment gap in the 0.5-mile radius surrounding each listing. Panel B uses $LockRateGap_{0.5ml}$ as the mortgage lock-in measure, which is the monthly mortgage rate gap in the 0.5-mile radius surrounding each listing. The dependent variable is log asking rent for a specific rental listing in Los Angeles County.

Table A.4: Mortgage Lock-In Effects on Rents (Weighted Least Squares)

	Panel A: Effects of $LockPayGap_{0.5ml}$ on Rents				
	(1) 2014-2023	(2) 2014-2023 Multi-Family	(3) 2021-2023	(4) 2021-2023 Multi-Family	(5) 2014-2023
$LockPayGap_{0.5ml}$	0.644***	0.563***	0.229***	0.216***	0.429***
	(10.19)	(9.40)	(17.65)	(11.39)	(2.91)
Controls	YES	YES	YES	YES	YES
Census Tract FE	YES	NO	YES	NO	YES
Building FE	NO	YES	NO	YES	NO
YM $\times$ Neighbor FE	NO	NO	NO	NO	YES
R-Square adj	0.817	0.910	0.819	0.927	0.848
N	2872733	827555	519795	127388	2980990

	Panel B: Effects of $LockRateGap_{0.5ml}$ on Rents				
	(1) 2014-2023	(2) 2014-2023 Multi-Family	(3) 2021-2023	(4) 2021-2023 Multi-Family	(5) 2014-2023
$LockRateGap_{0.5ml}$	8.408***	7.333***	3.019***	2.868***	5.360***
	(10.56)	(9.67)	(17.48)	(11.55)	(2.82)
Controls	YES	YES	YES	YES	YES
Census Tract FE	YES	NO	YES	NO	YES
Building FE	NO	YES	NO	YES	NO
YM $\times$ Neighbor FE	NO	NO	NO	NO	YES
R-Square adj	0.816	0.909	0.819	0.927	0.848
N	2872733	827555	519795	127388	2980990

Notes: The Table shows coefficients estimates from different specifications of equations (3) in columns (1) to (4), and equation (4) in column (5). Estimates are based on Weighted Least Squares, with weights determined by the share of locked-in properties within the half-mile radius surrounding each listing. They can be compared against the corresponding estimates in Table 2 and Table A.2. Panel A uses $LockPayGap_{0.5ml}$ as the mortgage lock-in measure, which is the monthly payment gap in the 0.5-mile radius surrounding each listing. Panel B uses $LockRateGap_{0.5ml}$ as the mortgage lock-in measure, which is the monthly mortgage rate gap in the 0.5-mile radius surrounding each listing. The dependent variable is log asking rent for each sample rental listing in Los Angeles County.

Table A.5: Event Study: Mortgage Lock-In ($LockRateGap_{0.5ml}$) Effects on Rents

	(1) 2018-2023	(2) 2018-2023	(3) 2018-2023	(4) 2018-2023
$I(2018H1) \times I(HighLockGap_{0.5ml,22:23})$	-0.005			
	(-0.31)			
$I(2018H2) \times I(HighLockGap_{0.5ml,22:23})$	-0.019			
	(-1.08)			
$I(2019H1) \times I(HighLockGap_{0.5ml,22:23})$	-0.002			
	(-0.15)			
$I(2019H2) \times I(HighLockGap_{0.5ml,22:23})$	0.003			
	(0.26)			
$I(2020H1) \times I(HighLockGap_{0.5ml,22:23})$	-0.001			
	(-0.13)			
$I(2020H2) \times I(HighLockGap_{0.5ml,22:23})$	0.004			
	(0.39)			
$I(2021H1) \times I(HighLockGap_{0.5ml,22:23})$	0.004			
	(0.40)			
$I(2021H2) \times I(HighLockGap_{0.5ml,22:23})$	-			
	(-)			
$I(2022H1) \times I(HighLockGap_{0.5ml,22:23})$	0.015***			
	(3.55)			
$I(2022H2) \times I(HighLockGap_{0.5ml,22:23})$	0.028***			
	(4.71)			
$I(2023H1) \times I(HighLockGap_{0.5ml,22:23})$	0.024***			
	(3.46)			
$I(2018H1) \times I(HighLockGap_{05ml,21})$		0.002		
		(0.09)		
$I(2018H2) \times I(HighLockGap_{05ml,21})$		-0.003		
		(-0.12)		
$I(2019H1) \times I(HighLockGap_{05ml,21})$		0.001		
		(0.07)		
$I(2019H2) \times I(HighLockGap_{05ml,21})$		0.003		
		(0.17)		
$I(2020H1) \times I(HighLockGap_{05ml,21})$		-0.002		
		(-0.13)		
$I(2020H2) \times I(HighLockGap_{05ml,21})$		0.001		
		(0.11)		
$I(2021H1) \times I(HighLockGap_{05ml,21})$		-0.008		
		(-0.76)		
$I(2021H2) \times I(HighLockGap_{05ml,21})$		-		
		(-)		
$I(2022H1) \times I(HighLockGap_{05ml,21})$		0.029***		
		(3.80)		
$I(2022H2) \times I(HighLockGap_{05ml,21})$		0.036***		
		(4.60)		
$I(2023H1) \times I(HighLockGap_{05ml,21})$		0.026***		
		(3.16)		
$I(2018H1) \times \overline{LockGap}_{0.5ml,22:23}$			-0.398	
			(-0.49)	
$I(2018H2) \times \overline{LockGap}_{0.5ml,22:23}$			-1.111	
			(-1.06)	
$I(2019H1) \times \overline{LockGap}_{0.5ml,22:23}$			-0.117	
			(-0.17)	
$I(2019H2) \times \overline{LockGap}_{0.5ml,22:23}$			-0.016	
			(-0.02)	
$I(2020H1) \times \overline{LockGap}_{0.5ml,22:23}$			0.013	
			(0.02)	
$I(2020H2) \times \overline{LockGap}_{0.5ml,22:23}$			0.623	
			(1.09)	
$I(2021H1) \times \overline{LockGap}_{0.5ml,22:23}$			0.260	
			(0.67)	
$I(2021H2) \times \overline{LockGap}_{0.5ml,22:23}$			-	
			(-)	
$I(2022H1) \times \overline{LockGap}_{0.5ml,22:23}$			0.808***	
			(7.52)	
$I(2022H2) \times \overline{LockGap}_{0.5ml,22:23}$			1.222***	
			(7.58)	
$I(2023H1) \times \overline{LockGap}_{0.5ml,22:23}$			1.163***	
			(5.35)	
$I(2018H1) \times \overline{LockGap}_{05ml,21}$				0.439
				(0.54)
$I(2018H2) \times \overline{LockGap}_{05ml,21}$				-0.686
				(-0.67)
$I(2019H1) \times \overline{LockGap}_{05ml,21}$				-0.162
				(-0.21)
$I(2019H2) \times \overline{LockGap}_{05ml,21}$				0.042
				(0.06)
$I(2020H1) \times \overline{LockGap}_{05ml,21}$				-0.139
				(-0.21)
$I(2020H2) \times \overline{LockGap}_{05ml,21}$				0.154
				(0.25)
$I(2021H1) \times \overline{LockGap}_{05ml,21}$				-0.489
				(-1.26)
$I(2021H2) \times \overline{LockGap}_{05ml,21}$				-
				(-)
$I(2022H1) \times \overline{LockGap}_{05ml,21}$				0.968***
				(5.18)
$I(2021H2) \times \overline{LockGap}_{05ml,21}$				1.340***
				(5.05)
$I(2023H1) \times \overline{LockGap}_{05ml,21}$				0.963***
				(3.30)
Controls	YES	YES	YES	YES
Census Tract FE	YES	YES	YES	YES
YM FE	YES	YES	YES	YES
R-Square adj	0.829	0.829	0.829	0.829
N	1046456	1046456	1045808	1040885

Notes: The Table shows estimates for equation (4.1.2). The dependent variable is log asking rent. $I(HighLockGap_{Xml,22:23})$ ($I(HighLockGap_{Xml,21})$) is a dummy equal to one in census tracts in which the mean of $LockRateGap_{Xml}$ (the average rate gap within X-miles) across listings in Q42022-Q12023 (2021) is above median. $\overline{LockGap}_{Xml,22:23}$ ($\overline{LockGap}_{Xml,21}$) is the mean value of $LockRateGap_{Xml}$ in each tract across listings in Q42022-Q12023 (2021). T-stats are in parentheses; standard errors are clustered by zip code and year-quarter.

Table A.6: Mortgage Lock-In ($LockRateGap_{0.5ml}$) Effects on TOM

	(1) 2014-2023 $I(\tau \leq 15d)$	(2) 2014-2023 $I(\tau \leq 15d)$	(3) 2014-2023 $I(\tau \leq 45d)$	(4) 2014-2023 $I(\tau \leq 45d)$	(5) 2014-2023 $log(\tau)$	(6) 2014-2023 $log(\tau)$
$LockRateGap_{0.5ml}$	5.783***	3.424**	2.681***	2.964**	-13.080***	-8.284**
	(4.73)	(2.26)	(4.10)	(2.48)	(-4.82)	(-2.11)
Controls	YES	YES	YES	YES	YES	YES
Census Tract FE	YES	YES	YES	YES	YES	YES
YM $\times$ Neighbor FE	NO	YES	NO	YES	NO	YES
R-Square adj	0.110	0.211	0.100	0.181	0.162	0.282
N	496050	540330	496050	540330	496050	540330

Notes: The Table shows coefficients estimates from different specifications of equations (3) and (4), in which the dependent variable is a function of a listings' time-on-market. In columns (1) and (2) the dependent variable is a dummy equal to one if the listing was removed after 15 days. In columns (3) and (4) the dependent variable is a dummy equal to one if the listing was removed after 15 days. In columns (5) to (6) it is the log of the number of days between the first date in which the listing appears in the data and the date on which it is removed. $LockRateGap_{0.5ml}$ is the mean rate gap in the 0.5-mile radius surrounding each listing. T-stats are reported in parentheses and are bases on standard errors clustered by neighborhood and year-quarter.

Table A.7: Robustness: Mortgage Lock-In Effects with Distance-to-CBD Fixed Effects

	(1) 2014-2023 $log(rent)$	(2) 2014-2023 $log(rent)$	(3) 2014-2023 $I(\tau \leq 15d)$	(4) 2014-2023 $I(\tau \leq 15d)$	(5) 2014-2023 $log(\tau)$	(6) 2014-2023 $log(\tau)$
$LockPayGap_{0.5ml}$	0.340**		0.253*		-0.618	
	(2.21)		(1.74)		(-1.63)	
$LockRateGap_{0.5ml}$		3.698**		3.196***		-8.301**
		(2.10)		(2.17)		(-2.11)
Controls	YES	YES	YES	YES	YES	YES
Census Tract FE	YES	YES	YES	YES	YES	YES
YM $\times$ Neighborhood $\times$ CBDdist Quartile FE	YES	YES	YES	YES	YES	YES
R-Square adj	0.858	0.858	0.217	0.217	0.286	0.286
N	3114179	3114179	523134	523134	523134	523134

Notes: This table shows the effects of mortgage lock-in on rents and rental listing's time on market, using year-month-neighborhood-distance-to-CBD fixed effects. The definition of CBD follows the 1982 economic census (Baum-Snow and Han, 2023; Ramani and Bloom, 2022). We calculate the distance from each census tract's centroid to the nearest CBD centroid. We then determine quartiles of this distance measures and interact them with year-month-neighborhood fixed effects.

Table A.8: Heterogeneous Effects of Mortgage Lock-In on TOM by Census Tract Characteristics

	(1) 2014-2023 $I(\tau \leq 45d)$	(2) 2014-2023 $I(\tau \leq 45d)$	(3) 2014-2023 $I(\tau \leq 45d)$
$LockPayGap_{0.5ml} \times PovertySh$	-0.001		
	(-0.74)		
$PovertySh$	0.000		
	(0.06)		
$LockPayGap_{0.5ml} \times BachelorEdSh$		0.001	
		(0.74)	
$BachelorEdSh$		-0.001	
		(-1.40)	
$LockPayGap_{0.5ml} \times UnempSh$			0.000
			(0.04)
$UnempSh$			0.000
			(0.37)
$LockPayGap_{0.5ml}$	0.173	0.278	0.180
	(1.63)	(1.43)	(0.95)
Controls	YES	YES	YES
Census Tract FE	YES	YES	YES
YM $\times$ Neighbor FE	YES	YES	YES
R-Square adj	0.198	0.193	0.215
N	423205	385606	303275

Notes: This Table reports estimates of equation (9), in which the interaction variable Z captures demographic characteristics of the census tract in which the listing is located, and the dependent variable is a dummy equal to one for properties rented our in less than 45 days. $PovertySh$, $BachelorEdSh$, and $UnempSh$ are the shares of households with income below the poverty rate, with household head with bachelor education or higher, and with unemployed household head in the census tract. These variables are constructed using data from the American Community Survey (ACS). More precisely, we use 5-year estimates from different vintages, matched by year to the rental listing data. For rental listings from 2016 and earlier, we use 2016 ACS estimates. For listings from 2017, 2018, and 2019, we use 2019 estimates, and for listings from 2020, 2021, 2022, and 2023, we use 2022 estimates.$LockPayGap_{0.5ml}$ is the monthly payment gap in the 0.5-mile radius surrounding the listing. T-stats are reported in parentheses and are bases on standard errors clustered by neighborhood and year-quarter.

Table A.9: Heterogeneous Effects of Mortgage Lock-In on TOM by Property Type

	(1) 2014-2023 Only SFR&Multi $I(\tau \leq 45d)$	(2) 2014-2023 Only Condo&Multi $I(\tau \leq 45d)$	(3) 2014-2023 No SFR-Condo $I(\tau \leq 45d)$	(4) 2014-2023 No SFR-Condo $I(\tau \leq 45d)$	(5) 2014-2023 All $I(\tau \leq 45d)$
$LockPayGap_{0.5ml} \times I_{SFR}$	0.023				
	(0.58)				
I_{SFR}	0.064***				
	(8.48)				
$LockPayGap_{0.5ml} \times I_{Condo}$		0.084**			
		(2.55)			
I_{Condo}		0.093***			
		(8.13)			
$LockPayGap_{0.5ml} \times I_{\geq 10\ Multi}$			-0.015		
			(-0.28)		
$I_{\geq 10\ Multi}$			-0.097***		
			(-11.15)		
$LockPayGap_{0.5ml} \times I_{\geq 20\ Multi}$				-0.043	
				(-0.66)	
$I_{\geq 20\ Multi}$				-0.129***	
				(-13.33)	
$LockPayGap_{0.5ml} \times I_{Corp}$					-0.024
					(-0.57)
I_{Corp}					-0.092***
					(-12.15)
$LockPayGap_{0.5ml}$	0.126	0.285	0.136	0.155	0.196*
	(1.17)	(1.47)	(0.80)	(0.93)	(1.96)
Controls	YES	YES	YES	YES	YES
Census Tract FE	YES	YES	YES	YES	YES
YM $\times$ Neighbor FE	YES	YES	YES	YES	YES
R-Square adj	0.200	0.197	0.220	0.224	0.188
N	423356	385690	303317	303317	507935

Notes: This Table reports estimates of equation (9), in which the interaction variable Z captures characteristics of the property and landlord, and the dependent variable is a dummy equal to one for properties rented our in less than 45 days. I_{SFR} is a dummy equal to one if the rental listing is a single-family residence. I_{Condo} is a dummy equal to if the listing is a condo. $I_{\geq 10\ Multi}$ is a dummy equal to one if the rental listing is a unit in a multifamily building with 10 or more units. $I_{\geq 10\ Multi}$ is a dummy equal to one if the listing is a unit in a multifamily building with 20 or more units. I_{Corp} is a dummy equal to one when the landlord is a legal entity or corporation. $LockPayGap_{0.5ml}$ is the monthly payment gap in the 0.5-mile square surrounding the listing. The sample is restricted to single-family and multi-family units only in column 1, to condos and multi-family units in column 2, to units that are not single-family and condos in columns 3 and 4. T-stats are reported in parentheses and are bases on standard errors clustered by neighborhood year-quarter.

Table A.10: Heterogeneous Effects of Mortgage Lock-In by Property Type (Census Tracts with Poverty Share Below Median)

	(1) 2014-2023	(2) 2014-2023	(3) 2014-2023	(4) 2014-2023	(5) 2014-2023
$LockPayGap_{0.5ml} \times I_{SFR}$	-0.100***				
	(-2.73)				
I_{SFR}	0.137***				
	(12.21)				
$LockPayGap_{0.5ml} \times I_{Condo}$		-0.114***			
		(-4.54)			
I_{Condo}		0.020**			
		(2.28)			
$LockPayGap_{0.5ml} \times I_{\geq 10\ Multi}$			0.080**		
			(2.70)		
$I_{\geq 10\ Multi}$			0.016		
			(0.87)		
$LockPayGap_{0.5ml} \times I_{\geq 10\ Multi}$				0.095***	
				(3.09)	
$I_{\geq 20\ Multi}$				0.044**	
				(2.64)	
$LockPayGap_{0.5ml} \times I_{Corp}$					0.093***
					(3.35)
I_{Corp}					0.013*
					(1.98)
$LockPayGap_{0.5ml}$	0.270*	0.458	0.564*	0.555*	0.181
	(1.88)	(1.62)	(1.89)	(1.84)	(1.16)
Controls	YES	YES	YES	YES	YES
Census Tract FE	YES	YES	YES	YES	YES
YM $\times$ Neighbor FE	YES	YES	YES	YES	YES
R-Square adj	0.874	0.851	0.852	0.852	0.864
N	1328012	1146949	963556	963556	1516726

Notes: This Table reports estimates of equation (9), in which the interaction variable Z captures characteristics of the property and landlord. The sample is restricted to census tracts with property share below median, based on data from the American Community Survey. I_{SFR} is a dummy equal to one if the rental listing is a single-family residence. I_{Condo} is a dummy equal to if the listing is a condo. $I_{\geq 10\ Multi}$ is a dummy equal to one if the rental listing is a unit in a multifamily building with 10 or more units. $I_{\geq 10\ Multi}$ is a dummy equal to one if the listing is a unit in a multifamily building with 20 or more units. I_{Corp} is a dummy equal to one when the landlord is a legal entity or corporation. $LockPayGap_{0.5ml}$ is the monthly payment gap in the 0.5-mile square surrounding the listing. The sample is restricted to single-family and multi-family units only in column 1, to condos and multi-family units in column 2, to units that are not single-family and condos in columns 3 and 4. T-stats are reported in parentheses and are bases on standard errors clustered by neighborhood year-quarter.

Table A.11: Effect Heterogeneity by Rental Unit Size

	(1) 2014-2023	(2) 2014-2023 No SFR	(3) 2014-2023	(4) 2014-2023 No SFR
$LockPayGap_{0.5ml} \times log(Size)$	-0.052**	-0.011		
	(-2.35)	(-0.49)		
$LockPayGap_{0.5ml} \times Beds$			-0.021**	0.001
			(-2.66)	(0.12)
$LockPayGap_{0.5ml}$	0.718***	0.609**	0.399**	0.528**
	(3.69)	(2.72)	(2.65)	(2.21)
Controls	YES	YES	YES	YES
Census Tract FE	YES	YES	YES	YES
YM $\times$ Neighbor FE	YES	YES	YES	YES
R-Square adj	0.857	0.848	0.857	0.848
N	3115319	2411164	3115318	2411164

This Table reports estimates of equation (9), in which the interaction variable Z captures characteristics of the listing. $log(Size)$ is the listing square fee size, and $Beds$ is the number of bedrooms. Both variables, when uninteracted, are spanned by the controls. $LockPayGap_{0.5ml}$ is the monthly payment gap in the 0.5-mile radius surrounding the listing. T-stats are reported in parentheses and are bases on standard errors clustered by neighborhood and year-quarter.

B Lock-In Measures and the Local Share of Locked-In Loans

The measures in Section 3 focus only on average rates for a subsample of homes in each X-mile radius. While these differences in rates are more likely to be unrelated to local market characteristics and trends, they ignore the composition of local mortgages. For instance, if the measures are systematically higher in areas where fixed-rate mortgages have a smaller market share, they might not be correlated with the actual share of locked-in homes. In this Appendix, we show that this is not the case.

Specifically, we calculate the share of locked-in residential properties as follows:

$$LockShare_{j,t,Xml} = \frac{1}{|N_{Xml,j,t}|} \sum_{i \in C_{Xml,j}} I(r_t^M - r_{i,\tau(i)}^M > 0), \tag{B.1}$$

where $N_{Xml,j}$ is the number of *all* starter homes built before t and located in the X-mile radius surrounding rental listing j. The set $N_{Xml,j}$ is larger than the set $C_{Xml,j}$, as the latter only includes properties with active FRMs. $I(.)$ is an indicator that equals one if the last mortgage rate $r_{i,\tau(i)}^M$ for property i is smaller than the prevailing market rate r_t^M. This measure captures the share of properties within the X-mile radius around j whose owner would face a higher mortgage cost if she were to move.

Table $B.1$ shows a strong association between $LockShare_{Xml}$ and the lock-in measures $LockRateGap_{Xml}$ and $LockPayGap_{Xml}$. We use three distance ranges Xml, which are 0.5, 1, and 2 miles, to test the robustness of the result. We find that the coefficient for $LockRateGap_{Xml}$ is positive and approximately equal to 13 across all three values of X. A 10 basis points rise in the average rate gap coincides with a 1.3% increase in the share of locked-in properties. For $LockPayGap_{Xml}$, a 1% increase in the payment gap is significantly associated with a roughly 1% increase in the locked-in share. Across all regressions, $LockRateGap_{Xml}$ or $LockPayGap_{Xml}$ alone explain more than 80% of the variation in $LockShare_{Xml}$.

To further establish the strong association between the gap measures and the share of locked-in properties, Figure A.6 plots the time series evolution of the mean, top and bottom quartile, and top and bottom decile of $LockShare_{0.5ml}$ in each quarter from 2014 to 2023. This series shows very similar patterns over time as those of $LockRateGap_{0.5ml}$ and $LockPayGap_{0.5ml}$ in Figure 2.

Therefore, the rate and payment gap measures are good proxies for mortgage lock-in. We use $LockRateGap$ and $LockPayGap$ as the main variables in our analysis because we find them more appropriate than the share of locked-in properties for several reasons. First, the definition of locked-in property in equation (B.1)) is partly arbitrary. Some theories predict a kink around zero if the existing rate serves as a reference point (Kahneman and Tversky, 1979, 1991). Thus, relying on a continuous measure accommodates alternative mechanisms that do not necessarily rely on a sharp cutoff. Second, variation in $LockShare_{Xml}$ is more likely to be endogenous to local market characteristics and trends since the composition of mortgages determines it. For instance, adjustable rate mortgages in times of increasing rates may become more attractive in neighborhoods with more constrained households. On the other hand, variation in $LockRateGap_{0.5ml}$ and $LockPayGap_{0.5ml}$ relies only on current changes in market-level rates and local variation in the precise timing of the last purchase or refinancing.

Table B.1: Associations between Mortgage Lock-In Measures and Share of Locked-In Properties

	(1) 2014-2023 $LockShare_{0.5ml}$	(2) 2014-2023 $LockShare_{1ml}$	(3) 2014-2023 $LockShare_{0.5ml}$	(4) 2014-2023 $LockShare_{1ml}$
$LockRateGap_{0.5ml}$	13.225***			
	(13.52)			
$LockRateGap_{1ml}$		13.169***		
		(13.45)		
$LockPayGap_{0.5ml}$			1.028***	
			(12.36)	
$LockPayGap_{1ml}$				1.021***
				(12.43)
R-Square adj	0.816	0.838	0.799	0.821
N	3677997	3694648	3677997	3694648

Notes: This Table reports regressions of $LockShare_{Xml}$ (equation B.1) on $LockRateGap_{Xml}$ and $LockPayGap_{Xml}$ (equations 1 and 2), over the period from January 2014 to April 2023. We set X equal to 0.5 and 1 mile. T-stats are reported in parentheses and are bases on standard errors clustered by zip code and year-quarter.