Mortgage Regulation in Segmented Housing Markets with Search Frictions*

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Abstract

This paper investigates how mortgage regulation affects housing market outcomes and household welfare in segmented housing markets with search frictions. Using unique transaction data from China, I estimate a structural model of home listing, selling, and purchasing for heterogeneous housing products to capture the housing market microstructure. Through counterfactual experiments, I quantify the impact of changes in mortgage credit conditions on house prices and market liquidity. The results suggest that the impact of mortgage credit tightening varies significantly across housing segments and markets, resulting in substantial cross-sectional and distributional effects, with particularly large losses for homebuyers of large properties in urban areas. Moreover, the effectiveness and welfare implications of mortgage policies depend on the source of market frictions and the duration of the policy intervention.

JEL-classification: G21, G28, R21, R30

Keywords: housing markets, mortgage regulation, market friction, structural estimation

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1 Introduction

Buying a home is one of the most important financial decisions households make. The process is often long and complex, as houses are highly heterogeneous and households tend to be selective in finding their dream home. Desirable properties often face intense competition from other buyers, information asymmetry is pervasive, and the processes of viewing and bargaining are slow, all of which contribute to extended search times. Between 1987 and 2008, U.S. home sellers needed an average of 7.3 weeks to sell their houses, while buyers took about 8.2 weeks to find a home, with considerable variation across time, regions, and market segments (Genesove and Han 2012). In the past decade, buyers and sellers have needed between 4 and 12 weeks to complete a transaction (FRED). This heterogeneity and the challenge of matching buyers to the right homes have important economic consequences: they contribute to the volatility and cyclicality of housing markets (Krainer 2001, Head, Lloyd-Ellis and Sun 2014) and increase valuation uncertainty (Giacoletti 2021, Sagi 2021), which further restricts borrowing capacity (Jiang and Zhang 2025) and limits the effectiveness of intermediation in certain market segments (Buchak, Matvos, Piskorski and Seru 2020).[1]

These features of the housing market, namely product heterogeneity and search frictions, are highly relevant from a policy perspective. On the one hand, many housing policies are designed to reduce market frictions by increasing transparency, reducing search costs, and improving households decision-making.[2] On the other hand, monetary and macroprudential policies, such as changes in interest rates or lending limits, have uneven effects across housing segments (Acharya, Bergant, Crosignani, Eisert and McCann 2022, Tzur-Ilan 2023, Kvaerner, Pavanini and Peng 2023). These policies can interact with search frictions, influencing policy transmission and resulting in disproportionately larger impacts in some market segments than in others.

The objective of this paper is to study the impact of mortgage regulations in housing markets characterized by search frictions and rich housing heterogeneity. It addresses three questions: First, how do mortgage credit conditions affect house prices and market liquidity in frictional housing markets? Second, what are the distributional effects of mortgage regulation across different housing market participants and segments? Third, how do market frictions shape the distributional impact of mortgage regulations? Answering these questions is essential for evaluating mortgage regulations in frictional housing markets.

To address these questions, this paper develops a structural model of home listing, selling, and purchasing that captures household decisions in segmented housing markets with search frictions. The

[1] A vast body of literature has examined search frictions in housing markets and the price-liquidity dynamices, see Han and Strange (2015) for an extensive survey.

[2] For example, the UK requires sellers to disclose key property information before a sale. countries like the Netherlands, Germany, and Sweden provide official housing statistics, historical transaction and land ownership records. In the US, though price disclosure policies vary across states, property information is shared through multiple listing services (MLS). In addition, the recent rise of modern property listing platforms, both government-regulated or private, has helped reduce search frictions by providing comprehensive property data to facilitate housing transactions.

model considers forward-looking households choosing homeownership to maximize their expected lifetime utility. Households are either owners or renters who can change their status only through the real estate market. Homeowners can list their property and become sellers, incurring a non-monetary cost at the time of listing, whereas renters can become buyers frictionlessly at any time. Buyers use mortgages to finance home purchases, in which mortgage interest rates and down payment requirements affect buyers' utility through determining the amount of upfront and subsequent recurring payments. Instead of imposing a strict search pattern across market segments, buyers are allowed to search flexibly in two steps. First, buyers evaluate all available housing types based on location, property attributes, and market prices, and select the type that offers the highest expected lifetime utility.[3] After determining the most desirable property type, buyers randomly meet sellers of that type, making bids based on property attributes and their private valuation of the match. In this way, the scope of search is endogenously determined by household preferences and the substitution patterns across housing attributes. Property sellers have the option to sell only if they receive bids from potential buyers within a given period. In such cases, a first-price sealed-bid auction is offered and the property will be allocated to the highest bidder. However, sellers have limited commitment and can reject current bids, waiting for bids from future buyers. This means that matched buyers and sellers may not complete a transaction, a common feature in housing markets but is not characterized in standard bargaining models.

The model builds on the dynamic discrete choice framework for housing demand in Bayer, McMillan, Murphy and Timmins (2016) and introduces three main extensions. First, it incorporates a dynamic equilibrium with homeowners and renters who can switch between owning, renting, buying, selling, or remaining inactive. This setup captures household mobility patterns similar to Anenberg and Bayer (2020) and allows joint analysis of tenure, transaction, and location choices. Second, by integrating the search, matching and transaction process into households' dynamic housing decisions, the model captures housing markets' microstructure, distinguishing market liquidity provided by buyers and sellers. This distinction helps explain the division of surplus between buyers and sellers (Jiang, Kotova and Zhang 2024) and sheds light on the distributional effect of mortgage regulation and liquidity-price dynamics. Third, the model incorporates price formation through auctions with limited commitment (Albrecht, Gautier and Vroman 2016), allowing sellers to accept or reject bids. This better reflects real housing market behavior and enables counterfactual analysis. Incorporating illiquid search and transaction processes into the dynamic discrete choice framework provides a microfoundation for both (i) market segmentation and (ii) search frictions. Household preferences for property attributes (i) determine segmentation, as greater substitutability implies less segmentation, and (ii) endogenize market tightness, as more desirable segments attract more buyers, leading to thicker markets and better matching efficiency.

[3]The utility of owning a property depends on the property's attributes, as widely confirmed by hedonic models. See e.g., the survey by Sirmans, Macpherson and Zietz (2005).

This modeling approach is made possible by rich home listing and transaction data from Lianjia, the largest real estate brokerage company in China. This data provides detailed listing and transaction information on all successful transactions on the platform. In particular, the unique information on the number of likes and visits by potential buyers is key to identify buyer-side liquidity (the probability of receiving bids), and in turn, seller-side liquidity (probability of accepting bids), enabling a distributional analysis across market participants. Moreover, China provides an ideal setting, as mortgage conditions are often regulated to intervene in housing markets. Sharp changes in mortgage interest rates and down payment requirements exist due to macroprudential policies.[4]

I first examine a mortgage credit tightening implemented in early 2017 by the People's Bank of China (PBOC), which guided commercial banks to reduce mortgage lending. This policy led to higher mortgage interest rates and increased down payment requirements in major Chinese cities, dampening housing demand and resulting in slower house price growth and lower transaction volumes. However, the effects vary considerably across market segments within local markets. Housing demand, as measured by the number of likes, declines for larger properties in urban areas but rises for smaller properties in suburban districts, indicating a demand shift toward lower-end segments. Correspondingly, transaction volumes and prices fall in more expensive segments, while they increase in more affordable ones. This empirical evidence is in line with Acharya, Bergant, Crosignani, Eisert and McCann (2022) and Tzur-Ilan (2023), highlighting the heterogeneous impact of mortgage regulation across different market segments.

To quantify how demand elasticity influences the transmission of mortgage credit tightening and the extent of market segmentation, I estimate a structural model. The estimated willingness-to-pay suggests the level of market segmentation: higher values for specific attributes indicate greater segmentation across corresponding segments. Households enjoy living in larger properties and derive the highest utility from living in a 12-year old property, and they have a strong preference for urban and school-concentrated districts. An average household in Beijing is willing to pay 714 CNY more per month for owning a 10 square meters larger property, and 350 CNY more for a property that is 5 years newer. In terms of location and amenities, the average household is willing to pay 3,673 CNY more per month to live in urban districts and 2,850 CNY more for districts with numerous schools. And households' willingness to pay for favorable attributes is increasing with their wealth. Estimating the structural model also suggests a large drop in market liquidity after the mortgage credit tightening, driven by the decrease in both the probability of receiving bids and the probability of selling. Moreover, the model estimates uncover an effect not evident in the reduced-form evidence: the impact on liquidity is more pronounced on the seller side than on the buyer side, reflecting sellers' expectations that the policy is temporary and that the market will recover.

To assess the impact of mortgage regulation on housing markets, I simulate a 1 percentage point

[4]To ensure that the estimates are identified through changes in mortgage credit conditions, the introduction of alternative regulations in Chinese local real estate markets is controlled for.

increase in mortgage interest rates. The interest rate increase leads to a 1.7% decline in the median market-level transaction volume and a 6.5% decline in the average transaction price overall. However, effects vary significantly across segments: Demand for larger properties drop significantly, leading to sharper declines in average transaction volume (-7.6%) and transaction prices (-6.0%), while demand shift to smaller properties, leading to even more transactions (6.1%) and only a slight price drop (-0.2%). Similarly, the increase in mortgage interest rates has a larger impact in urban than in suburban districts, though the difference is smaller. This finding aligns with the segmented search behavior documented by Piazzesi, Schneider and Stroebel (2020), which shows that homebuyers impose stronger restrictions on location than on property size during their searches, indicating greater segmentation across geographical locations. By estimating household preferences across multiple housing attributes, this paper provides a microfoundation for the extent of market segmentation, suggesting that limited demand shifting across locations is driven by households' higher willingness to pay for urban areas relative to attributes such as larger size.

Mortgage regulation also exhibits distributional effects across market participants. Comparing welfare changes for homeowners, buyers, and sellers, there are minimal welfare changes for homeowners and sellers. Mortgage credit policies primarily affect buyers, reducing their welfare by 123.0 thousand CNY (approximately 18 thousand USD) when mortgage interest rates increase by 1 percentage point. Welfare effects also vary significantly across housing segments. Buyers of larger and urban area properties face greater welfare losses due to higher financing costs. Homeowners and sellers of these segments are also adversely affected by falling prices and weaker liquidity, though with a much smaller magnitude. In contrast, owners and sellers of smaller or suburban area properties benefit from increased demand, leading to improved liquidity and higher prices.

To examine the role of expectations, I simulate the counterfactual increase in mortgage interest rates without the expectation channel. In this scenario, the regulation is perceived as temporary and does not affect households' expectations about future market conditions or the value of homeownership. Without this forward-looking channel, the impact of tighter mortgage credit on housing market outcomes and household welfare is weaker. Since households do not factorize the long-term effect, sellers are less likely to accept bids. This explains the model estimated decline in seller-side liquidity following mortgage tightening, suggesting that sellers tend to view such policies as short-term.

I further investigate the role of market friction in determining housing market outcomes and household welfare by simulating changes in mortgage credit conditions under three scenarios: (i) a decrease in transaction costs, representing a *general* reduction in transaction frictions; (ii) an increase in matching efficiency, corresponding to a reduction in search frictions for *buyers*; (iii) a decrease in the non-monetary cost of selling, equivalent to a reduction in the non-monetary benefits for *owners*. Overall, reducing market frictions lowers total welfare losses, but the transmission mechanisms differ by the type of friction. Compared to the baseline, reducing transaction costs benefits both

homeowners and buyers directly through reduced transaction expenses. Lowering matching frictions helps buyers more easily find properties that better match their private valuations, increasing market liquidity and house prices, thus improving welfare for buyers, sellers, and homeowners. In contrast, reducing non-monetary selling costs leads to an increase in housing supply, which lowers prices and results in welfare losses for sellers, while buyers benefit from improved affordability.

These findings highlight the importance of accounting for market frictions and market segmentation when evaluating the effects of mortgage regulation and the transmission of monetary policy. First, strict mortgage conditions have heterogeneous impacts across housing segments, reducing households' access to favorable housing attributes or geographical locations, consistent with Kvaerner, Pavanini and Peng (2023). In particular, larger properties experience greater declines in liquidity and prices than smaller ones due to increased financing costs, while also shifting demand toward smaller properties. Such spillover effects can further exacerbate demand pressures in lower-end segments, which are primarily targeted by low-income, first-time buyers (Landvoigt, Piazzesi and Schneider 2015). Second, mortgage regulation has distributional effects that are shaped by market frictions, depending on whether they are general or stem from buyers or sellers. Reducing market frictions helps mitigate the welfare losses experienced by buyers due to stricter lending conditions. Finally, households' expectations about policy duration matter. Long-term policy expectations are more effective, resulting in stronger responses in listing and selling behavior, and thus greater welfare losses for homeowners and sellers compared to short-term policies, suggesting the importance of forward guidance in household financing and housing decisions.

Related Literature. This paper contributes to three strands of the existing literature. First, it adds to the growing body of research that uses structural frameworks to study housing choices. Two main approaches have been applied in this area. One prominent approach builds on discrete choice models from industrial organization and urban economics. While earlier applications primarily focus on static residential location decisions,[5] more recent work incorporates dynamic considerations into housing market equilibria (Bayer, McMillan, Murphy and Timmins 2016, Ouazad and Rancière 2019, Epple, Quintero and Sieg 2020). This paper aligns most closely with this approach. Recent contributions include Kvaerner, Pavanini and Peng (2023), who apply a similar model to analyze the distributional effects of leverage regulation on household mobility and access to high-quality housing by explicitly modeling financial constraints, investor behavior, and rental markets. Another example is Almagro and Domínguez-Iino (2024), who develop a dynamic residential choice model to estimate household preferences for endogenous amenities in a sorting equilibrium, quantifying the distributional impact of tourism based on household heterogeneity.

The second approach builds on life-cycle models from the household finance and macro-finance literature (Cocco 2005, Gomes and Michaelides 2005, Attanasio, Bottazzi, Low, Nesheim and Wake-

[5] See, e.g., Barrow (2002), Bayer and Timmins (2005), and Bayer, Ferreira and McMillan (2007). For a comprehensive overview, see Holmes and Sieg (2015).

field 2012, Bajari, Chan, Krueger and Miller 2013), with extensions incorporating general equilibrium features (Kiyotaki, Michaelides and Nikolov 2011, Favilukis, Ludvigson and Van Nieuwerburgh 2017, Kaplan, Mitman and Violante 2020). A key distinction between the two approaches lies in how they capture housing heterogeneity: life-cycle general equilibrium models typically focus on a homogeneous housing product and analyze housing choices from an aggregate perspective, whereas discrete choice models allow for rich heterogeneity in housing attributes, geographic locations, and household preferences. Recent spatial equilibrium models have extended the life-cycle framework to incorporate more housing heterogeneity (Mabille 2023, Gupta, Hansman and Mabille 2024, Fonseca, Liu and Mabille 2024), but the level remains limited. This restricts their ability to fully capture the cross-sectional and distributional effects of mortgage regulation and housing policies.[6]

Recent studies have further shown that housing policies can have a considerable welfare impact on diverse households, such as through the allocation of rental subsidies (Favilukis, Mabille and Van Nieuwerburgh 2023) and regulations on home-sharing platforms (Calder-Wang 2021). However, the distributional welfare implications through mortgage lending in frictional housing markets remain unclear. Compared to existing structural models, this paper highlights the illiquidity of housing markets arising from market segmentation and various transaction frictions, and investigates how these frictions affect regulation outcomes. In this regard, this paper enriches the literature on industrial organization regarding decentralized asset markets with search frictions. See e.g., Gavazza (2011, 2016)

Second, this paper speaks to the literature on the microstructure of real estate markets. Since residential properties need time on the market to be sold, the speed at which a property can be sold under the optimal selling strategy reflects its liquidity.[7] To analyze liquidity as an equilibrium outcome of the interaction between buyers and sellers, search and matching models have been applied to housing markets, e.g., Wheaton (1990), Krainer (2001), Albrecht, Anderson, Smith and Vroman (2007), Novy-Marx (2009), Genesove and Han (2012), Head, Lloyd-Ellis and Sun (2014), and Ngai and Tenreyro (2014). Recent work also considers households that use mortgages to finance home purchases, allowing mortgage credit to play a role in search models, e.g., Hedlund (2016), Garriga and Hedlund (2020). Compared to existing research, this paper adopts a more micro-founded approach to capture housing market heterogeneity using a discrete choice framework, leading to two key extensions. First, the model emphasizes heterogeneity in housing demand, allowing buyers to search flexibly for the most desirable property type based not only on price, but also on characteristics such as size, age, and location, similar to the search pattern documented by Piazzesi, Schneider and Stroebel (2020). While Piazzesi, Schneider and Stroebel (2020) use detailed buyer search data

[6] See Kvaerner, Pavanini and Peng (2023) for a detailed discussion and comparison of different modeling frameworks.

[7] See Lippman and McCall (1986), Kluger and Miller (1990), Krainer (2001), Head and Lloyd-Ellis (2012) for measuring liquidity in real estate markets.

to show that broader searchers can crowd out narrower searchers in local markets and spread shocks across segments, highlighting the importance of characterizing market segmentation for housing policies, this paper endogenously determines the scope of buyers' search based on heterogeneous preferences for housing attributes. Second, the paper models price determination through an auction framework, where sellers may receive multiple bids and either accept the highest offer or reject all bids. While this mechanism is common in real-world housing markets, it is rarely modeled in the literature (Han and Strange 2014), with the exception of Albrecht, Gautier and Vroman (2016), who propose a theoretical framework combining directed search with auctions and limited commitment. As a result, the model disentangles liquidity from buyers and sellers – an element not captured in matching models based on bargaining.

Finally, this paper contributes new empirical evidence to the growing body of empirical research examining the impact of mortgage credit conditions on housing markets and real economic activities.[8] To demonstrate that expansive mortgage credit contributes to rising house prices, various changes in credit supply have been employed in extant research, such as the geographical heterogeneity in subprime mortgage securitization (Mian and Sufi 2009), conforming loan limits (Adelino, Schoar and Severino 2012), and bank deregulation (Favara and Imbs 2015). This paper examines the tightening of mortgage lending under China's macroprudential assessment framework, contributing new evidence to the growing literature on macroprudential policies targeting housing markets through mortgage regulation (DeFusco, Johnson and Mondragon 2020, Peydro, Rodriguez-Tous, Tripathy and Uluc 2023). In particular, Acharya, Bergant, Crosignani, Eisert and McCann (2022) show that the introduction of Loan-to-Value (LTV) and Loan-to-Income (LTI) limits in Ireland led to a reallocation of credit from low- to high-income households and from urban to rural areas. Similarly, Tzur-Ilan (2023) find that LTI caps in Israel make borrowers to select more affordable homes – smaller, cheaper, located farther from central business districts. This paper also finds evidence of household reallocation across market segments, but emphasizes the role of housing demand substitution in response to mortgage regulation instead of banks' portfolio choice. Moreover, unlike existing studies that rely on reduced-form methods to estimate local average treatment effects, this paper develops a structural model to estimate household preferences for housing attributes, quantifying of the distributional effects of mortgage regulation driven by shifts in demand across segmented and frictional housing markets.

The rest of the paper is organized as follows. Section 2 presents the institutional details and describes the data. In Section 3, I present the structural model. Section 4 describes the econometric framework, including price prediction and identification strategies. The estimation results are presented in Section 5. In Section 6, I present the counterfactuals, and in Section 7 concludes.

[8]Much extant work attributes booming housing demand and prices to low interest rates (Himmelberg, Mayer and Sinai 2005, Hubbard and Mayer 2009), easy access to credit (Khandani, Lo and Merton 2013, Favilukis et al. 2017), and mortgage credit expansion (Mian and Sufi 2009, Adelino, Schoar and Severino 2012, Favara and Imbs 2015, Landvoigt et al. 2015).

2 Institutional Background, Data, and Descriptive Evidence

2.1 China's Real Estate Markets in the Digital Age

Given large scale urbanization and steady economic growth, it is not surprising to see booming housing markets in China. Housing affordability, however, becomes a pressing issue. In the past decade, house prices of Chinese cities have grown at more than 10 percent annually, and for major cities the rate reached 17 percent, much higher than the average income growth rate of 11 percent for the same period (Chen and Wen 2017, Fang, Gu, Xiong and Zhou 2016). In 2018, China was among the least affordable countries for home purchases, and the situation in large Chinese cities was even worse.

Moreover, Chinese housing markets have other stylized facts. First, despite a large construction boom in many cities, there is still a demand-supply imbalance, with substantial heterogeneity among cities. While many cities experienced hot markets, where housing demand outpaced supply, ghost cities appeared, where housing supply outpaced demand.[9] Second, high house prices coincide with a notable vacancy rate in China, a signal of speculative investment behavior.[10] However, this phenomenon is primarily observed in newly constructed houses - a market distinct from the secondary one, as new constructions typically take a few months to years for delivery and are often located outside well-established areas. Furthermore, the government may set price cap for new houses, making the purchase in the primary market profitable, albeit with increased competition, stimulating investment incentives in this segment. Conversely, in secondary markets, the dominant factor driving housing demand is housing consumption needs. The data also confirm a decline in the fraction of roughcast housing units (i.e., never been occupied) from 15% for houses constructed within 5 years to 6% for houses constructed less than 10 years, and to 2% for houses older than 10 years.

Third, the government controls the supply of land and consequently housing construction opportunities. The limited prospects of (re)constructing their own houses makes households reliant on secondary housing markets to change their residence in large cities where most of the urban area has been developed. In 2016, the transaction volume in secondary housing markets is larger than that of newly-built houses in numerous major cities, especially in super cities such as Beijing (by 3.5 times), Shanghai (2 times), and Shenzhen (2.3 times), and this trend has been on the rise over the years (Zheng and Dong 2016). Finally, the overall rate of homeownership is high in China, partly due to a series of housing reforms since the late 1980s that privatized state-owned housing to existing residents and increased the homeownership rate to over 80% in urban areas.[11] Though major cities witnessing a substantial influx of immigrants have seen a decline in homeownership rates,[12]

[9] See, e.g., Glaeser, Huang, Ma and Shleifer (2017), Wu, Gyourko and Deng (2016).
[10] See, e.g., Wu, Gyourko and Deng (2016).
[11] See, e.g.,Wang (2011)
[12] In 2018, the estimated homeownership rate for cities like Beijing and Shanghai was between 70% and 80%.

the ownership market in China continues to outweigh the rental sector significantly.

To study real estate markets, I collect data from the largest Chinese real estate brokerage company Lianjia,[13] which provides both online and offline real estate services.[14] The offline offices provide traditional purchase advice, arrange visits for potential buyers, and ensure the reliability of property information. The online service provides a market place for residential property buyers and sellers. Households that intend to sell their residence can list their properties on Lianjia's website or contact local agents for listing without any cost. Detailed standardized information of those properties is available online for households interested in buying property. Potential buyers can browse the description of all listed properties, historical transactions, and follow preferred properties. For very desirable properties, potential buyers can contact Lianjia's local agent for more information or to arrange a visit. There is no monetary cost for services unless a transaction takes place. In a transaction, the commission fee is about 3 percent of the price, shared by buyers and sellers. Potential buyers submit bids on a first-come, first-served basis, with the seller deciding whether to accept each bid as it arrives.

Besides information on listed properties, all historical transaction records are available. For every transaction, there is detailed information about the property and the transaction. In addition to these details for historical transactions, listed properties that have not yet been sold on the platform include additional information, such as the number of visits by potential buyers, which is especially useful for identifying buyers' arrival rates. This information is typically unobservable and unavailable in other data sources, which largely limits the incorporation of the auction feature in most housing structural models. However, those unsold properties lack the key information of the final transaction price. The estimation will focus on sold properties, while the properties on the market are used to construct the number of available listings and to approximate the number of visits for all properties in each market.[15]

Table 1 Panel A summarizes real estate properties listed on Lianjia from 15 major cities in China from December 2015 to January 2018. The sample comprises 368,178 observations of historical transactions and 81,433 unsold properties on the market as of the end of January 2018. For historical transactions, the average total listing price is 2.48 million CNY (approx., 0.37 million USD) and the average total transaction price is 2.40 million CNY (approx., 0.36 million USD). On average, a property is sold after 2.6 months. Properties that are still on the market by the end of the sample pe-

[13] Publicly available data from Lianjia.com were collected via web scraping. Fan, Fan and Zhou (2025) use proprietary Lianjia data to study buyers' dynamic search behavior in a non-stationary environment.

[14] By the end of 2016, Lianjia operated over 8,000 offices with more than 150,000 agents across 28 Chinese cities, holding the largest market share in first-tier cities. In 2016, Lianjia dominated markets in Beijing, Shanghai, Guangzhou, Shenzhen, and several other major cities. In 2017, its market share in Beijing was 46.39%, with the second-largest player at 12.28%, and in Shanghai, it held 18.38%, compared to 6.08% for the second-largest player.

[15] I exploit the relationship between the number of likes and the number of visits for listed properties to estimate on average how many likes will lead to a visit in each city and use these estimates to predict the number of visits for all properties in the sample.

riod tend to have a higher listing price and (naturally) longer time on the market compared with sold properties. The online platform records how many people have liked a property, a direct measure of interest in each property.[16] On average, a sold property has 48.3 likes, while an unsold property has 36.7 likes and 2.2 visits by potential buyers.

While the dataset provides extensive information on property attributes, the most significant determinants of house prices are the property's size and its age since construction. On average, historical transactions involve properties with a construction size of 86.4 square meters and an age of 11.5 years. In contrast, properties still on the market tend to be larger and older. For later analysis, I categorize housing products based on size deciles, age quintiles, and district locations. As indicated in Online Appendix Table A.1, these categorizations - five age groups and 10 size groups - account for 63% of the variation in log transaction prices. This explanatory power increases to 87% when district fixed effects are included, indicating that the classification captures the vast majority of price variation. Adding housing project fixed effects provides only a modest further improvement, suggesting that the remaining variation reflects households' idiosyncratic preferences.

Further information on real estate projects includes the project scale and the address of the project. There are 1,606.5 apartments in total for an average size project. The address information can be used to identify the subdistrict zone, the smallest administrative level in China. With information on listing and transaction dates, the number of competing properties in the same zone at the time of sale can be determined. On average, 102.9 alternative properties are available online in the same zone when a transaction occurs. While the data from Lianjia provide extensive information on property features and transaction details, they lack demographic and financial information on buyers and sellers. To address this gap and account for household heterogeneity, I supplement these data with city-level household income and savings statistics from the National Bureau of Statistics of China.

2.2 The Booming Housing Market and Mortgage Regulation

House prices grew fast during the sample period, in particular during the year 2016.[17] Despite overall high house price growth, each market varies. In the sample, monthly growth rates range from 0.5% to 2.5%. Properties in Shanghai take an average of 8.7 months to sell, while in most other cities, properties remain on the market for 2 to 3 months.[18] After experiencing surging house prices in many cities during the year 2016, the Chinese central government decided to regulate

[16] By clicking the "like" button, a property is saved for comparison and review in the future. Any updates of the property will be delivered to its followers in real time. Since the platform does not rank properties by popularity, there is little benefit from manipulating the number of likes.

[17] According to the National Bureau of Statistics of China, the average price index of newly-build homes in 70 large or median size cities rose by 12.4 percent year-on-year in December of 2016 and 5.3 percent in December of 2017. However, these statistics are widely criticized for underestimating house price growth (Wu, Deng and Liu 2014).

[18] For more details on house price growth rates and the time on the market, see Online Appendix A.1.

Table 1: Summary Statistics

	Transactions			On The Market		
Statistic	N	Mean	St. Dev.	N	Mean	St. Dev.
Panel A: Properties						
Total listing Price	368,178	248.1	231.8	81,433	420.0	335.6
Total Transaction Price	368,178	240.5	222.8			
Time On The Market	368,178	2.6	3.1	81,433	8.9	3.1
Number of Likes	368,178	48.3	70.0	81,433	36.7	53.0
Number of Visits				81,433	2.2	4.8
Size	368,178	86.4	35.2	81,433	100.4	45.8
Age	368,178	11.5	6.8	81,433	13.2	6.9
Total Number of Apartments	368,178	1,606.5	1,039.7	81,433	1,431.0	961.7
Number of Alternatives	368,178	102.9	135.8	81,433	89.8	120.8
Panel B: Mortgage Markets						
Number of Banks	6,877	20.0	6.3			
Number of Branches	6,877	86.1	151.1			
Average Interest Rate	6,877	4.6	0.4			
Down Payment Requirement	6,877	28.3	4.5			

Note: Panel A presents summary statistics for historical transactions and properties on the market. The sample period average exchange rate was 6.68 USD/CNY. Total Listing (Transaction) Price is the total listing (transaction) price of a property in 10,000 CNY. Time On The Market represents the number of days between listing and transaction divided by 30. Number of Likes is the total number of people who followed the property. Number of Visits is the number of visits by potential buyers. Size is the living space in square meters. Age is the number of years since construction. Total Number of Apartments is the number of apartments in one project. Number of Alternatives is a variable representing the number of other listed properties from the same zone at the time of transaction. Panel B shows the summary statistics for mortgage markets at monthly city-bank level. Number of Banks is the number of active banks in a city month combination. Number of Branches is the total number of branches of all active banks in a city and a month. Average Interest Rate is the average annual mortgage interest rate for first mortgage in percentage points. Down Payment Requirement is the average down payment requirements for first mortgage as a fraction of house value in percentage points.

housing markets using financial tools.[19] At the end of that year, the central government first revealed the intention to regulate housing markets. In March 2017, the central bank, People's Bank of China (PBOC), along with the China Banking Regulatory Commission released guidelines for controlling mortgage credit through window guidance; the State Council distributed government work directives to provincial governments to emphasize controlling mortgage credit based on local real estate market conditions.[20] While the policy on mortgage supply may be influenced to some extent by the state of hot housing markets, the policy itself was a shock to the market, particularly in terms of its scope and magnitude. In the following months, almost all cities experienced significant increases in mortgage interest rates and down payment requirements.

Table 1 Panel B summarizes monthly city-bank level mortgage data obtained from Rong360, a fintech company in China providing financial data services. The sample contains the actual monthly city-bank level mortgage interest rates, and down payment requirements for the 67 largest banks in China from December 2015 to January 2018. I use banks' branch location data from S&P Global Market Intelligence to proxy their market shares and calculate the average mortgage interest rate and down payment requirement of each city and month weighted by each bank's market share. On average, there are 20 lending banks in each city and each bank has 86 operating branches in a city. The average annual mortgage interest rate for purchasing the first residential property in the sample is 4.6 percentage points; the average down payment requirement for the first mortgage is 28.3%, i.e., 71.7% the loan-to-value ratio. During the sample period, commercial banks in China set their mortgage interest rates based on the benchmark interest rate established by the PBOC, with a spread that is fixed for the lifespan of the mortgage loan, typically 20 or 30 years.[21] Mortgage refinancing is uncommon in China, as most commercial banks do not offer refinancing services. Online Appendix A.1 provides more description on the mortgage credit regulation.

The mortgage credit tightening effectively dampened housing demand, creating heterogeneous effects across cities and market segments. As illustrated in Figure A.2, house prices in Beijing began to decline after March 2017, as well as housing demand and transactions. This pattern was not unique to Beijing: across the fifteen major cities, the average monthly house price growth rate at the residential zone level fell from 2% before March 2017 to 1.1% afterward. Moreover, mortgage regulation had differential impacts across housing market segments within each local market. Compared with smaller properties in suburban districts, larger properties located in urban districts experience

[19] China's banking system has transformed from wholly state-owned to market-oriented in recent decades, though large banks remain fully or partially state-owned. The government's strong influence on banks facilitates the implementation of central bank credit policy through window guidance, which involves direct instructions to commercial banks on lending activities. Consequently, real estate policy is often enacted through mortgage credit policies, such as adjusting interest rates or down payment requirements.

[20] For a detailed discussion of the policy implementation, institutional background, and commercial banks' responses, see (Habib, Peng, Wang and Wang 2023).

[21] The long-term lending rate of the PBOC has been anchored at 4.9% since October 2015. Banks adjust their actual interest rates by setting a spread relative to the PBOC benchmark rate. The actual interest rate changes in line with PBOC rate changes, which did not occur during the sample period.

a more pronounced decline in housing demand. This is reflected in a sharper drop in the number of likes from potential buyers, as well as a more consistent decrease in transaction volumes and prices, as illustrated in the top panel of Figure 1. In contrast, housing demand increases for small properties in suburban districts, suggesting a demand shift from more expensive to more affordable properties. Overall, we observe a consistent pattern when examining size and location separately. As shown in the bottom panel, housing demand tends to decline in both segments where financing becomes more costly due to the mortgage regulation.

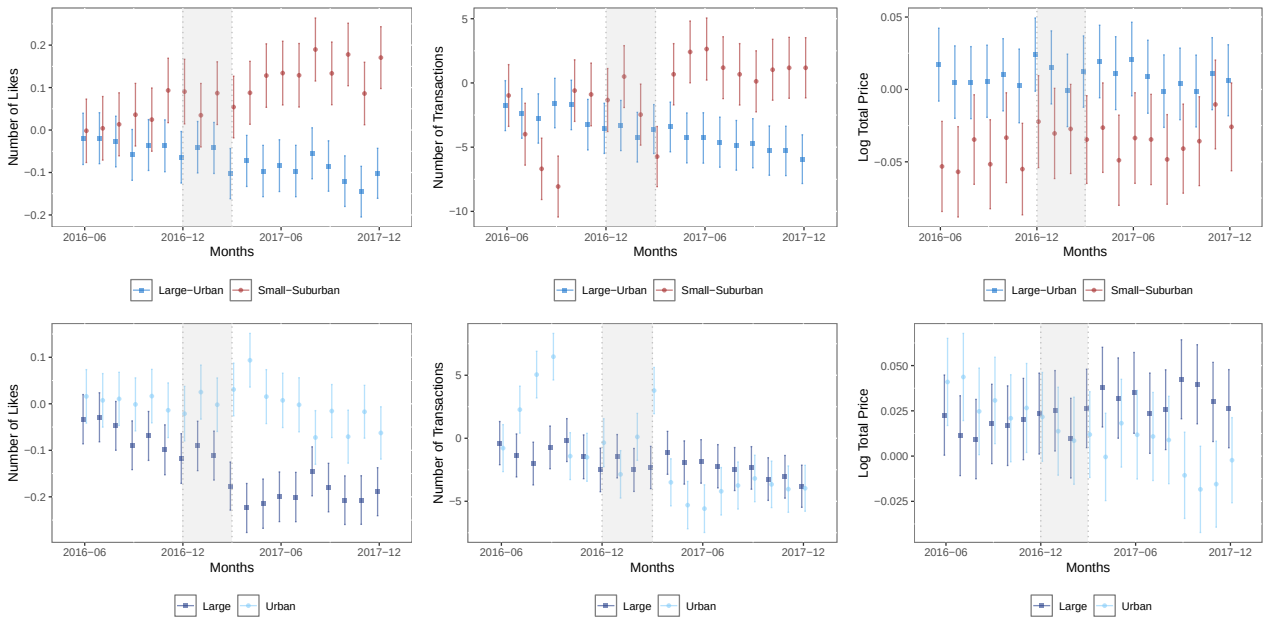


Figure 1: Housing Market Dynamics across Market Segments

Note: This figure illustrates the dynamics of the average number of likes, the number of transactions, and the logarithm of total transaction prices across market segments within local markets. Each subfigure plots the coefficients from a regression of the dependent variable on the interaction between market segment and time, including city-time fixed effects, with bars indicating the 90% confidence intervals. The subfigures in the top panel compare large properties located in urban districts (Large-Urban) with small properties in suburban districts (Small-Suburban), while the bottom panels separately show large properties and urban properties. Large properties are defined as those above the median size (greater than 83 square meters).

Although this paper primarily examines regulations on mortgage lending, additional measures have been implemented across local Chinese real estate markets to address the challenges of overheated housing sectors. One such regulation is the housing purchase restrictions enacted between 2010 and 2011, designed to deter speculative home buying by limiting eligibility for home purchases to local residents and restricting households' ability to acquire second or third residential properties (Fang, Gu, Xiong and Zhou 2016). Another, more recent, measure is the housing selling restrictions, introduced in some cities in 2017, mandating a minimum ownership duration before a property can be sold. Given that the limited sale policy was introduced within our sample period, it is crucial to account for its effects in the analysis to identify the impact of mortgage credit conditions on housing market outcomes. The approach to address this concern is discussed in the econometric model,

while more information regarding the implementation of selling restrictions is available in Online Appendix A.1.4.

3 The Model

The model considers infinitely lived households in a city where housing markets are dominated by secondary real estate market $m \in \mathcal{M}$.[22] Households make decisions on homeownership to maximize their lifetime expected utility, choosing between renting (non-owners) and owning (owners) a specific type of property. If households decide to change their homeownership status, they search in the real estate market to complete the transaction. For the sake of simplicity, the remaining part of this section focuses on a given market, and thus the subscript m is omitted.

Property type $j \in \mathcal{J} = \{0, 1, 2, \cdots, J\}$ is classified by property characteristics X_j, such as property age, size, and location. Specially, $j = 0$ indicates the outside option, being non-owners living in rented houses.[23] Time is discretized into months.[24] In each time period $t > 0$, household $i \in \{1, \cdots, N\}$ makes decisions $d_{i,t} = \{h_{i,t}, l_{i,t}\} \in \mathcal{D}_{i,t} = \mathcal{H}_{i,t} \times \mathcal{L}$, where $h_{i,t} = j \in \mathcal{H}_{i,t} \subseteq \mathcal{J}$ denotes the decision on which housing product to consume and $l_{i,t} = l \in \mathcal{L} = \{1, 0\}$ denote the participation in the real estate market or not. The set of available housing choices $\mathcal{H}_{i,t}$ depends on the household's decision in the previous period, as well as their participation in the real estate market. For households that are not active in the real estate market $l_{i,t} = 0$, they can only keep their housing choice as in the previous period, that is, $\mathcal{H}_{i,t} = \{h_{i,t-1}\}$.

To change housing choices, households need to participate in the real estate market. There is sizable non-monetary cost for selling, such as the psychological value owners attached to their home, efforts of cleaning, preparation. In contrast, buyers can easily view properties online with little costs. Therefore, a non-monetary moving cost for homeowners $k_{i,t} \sim N(k, \sigma_k)$ incurs at the time of listing.[25] After that homeowners (i.e., $h_{i,t-1} \neq 0$) become sellers and can choose to sell the property if they receive bids in that period. Non-owners (i.e., $h_{i,t-1} = 0$) become buyers without additional costs and can purchase any type of property in the market. Upon completing a transaction, buyers and sellers automatically exit the market as homeowner and non-owner.

[22] As discussed in Section 2.1, this assumption is based on the observation that secondary housing markets in large Chinese metropolises are much larger and geographically and temporally segmented from primary markets. New constructions are mainly located outside urban areas and take several years to complete, reinforcing this segmentation.

[23] Since the model focuses on homeownership decisions, the outside option represents households choosing to rent instead of owning. This normalization means that households' utility from owning a property reflects the added value of owning compared to renting.

[24] While transactions can occur at any time in reality, our observations are limited to a daily basis. Other variables, like mortgage credit conditions, are only available on a monthly level. Moreover, housing market decisions usually need a few months. This makes the use of a one-month period a reasonable choice for analysis in this context.

[25] Technically, assuming a non-monetary cost for home-listing is similar to assuming homeowners experience a moving shock that makes them leave their current houses with a probability as in Krainer (2001), Ngai and Tenreyro (2014).

Let $S_{i,t} = 1$ to indicate that seller i receives bids from potential buyers after listing and $S_{i,t} = 0$ otherwise. The decision set $\mathcal{D}_{i,t}$ for household i at time t includes the following cases:

$$\mathcal{D}_{i,t} = \begin{cases} d_{i,t-1} \bigcup \{j, 1\} & \text{if } d_{i,t-1} = \{j, 0\} \\ d_{i,t-1} \bigcup \mathcal{J}^+ \times \{0\} & \text{if } d_{i,t-1} = \{0, 1\} \\ d_{i,t-1} \bigcup \{0, 0\} & \text{if } d_{i,t-1} = \{j \neq 0, 1\} \text{ and } S_{i,t} = 1 \\ d_{i,t-1} & \text{if } d_{i,t-1} = \{j \neq 0, 1\} \text{ and } S_{i,t} = 0. \end{cases}$$

The first case corresponds to households outside of real estate markets, who can either keep their housing decision as before or enter into the market. The second case corresponds to buyers who can choose any type of property in the market. The third case corresponds to sellers who receive bids $S_{i,t} = 1$. In this case, she can keep the property as before ($d_{i,t} = d_{i,t-1}$) or sell it and exit the market ($d_{i,t} = \{0, 0\}$). The last case corresponds to sellers who receive no bids. Therefore, she can only choose to keep owning the property. Notably, the model accommodate home switching by allowing sellers, after selling their property and becoming a non-owner, subsequently re-enter the market as a buyer and purchase a different property. However, the joint buyer-seller problem, such as buy-first or sell-first decisions, are not considered in this model.[26]

Suppose that the utility of type j property ownership at time t is determined by the state variables $\Omega_{j,l,t}$ and the idiosyncratic shock $\varepsilon_{i,j,l,t}$. The state variables $\Omega_{j,l,t}$ include property characteristics X_j, mortgage credit conditions Y_t, house prices $P_{j,t}$, and unobserved quality $\xi_{j,t}$, for instance, the congestion in the neighbourhood.[27] There are two components in mortgage credit conditions, mortgage interest rates Y_t^I and down payment requirements Y_t^D. The idiosyncratic shock $\varepsilon_{i,j,l,t}$ is assumed to be independently and identically type I extreme value distributed. Assume that the utility of owning a type j property with market participation status l, ignoring any cost associated with listing and the transaction, is linear and additively separable as follows

$$u(\Omega_{j,l,t}, \varepsilon_{i,j,l,t}) \quad = \quad \delta(\Omega_{j,l,t}) + \varepsilon_{i,j,l,t}, \tag{1}$$

where $\delta(\Omega_{j,l,t})$ is the mean utility of type j property ownership, with the mean utility of no property ownership normalized to zero, i.e., $\delta(\Omega_{0,t}) = 0$. In other words, $\delta(\Omega_{j,l,t})$ captures the additional utility one gains from homeownership as opposed to renting, such as savings on rental payments, advantages in school admissions, and other convenience benefits. To keep simplicity and generality, the specific functional form of the average utility function is not specified yet, which will be

[26] For papers on this problem, see e.g., Anenberg and Bayer (2020), Moen, Nenov and Sniekers (2021), Grindaker, Karapetyan, Moen and Nenov (2021).

[27] Note that these state variables are property-time specific, and house prices $P_{j,t}$ represent the average transaction price of property type j at time t. These prices are important benchmarks for households to evaluation the value of homeownership.

addressed in the econometric model presented in Section 4.3.

Changing the ownership status is associated with costs. A one-time non-monetary cost $k_{i,t}$ is incurred by homeowners when listing their property. The function $\chi(\Omega_{j,l,t}, h_{i,t-1})$ reflects how payments between buyers and sellers, along with the financial transaction costs, affect household utility. Its functional form depends on the property's price and whether the household is a buyer or seller. The adjusted utility function is

$$u^A(\Omega_{j,l,t}, \varepsilon_{i,j,l,t}, d_{i,t-1}) = u(\Omega_{j,l,t}, \varepsilon_{i,j,l,t}) + \mathbb{1}_{\{List_{i,t}=1\}} k_{i,t} + \mathbb{1}_{\{Trans_{i,t}=1\}} \chi(\Omega_{j,l,t}, h_{i,t-1}). \tag{2}$$

Based on the current and historical realizations of state variables, households form expectations of future states and choose $\{d_{i,t}\}_{t>0}$ to maximize their lifetime expected utility. Under the optimal decision rule, the lifetime expected utility of households can be represented by the value function V such that

$$V(\Omega_t, \varepsilon_{i,t}, d_{i,t-1}) = \max_{\{j,l\} \in \mathcal{D}_{i,\tau}} \left\{ \mathbb{E} \left[\sum_{\tau=t}^{\infty} \beta^{\tau-t} u^A(\Omega_{j,l,\tau}, \varepsilon_{i,j,l,\tau}, d_{i,\tau-1}) \;\middle|\; \Omega_t, \varepsilon_{i,t}, S_{i,t}, d_{i,t-1} \right] \right\}, \tag{3}$$

where $\beta \in (0,1)$ is households' discount factor, Ω_t and $\varepsilon_{i,t}$ are the vector containing all choices. When $h_{i,t-1} = 0$, the value function is for non-owners if $l_{i,t-1} = 0$ and buyers if $l_{i,t-1} = 1$, while when $h_{i,t-1} = j \neq 0$, the value function is for owners if $l_{i,t-1} = 0$ and sellers if $l_{i,t-1} = 1$ of type j property. Assuming that the transition probabilities are Markovian, lifetime expected utility of households can be divided into the flow utility at time t and the expected sum of flow utility from time $t+1$ onwards, which yields the following recursive form

$$V(\Omega_t, \varepsilon_{i,t}, d_{i,t-1}) = \max_{\{j,l\} \in \mathcal{D}_{i,t}} \left\{ u^A(\Omega_{j,l,t}, \varepsilon_{i,j,l,t}, d_{i,t-1}) + \beta \mathbb{E} \left[V(\Omega_{t+1}, \varepsilon_{i,t+1}, d_{i,t} = \{j,l\}) \;\middle|\; \Omega_t, S_{i,t}, \varepsilon_{i,t} \right] \right\}. \tag{4}$$

I define the choice-specific value function as the expectation of $V(\Omega_t, \varepsilon_{i,t}, d_{i,t-1})$ over $\varepsilon_{i,t}$ conditional on making decision $d_{i,t} = \{j,l\}$ and the previous period decision $d_{i,t-1} = \{j^-, l^-\}$. Under the regular assumption of Conditional Independence, the choice-specific value function satisfies

$$\begin{aligned} \overline{V}(\Omega_{j,l,t}, j^-, l^-) \;=\; & \delta(\Omega_{j,l,t}) + \mathbb{1}_{\{l^- \neq l = 1 \wedge j^- \neq 0\}} k + \mathbb{1}_{\{j^- \neq j\}} \chi(\Omega_{j,l,t}, j^-) \\ & + \beta \mathbb{E} \left[\mathbb{E}_\varepsilon \left[V(\Omega_{t+1}, \varepsilon_{i,t+1}, d_{i,t} = \{j,l\}) \right] \;\middle|\; \Omega_{j,l,t}, S_{i,t} \right], \end{aligned} \tag{5}$$

where

$$\mathbb{E}_\varepsilon \left[V(\Omega_{t+1}, \varepsilon_{i,t+1}, d_{i,t} = \{j,l\}) \right] \;=\; \ln \left(\sum_{\{j^+, l^+\} \in \mathcal{D}_{i,t+1}} \exp\left(\overline{V}(\Omega_{j^+, l^+, t+1}, j, l) \right) \right). \tag{6}$$

Equation (6) holds because of the finite discrete choice set and the property of i.i.d. Type I extreme value distributed idiosyncratic shocks $\varepsilon_{i,t}$. It means that the expected value of households depends on the value of all options that households have in that time period. The more and the better are the options, the better off households are. To simplify the notation, denote $v_{j,l,t}^{j^-,l^-} := \overline{V}(\Omega_{j,l,t}, j^-, l^-)$ the expected value of household i which makes decision $\{j, l\}$ at time t with previous period decision $\{j^-, l^-\}$. For example, for owners of a type $j \neq 0$ property, the expected value of staying and listing in time period t is $v_{j,0,t}^{j,0}$ and $v_{j,1,t}^{j,0}$, respectively; for sellers, the expected value of holding and selling is $v_{j,1,t}^{j,1}$ and $v_{0,0,t}^{j,1}$, respectively; for non-owners the expected value of staying and searching is $v_{0,0,t}^{0,0}$ and $v_{0,1,t}^{0,0}$, respectively. The expected values of buyers who keep renting and who purchase a type $j \neq 0$ property are $v_{0,1,t}^{0,1}$ and $v_{j,0,t}^{0,1}$, respectively. For more details about the derivation and notation, see Online Appendix A.2 and Table A.3.

3.1 Homeowners' Listing Decisions

Consider household i who lives in her property of type $j \neq 0$ at time t and does not currently list her property in the market. She can choose to stay in her current house being inactive in the real estate market, or she can enter into the market by listing her property. In the latter case, assume that she sets the listing price at or above her reservation value, which is equal to that of others with the same property type. The expected value of the two actions can be expressed as follows

$$v_{j,0,t}^{j,0} = \delta(\Omega_{j,0,t}) + \beta \mathbb{E}\left[\ln(e^{v_{j,0,t+1}^{j,0}} + e^{v_{j,1,t+1}^{j,0}}) \,\middle|\, \Omega_{j,0,t}, d_{i,t} = \{j, 0\}\right]; \tag{7}$$

$$v_{j,1,t}^{j,0} = -k + v_{j,1,t}^{j,1}. \tag{8}$$

Equation (7) represents the expected value for owners of type j who opt to remain inactive in the real estate market. This value is a combination of the current utility derived from owning their property and the anticipated value in the subsequent period. Looking ahead, these owners face two possible scenarios: either continue being inactive, which has an expected value of $v_{j,0,t+1}^{j,0}$ or decide to list their property, leading to an expected value of $v_{j,1,t+1}^{j,0}$. Equation (8) indicates that inactive homeowners who choose to list their property incurs an average non-monetary cost denoted by k at the time of listing and subsequently transition into sellers and assume the same expected value as sellers who initially chose not to sell. This non-monetary cost reflects homeowners' attachment to their homes, along with the psychological cost of moving and selling. Sellers' decisions and expected value functions are discussed in greater details in the following section.

The probability that homeowners list their property of type j at time t has the following logit form due to the i.i.d. Type I extreme value distributed ε_{it},

$$\omega_{j,t} = \frac{e^{v_{j,1,t}^{j,0}}}{e^{v_{j,1,t}^{j,0}} + e^{v_{j,0,t}^{j,0}}}. \tag{9}$$

This expression suggests that the higher the expected value of listing compared to the alternative option of staying inactive, the more likely it is that a homeowner will choose to list her property. Detailed discussions about the distributional assumption and the derivation of the results can be found in the Online Appendix A.2.

3.2 Sellers' Ownership Decisions

After listing the household becomes a seller, receiving bids from buyers. In each period, there are at most two options for the seller, holding or selling. Denote the expected value of holding and selling a property of type j by $v^{j,1}_{j,1,t}$ and $v^{j,1}_{0,0,t}$ respectively as defined above; these expressions can be derived directly from equation (5).

$$v^{j,1}_{j,1,t} = \delta(\Omega_{j,1,t}) + \beta \mathbb{E}\left[q_{j,t+1} \ln(e^{v^{j,1}_{0,0,t+1}} + e^{v^{j,1}_{j,1,t+1}}) + (1 - q_{j,t+1}) v^{j,1}_{j,1,t+1} \;\middle|\; \Omega_{j,1,t}, d_{i,t} = \{j, 1\} \right]; \tag{10}$$

$$v^{j,1}_{0,0,t} = \alpha^w \left((1 - O_{j,t}) P_{j,t} - C_{j,t} \right) + v^{0,0}_{0,0,t}. \tag{11}$$

The expected value of holding the property, as shown in equation (10), equals the flow utility of owning this type of property plus the present value of the expected value in the next period – with probability $q_{j,t+1}$ the next period will be in the decision state and with probability $1 - q_{j,t+1}$ in the waiting state. If the next period is in the decision state, sellers can choose between selling and holding, and hence there are two components in the logarithm: the exponential value of selling and holding respectively. If the next period is in the waiting state, the value equals $v^{j,1}_{j,1,t+1}$. The expected value of selling the property, as shown in equation (11), equals the value generated from the transaction plus the continuing value. In the transaction, the seller on average receives a fraction $1 - O_{j,t}$ of the transaction price $P_{j,t}$ where $O_{j,t}$ denotes the remaining share of outstanding mortgage debt that must be paid, and bears transaction costs $C_{j,t}$, i.e., $\chi(\Omega_{0,0,t}, j) = \alpha^w((1 - O_{j,t})P_{j,t} - C_{j,t})$, where α^w measures the marginal utility of liquid wealth, which depends on households' liquidity constraints and the implementation of alternative real estate policies in each market.[28] The parameterization of α^w will be elaborated on in the econometric model. In other words, this term captures the utility generated from replacing illiquid housing wealth with liquid financial wealth, driven by the opportunity cost and the liquidity premium of movable assets. After selling, the household becomes non-owners with the continuing value of non-owners who choose no property in that period $v^{0,0}_{0,0,t}$.

In the decision state, a seller sells the property if the value of selling exceeds the value of owning. As can be seen from equation (6), the expected value of selling and holding together determines sellers' utility. The higher the expected value of selling compared to holding, the more likely we are

[28] Ideally, α^w would be individual-specific, capturing household heterogeneity, such as income and wealth, which affect budget constraints and price elasticities. However, due to limitations in household data, I allow α^w to depend on household statistics at the city-time level.

to observe selling. For a seller of type j property at time t, the probability of selling given that she received bids equals

$$p_{j,t} = \frac{e^{v^{j,1}_{0,0,t}}}{e^{v^{j,1}_{0,0,t}} + e^{v^{j,1}_{j,1,t}}}. \tag{12}$$

3.3 Buyers' Ownership Decisions

The decisions of buyers are modeled statically following Bayer, McMillan, Murphy and Timmins (2016) for two main reasons. First, non-owners face minimal entry and exit costs, allowing them to access the market with ease. Second, the data lack specific information on buyers' entry and exit activities, precluding dynamic modeling. Therefore, I use a static model to capture buyers' decisions regarding property ownership. Due to the frictionless assumption of entry and exit for buyers, the expected value for non-owners remains the same, whether active or inactive in the real estate market: $v^{0,0}_{0,0,t} = v^{0,0}_{0,1,t} = v^{0,1}_{0,1,t}$.

Conditional on purchasing, buyers choose the property type that yields the highest value from all available options based on observable characteristics and prices.[29] The value of buyers who purchase a type $j \neq 0$ property is denoted by $v^{0,1}_{j,0,t}$, and

$$v^{0,1}_{j,0,t} + \varepsilon_{i,j,0,t} > \max_{k \in \mathcal{H}_{i,t}} v^{0,1}_{k,0,t} + \varepsilon_{i,k,0,t}, \ \forall k \neq j,$$

where

$$v^{0,1}_{j,0,t} = v^{j,0}_{j,0,t} - \alpha^w (D_{j,t} + C_{j,t}) - \alpha^y I_{j,t}. \tag{13}$$

Notice that the expected value of buyers who purchase a property $v^{0,1}_{j,0,t}$ in equation (13) is different from the value of sellers who sell the property $v^{j,1}_{0,0,t}$ defined in equation (11). To obtain the expected value of owning property $v^{j,0}_{j,0,t}$ as owners defined in equation (7), buyers use mortgage credit, which requires a down payment $D_{j,t} = P_{j,t} Y^D_t$ paid together with the transaction cost $C_{j,t}$ at the time of transaction, as well as mortgages repaid in subsequent periods. That is, $\chi(\Omega_{j,1,t}, 0) = -\alpha^w (D_{j,t} + C_{j,t}) - \alpha^y I_{j,t}$. The first term captures the disutility of reducing liquid wealth, and the second term captures the disutility of reducing future disposable income. The present value of all mortgage repayments $I_{j,t}$ is approximated by $\frac{\beta}{1-\beta} P_{j,t}(1 - Y^D_t) Y^I_t$, assuming that the number of repayment periods is large and the mortgage interest rate is low. Households take all future repayments into account at the time of purchase, as Chinese commercial banks provide fixed-spread, long-term mortgages with limited refinancing options.[30] The mortgage repayments

[29] In other words, buyers can bid on any type of properties. In fact, there are always at least as many properties listed than the number of transactions for every type of properties in a market and time combination. There is no situation that one or more types of properties are not available. Buyers can observe both the average transaction prices and the average listing prices of each property type, but making ownership decisions based on average transaction prices.

[30] Before the Loan Prime Rate (LPR) reform in August 2019, Chinese commercial banks offered mortgage contracts

depend on the total amount of the mortgage $P_{j,t}(1 - Y_t^D)$ and the mortgage interest rate Y_t^I at the time of purchasing. Similarly, α^y measures how a marginal increase in mortgage repayment affects the utility of homeownership; this effect also depends on households' liquidity constraints and the implementation of alternative regulations in the econometric model.

Similar to seller's decision, the higher the expected value of choosing a given property type, the higher the probability the buyer chooses that type. The probability of choosing type $j \neq 0$ property ownership by a buyer $\pi_{j,t} := \Pr(d_{i,t} = \{j, 0\} | d_{i,t-1} = \{0, 1\}, j \neq 0)$ has a closed form expression thanks to the property of i.i.d. Type I extreme value distributed $\varepsilon_{i,t}$, that is,

$$\pi_{j,t} = \frac{e^{v_{j,0,t}^{0,1}}}{\sum_{k=1}^{J} e^{v_{k,0,t}^{0,1}}}. \tag{14}$$

This equation suggests a positive relationship between the value of owning a property type and the proportion of buyers who choose that type in a given period.

3.4 The Matching between Buyers and Sellers

Once buyers choose their most desired property type j, they search exclusively for that type, submit bids, and sellers can choose to accept or reject those bids. In each period, a buyer randomly meets a seller and draws a matching-specific value ν from an i.i.d. distribution. This information is private; buyers do not observe the number of competitors or their matching quality. Buyers send out a bid using the optimal bidding strategy $b(\nu)$ to maximize their expected payoff. The winning buyer receives a payoff of $\nu - b(\nu)$, completes the transaction with the seller, and exits the market, while unsuccessful buyers receive a payoff of zero and continue their search.

The average number of bids received by a seller of property type j at time t is given by $\lambda_{j,t} = N_{j,t}^{bids}/N_{j,t}^{seller}$, where $N_{j,t}^{bids}$ is the total number of bids submitted and $N_{j,t}^{seller}$ is the number of sellers. Note that only bids accepted by sellers result in transactions. The ratio between the number of bids and the number of transacted buyers, denoted by $\psi_{j,t}$, reflects the level of search friction, with $N_{j,t}^{bids} = \psi_{j,t} N_{j,t}^{buyer}$. A higher $\psi_{j,t}$ implies greater search friction, meaning that buyers need to make more bids before having a transaction, corresponding to longer time-on-the-market. Moreover, the number of buyers for product j depends on the fraction of buyers prefer that product $N_{j,t}^{buyer} =$

with a fixed spread over a stagnant central bank benchmark rate, with limited options for refinancing or repricing. Supposing that mortgages have T periods with equal principal payments, the amount to repay in each period equals the principal $(1-Y_t^D)P_{j,t}/T$ plus the interest accrued on the remaining debt. The implicit assumption is that buyers project future mortgage payments using the same interest rate as at the time of purchase. If T is large and Y_t^I is small, the sum of discounted mortgage repayments is

$$I_{j,t} = \sum_{\tau=1}^{T} \beta^\tau (1 + (T - \tau + 1) Y_t^I) \frac{(1 - Y_t^D) P_{j,t}}{T} \approx \frac{\beta}{1 - \beta} P_{j,t} (1 - Y_t^D) Y_t^I.$$

$\pi_{j,t}N_t^{buyer}$. Similarly, the number of sellers of product j is the fraction of homeowners who choose to list their property $N_{j,t}^{seller} = \omega_{j,t}N_{j,t}^{owner}$. When the market is large, the number of bids is a Poisson random variable with arrival rate $\lambda_{j,t}$, and sellers' probability of receiving bids is

$$q_{j,t} = 1 - e^{-\lambda_{j,t}}. \tag{15}$$

If a seller doesn't receive any bids, she continues to own the property during that time period. If a seller receives at least one bid, the seller can accept the highest bid or reject it if it is below her reservation price.[31]

For seller i of property type j who receives n competing bids from potential buyers in time period t, with ascending order $B_{i,j,t}^{(1)}, \cdots, B_{i,j,t}^{(n)}$, if she decides to sell, the transaction price $P_{i,j,t}$ is equal to $B_{i,j,t}^{(n)}$. The average price of housing product j is the expectation over the highest bids, given that at least one bid has been received.

$$P_{j,t} = \mathbb{E}\left[B_{i,j,t}^{(n)} \mid n \geq 1\right]. \tag{16}$$

The equilibrium is defined by value functions v, homeowners' listing decisions ω, non-owners' purchasing decisions π, sellers' selling strategies p, buyers' bidding strategies b, buyers' arrival rates λ, and house prices P, such that equations (7) - (16) are satisfied. The market clearing condition is not included in the equilibrium definition because the market does not clear – buyers who fail to win bids remain in the market for future searches, while sellers without bids continue listing their properties for sale. Furthermore, only symmetric equilibrium is considered, where sellers within the same property category adopt identical listing and selling strategies, and buyers for a given property type use the same bidding strategies, each constituting the best response to the other. Additionally, it is important to recognize that the equilibrium model does not account for mobility across cities. While market tightness emerges from the optimal listing and purchasing decisions of homeowners and non-owners, the overall number of homeowners and the aggregate number of buyers are considered exogenous, due to the lack of comprehensive household data. Note that deriving the buyers' bidding strategy theoretically is beyond the scope of this paper and will be empirically specified later in the econometric model. In particular, Section 4.2.1 explains market liquidity provided by buyers and sellers, while Section 4.2.2 discusses buyers' bidding strategy and equilibrium prices.

4 Econometric Model

In the econometric model, the model of the housing market m applies to all cities. Thus, I will bring back the subscript m for all relevant variables that differ across markets. I estimate the model

[31] As demonstrated by Albrecht et al. (2016), any distribution of listing prices above sellers' reservation price constitutes a payoff-equivalent equilibrium. In this paper, buyers do not pre-search based on listing price, but on the average market price and property attributes.

in three stages. In the first stage, I use buyers' choice of property types to estimate the expected value of owning each property type in the market an in each time period. In the second stage, I use observed transaction prices and the time on the market to estimate the liquidity of real estate markets. In the last stage, I recover the estimates of the per-period utility based on a set of observable characteristics.

4.1 First Stage: Property Type Decision and Expected Value Function

This stage focuses on buyers' property type decisions. In each market and time period, the total number of transactions for each property type through Lianjia is observable. The empirical proportion of buyers who decided to purchase a type j property in a given market-period combination provides us an estimate for the expected lifetime value of homeownership. Since buyers' property types choice π is conditional on they having entered the market as buyers, their expected value of purchasing is identifiable up to an additive constant and requires a normalization. Thus, the value of purchasing a property in $v^{0,1}_{j,0,m,t}$ is normalized by the market-time average value of buying a property $\bar{v}^{0,1}_{m,t}$, such that

$$v^{0,1}_{j,0,m,t} = \bar{v}^{0,1}_{m,t} + \widetilde{v}^{0,1}_{j,0,m,t}, \tag{17}$$

and the normalized value functions for buyers $\widetilde{v}^{0,1}_{j,0,m,t}$ have mean zero. Maximizing the likelihood of observed buyers' property type decisions in equation (14) yields a closed-form expression for the normalized value function,

$$\widehat{\widetilde{v}}^{0,1}_{j,0,m,t} = \log(\widehat{\pi}_{j,m,t}) - \frac{1}{J_m}\sum_{k=1}^{J_m}\log(\widehat{\pi}_{k,m,t}), \tag{18}$$

where $\widehat{\pi}_{j,m,t}$ is the empirical probability of buyers choosing a type j property in market m at time t. As the number of types increases, the observed transactions belonging to each property type become small, and thus the empirical probabilities. To address this issue, I use a kernel smoothing method similar to that of Bayer, McMillan, Murphy and Timmins (2016). More details about estimating the normalized value function are presented in Online Appendix A.3.1.

4.2 Second Stage: Market Liquidity and House prices

The second stage aims at estimating the parameters that determine the market liquidity provided by buyers and sellers and then recovering the determinants of the per-period utility function. To do this, I will express the probability of receiving bids, the probability of selling to the buyer, and the probability of the transaction price to construct the likelihood function.

4.2.1 Market Liquidity

Use the estimated $\widehat{\widetilde{v}}^{0,1}_{j,0,m,t}$ from (18), and combine equation (8), (9), (11), (13), and (17), the probability of selling in the decision state defined in equation (12) can be expressed as follows:

$$p_{j,m,t} = \left(1 + \exp\left(\widehat{\widetilde{v}}^{0,1}_{j,0,m,t} + \alpha^{w}_{m,t} W_{j,m,t} + \alpha^{y}_{m,t} I_{j,m,t} - \ln\left(\frac{1}{\widehat{\omega}_{j,m,t}} - 1\right) + k_m\right)\right)^{-1}, \tag{19}$$

under the assumption of no arbitrage opportunity in housing markets. That is, the average value of purchasing property $\bar{v}^{0}_{m,t}$ in equation (17) equals zero; otherwise, if $\bar{v}^{0}_{m,t}$ is greater (less) than zero, properties are undervalued (overvalued) and investors can hold a long (short) position in real estate to earn a positive return. Liquidity wealth related variation $W_{j,m,t} = 2C_{j,m,t} + D_{j,m,t} - (1 - O_{j,m,t})P_{j,m,t}$, where the transaction costs including taxes, fees, and commissions are roughly 5% of transaction prices,[32] assumed to be shared equally between buyers and sellers; thus $C_{j,m,t}$ is parametrized by $0.025P_{j,m,t}$. The down payment $D_{j,m,t}$ equals the property price times the down payment requirement $P_{j,m,t}Y^{D}_{m,t}$. The outstanding mortgage debt ratio is calculated based on the assumption that houses were purchased 10 years ago using 30-year mortgages with a 30% down payment, incorporating both price appreciation and mortgage repayment over past years. In Online Appendix A.4.2, an alternative assumption that sellers have no outstanding mortgage debt is considered, and it has no significant impact on the estimates. The present value of mortgage repayments $I_{j,m,t}$ is approximated by $\frac{\beta}{1-\beta}P_{j,m,t}(1 - Y^{D}_{m,t})Y^{I}_{m,t}$. $\widehat{\omega}_{j,m,t}$ denotes the empirical probability of homeowners who list their property in market m at time t, and k_m denotes the psychological disutility involved in listing for homeowners.

The parameters to be estimated in equation (19) are households' marginal utility of liquid wealth $\alpha^{w}_{m,t}$ and marginal utility of income $\alpha^{y}_{m,t}$, and psychological cost of moving k_m. Notably, the marginal utilities of liquid wealth and income are allowed to vary across markets and over time, capturing the heterogeneity in marginal utilities due to households' liquidity constraints. Moreover, to account for other regulations in local real estate markets, I also control for the staggered implementation of a new policy that restricts the minimum holding periods for homeowners, which may affect households' decisions. Thus, these two coefficients depend on households' average savings in each market and the implementation of other regulations in local real estate markets, i.e., $\alpha^{w}_{m,t} = Z_{m,t}\alpha^{w}$ and $\alpha^{y}_{m,t} = Z_{m,t}\alpha^{y}$, where $Z_{m,t}$ is a matrix including a column of ones, a column of household average saving in market m,[33] and a column of a dummy variable indicating the

[32] Lianjia charges 2% to 3% of transaction price as commission fees, shared by buyers and sellers. The transaction tax for buyers is between 1% to 3% of the transaction price, depending on property size and number of properties owned by the buyer. The transaction tax for sellers ranges from 0.05% to 5.6%, depending on the time of the ownership and how many properties owned by the seller. For most transactions, the total transaction cost falls between 4% to 6% of the transaction price.

[33] The average household saving in the year 2016 for cities in the sample is obtained from China National Bureau of Statistics: Beijing 20.55, Changsha 7.00, Chengdu 7.73, Chongqing 3.95, Dalian 8.86, Guangzhou 16.08, Hangzhou 11.30, Nanjing 8.89, Qingdao 6.73, Shanghai 16.30, Shenzhen 27.02, Suzhou 11.67, Tianjin 8.74, Wuhan 7.75, Xiamen

implementation of the minimum holding period requirements for homeowners.[34]

For the probability of receiving bids $q_{j,m,t}$, the key parameter is the arrival rate of bids $\lambda_{j,m,t} = \psi_{j,m,t}\gamma_{j,m,t}$, which is parameterized by the bidding multiplier $\psi_{j,m,t}$ and market tightness $\gamma_{j,m,t}$. I use the empirical number of visits per month as a proxy of the arrival rate of bids $\widehat{\lambda}_{j,m,t}$, taking the average number of visits for listed properties of type j in market m in month t. The estimated probability of receiving bids is thus $\widehat{q}_{j,m,t} = 1 - e^{-\widehat{\lambda}_{j,m,t}}$. To determine the market tightness, I use two pieces of information – the number of buyers (i.e., transactions) in that market and month, denoted by $\widehat{N}^{buyer}_{m,t}$, and the number of listed properties of that type, denoted by $\widehat{N}^{seller}_{j,m,t}$, which are directly observable from the data. The number of observed buyers targeting type j property is $\widehat{N}^{buyer}_{j,m,t} = \widehat{\pi}_{j,m,t}\widehat{N}^{buyer}_{m,t}$. Thus, the estimated market tightness is $\widehat{\gamma}_{j,m,t} = \widehat{N}^{buyer}_{j,m,t}/\widehat{N}^{seller}_{j,m,t}$. With the estimated arrival rate of bidders and the market tightness, the bidding multiplier can be estimated, reflecting the intensity of buyers' searching activity. In counterfactuals, they are kept fixed while housing demand and supply are allowed to change the market tightness.

4.2.2 House Prices

The distribution of transaction prices offers valuable information about potential bids. When combined with the arrival rate of potential buyers, these transaction prices, representing the maximum bid within the context of competing buyers, effectively reveal unobserved bids from potential buyers. To model potential buyer bids, I adopt a reduced-form approach, assuming that buyers' bidding strategies are determined by property characteristics (reflecting common valuation), market tightness (reflecting strategic considerations), and a private buyer-seller match valuation, which follows a log-normal distribution. This assumption is motivated by two factors. First, real estate markets are decentralized and opaque, providing buyers with limited information about competing bidders. Second, most participants are non-professional households with limited bidding experience. A reduced-form approach therefore offers a flexible framework, avoiding strong assumptions about bidders' information sets, rationality, or beliefs. Furthermore, the distributional assumption is supported by analyzing the distribution of transaction price, which is further elaborated in Online Appendix A.1.[35] An important assumption here is that price residuals reflect individual preferences for the matched property rather than unobserved housing characteristics. As illustrated in Table A.1, most of the variation in housing prices is explained by observable product attributes, namely size, age, and district location. Adding project fixed effects, which capture unobserved characteristics of the building project, only slightly improves the explanatory power, further supporting this modeling

9.85, denoted in 10,000 CNY.

[34]During the sample period, Beijing, Guangzhou, Xiamen, Hangzhou, Nanjing, Qingdao, Chengdu, Changsha, and Chongqing introduced the limited sale policy that precludes transactions within certain periods since the start of ownership. The periods often range between 2 years and 5 years across different cities. More details on the introduction of the limited sale policy can be found in Online Appendix A.1.4

[35]Examining the distribution of transaction prices suggests that transaction prices are log-normally distributed. See Figure A.3 for the graphical illustration in the case of Beijing

assumption.

Suppose the seller i receives n bids at time t in ascending order $B^{(1)}_{i,j,m,t}, \cdots, B^{(n)}_{i,j,m,t}$, where

$$\log B^{(k)}_{i,j,m,t} = \eta_j X_j + \phi_\lambda(\lambda_{j,m,t}) + \nu^{(k)}_{i,j,m,t} \text{ for } k = 1, \cdots, n. \tag{20}$$

The common valuation is represented by $\eta_j X_j$, which reflects all time-invariant characteristics that affect the bids received. The strategic component is captured by a second-order polynomial function of market tightness $\phi_\lambda(\lambda_{j,m,t})$. Finally, the private valuation is represented by $\nu^{(\cdot)}_{i,j,m,t}$, which is a random draw from a normal distribution $\nu^{(\cdot)}_{i,j,m,t} \sim \mathcal{N}(0, \sigma_m)$, capturing variation in bids across potential buyers and over time for each market. This parameterization simplifies buyers' bidding strategy in response to the number of competing buyers. The highest bid received by seller is the bid with the highest private valuation, that is $P_{i,j,m,t} = B^{(n)}_{i,j,m,t}$.

The probability of observing a property of type j transacted at price $P_{i,j,m,t}$ is

$$\Pr(P_{i,j,m,t}, \lambda_{j,m,t}) = f\left(\log P_{i,j,m,t} - \eta_j X_j - \phi_\lambda(\lambda_{j,m,t}); \sigma_m, \lambda_{j,m,t}\right),$$

where $f(\nu; \sigma_m, \lambda_{j,m,t})$ is the probability density that a bidder with private valuation ν wins a type j property given parameters σ_m and $\lambda_{j,m,t}$. The functional form is detailed in Appendix A.3.2. This expression shows clearly that house prices are modeled as a result of potential home buyers' demand, for which the joint distribution of unobserved private valuation and the arrival rate of bids is specified in the model. Using the empirical arrival rate of potential buyers, the log-likelihood of observing transaction prices P_{i,j,m,t^1_i} that sold at time t^1_i is

$$L_P(\eta_j, \sigma_m) = \sum_{m \in \mathcal{M}} \sum_{i=1}^{N_m} \log\left(\Pr(P_{i,j,m,t^1_i}, \widehat{\lambda}_{j,m,t^1_i})\right). \tag{21}$$

Maximizing the log-likelihood function above delivers the estimates for $\{\widehat{\eta}_j, \widehat{\sigma}_m\}$, which allows us to obtain house prices of a property type as the expected highest bid received by sellers,

$$\widehat{P}_{j,m,t} = \int \exp(\widehat{\eta}_j X_j + \nu) f(\nu, \widehat{\sigma}_m, \widehat{\lambda}_{j,m,t}) \mathrm{d}\nu \tag{22}$$

where the integration is calculated by simulation.

Finally, I use the estimated house prices $\widehat{P}_{j,m,t}$ and the probability of receiving bids $\widehat{q}_{j,m,t}$ to express the probability of observing a property of type j listed at time t^0_i and sold in t^1_i as follows

$$\Pr\left(\{d_{i,m,t}\}_{t=t^0_i}^{t^1_i} \mid \widehat{\Omega}_{j,m,t}, \widehat{\lambda}_{j,m,t}\right) = \left\{\prod_{t=t^0_i}^{t^1_i - 1} (1 - \widehat{q}_{j,m,t} p_{j,m,t})\right\} \times \widehat{q}_{j,m,t^1_i} p_{j,m,t^1_i}. \tag{23}$$

The equation above says that in periods between t_i^0 and $t_i^1 - 1$, there is no transaction with probability $1 - \widehat{q}_{j,m,t} p_{j,m,t}$; in time period t_i^1 the property is transacted with probability $\widehat{q}_{j,m,t_i^1} p_{j,m,t_i^1}$. The log-likelihood function of the observed time on the market for all the observations in the sample is

$$L_{TOM}(\alpha_{m,t}^w, \alpha_{m,t}^y, k_m) = \sum_{m \in \mathcal{M}} \sum_{i=1}^{N_m} \log \left(\Pr \left(\{d_{i,m,t}\}_{t=t_i^0}^{t_i^1} \mid \widehat{\Omega}_{j,m,t}, \widehat{\lambda}_{j,m,t} \right) \right), \tag{24}$$

where $\{\alpha_{m,t}^w, \alpha_{m,t}^y, k_m\}$ are the parameters to be estimated.[36]

4.3 Third Stage: Per Period Utility

The estimated lifetime utility, together with the estimated probability of receiving bids, are used to recover the per period utility of homeownership for homeowners and sellers as suggested by equation (7) and (10), respectively, that is,

$$\widehat{\delta}(\Omega_{j,0,m,t}) = \widehat{v}_{j,0,m,t}^{j,0} - \beta \mathbb{E} \left[\ln(e^{\widehat{v}_{j,0,m,t+1}^{j,0}} + e^{\widehat{v}_{j,1,m,t+1}^{j,0}}) \right]; \tag{25}$$

$$\widehat{\delta}(\Omega_{j,1,m,t}) = \widehat{v}_{j,1,m,t}^{j,1} - \beta \mathbb{E} \left[\widehat{q}_{j,m,t+1} \ln(e^{\widehat{v}_{0,0,m,t+1}^{j,1}} + e^{\widehat{v}_{j,1,m,t+1}^{j,1}}) + (1 - \widehat{q}_{j,m,t+1}) \widehat{v}_{j,1,m,t+1}^{j,1} \right]. \tag{26}$$

Having estimated the value of purchasing each property type for buyers in the first stage and the marginal utility of wealth, income, psychological cost of selling, and house prices for each product type in the second stage, we can compute the estimated value of owning property for owners and sellers using equation (8), (9), (13), namely

$$\widehat{v}_{j,0,m,t}^{j,0} = \widehat{v}_{j,0,m,t}^{0,1} + \widehat{\alpha}_{m,t}^w (\widehat{D}_{j,m,t} + \widehat{C}_{j,m,t}) + \widehat{\alpha}_{m,t}^y \widehat{I}_{j,m,t} \tag{27}$$

$$\widehat{v}_{j,1,m,t}^{j,1} = \widehat{v}_{j,0,m,t}^{j,0} - \ln \left(\frac{1}{\widehat{\omega}_{j,m,t}} - 1 \right) + \widehat{k}_m. \tag{28}$$

Equation (27) highlights the two types of factors that affect sellers valuation of homeownership. Firstly, cross-sectional variation of ownership value is captured by buyers' preference for different housing products $\widehat{v}_{j,0,m,t}^{0,1}$.[37] Secondly, house price dynamics affect purchasing and transaction costs, in turn influencing the value of homeownership. For homeowners, higher house prices offer them an opportunity to convert more housing equity into liquid wealth by selling, implying higher utility of being a homeowner than a renter. Moreover, the ownership value is higher when financing costs and transaction costs are high, reflecting prospective repurchasing costs. Equation (28) reflects differential valuation of homeownership between homeowners and sellers. The greater the fraction

[36] Following Rust (1987) and Hotz and Miller (1993), the log-likelihood function are divided into different parts and estimated separately. More explicitly, the log-likelihood of buyers' observed property type choices, the observed transaction price, the observed time-on-the-market, and the transition probabilities are estimated separately.

[37] Note that the average of buyers' value function $v_{j,0,m,t}^{0,1}$ in each market-time combination is normalized to zero.

of homeowners listing $\widehat{\omega}_{j,m,t}$, the more beneficial to be a seller compared to an owner. Similarly, a higher $\widehat{k}_m$ indicates higher sunk cost of listing, thereby making the status of being a seller more valuable.

To compute the second term on the right side of equation (25) and (26), we need to estimate transition probabilities for the choice-specific value functions. For the transition probabilities of the choice-specific value functions, I assume that households predict value functions in the next period based on today's states.[38] Given considerable evidence showing that households form extrapolative beliefs in housing markets based on recent trends in the experimental environment (Smith, Suchanek and Williams 1988, Haruvy, Lahav and Noussair 2007, Armona, Fuster and Zafar 2018) and in surveys (Case, Shiller and Thompson 2012, Greenwood and Shleifer 2014), I estimate the transition probability of choice-specific value functions assuming that they evolve as an autoregressive process of order two, such that:

$$\widehat{v}^{j,l}_{j,l,m,t} = \bar{\zeta}_{j,m} + \zeta_{j,m}t + \sum_{\tau\in\{t-1,t-2\}} \left(\zeta^{v,\tau}_m \widehat{v}^{j,l}_{j,l,m,\tau} + \zeta^{P,\tau}\widehat{P}_{j,m,\tau} + \zeta^{Y,\tau}Y_{m,\tau}\right) + \epsilon_{j,m,t}. \quad (29)$$

Here, the constants and time trends for the value functions, denoted as $\bar{\zeta}_{j,m}, \zeta_{j,m}$, are specific to each property type. The estimated values $\hat{\zeta}^{v,\tau}_m, \hat{\zeta}^{P,\tau}, \hat{\zeta}^{Y,\tau}$ represent how households form expectations based on past value of homeownership, house prices, and mortgage credit conditions. Notably, the transition of the choice-specific value functions of homeowners ($l = 0$) and sellers ($l = 1$) are considered, reflecting the dynamic nature of homeowners' and sellers' decisions. The value of homeownership can evolve differently across markets, accounting for heterogeneous housing market dynamics observed in different cities.[39] For each explanatory variable, I consider two lagged periods, i.e., $\tau \in \{t-1, t-2\}$. The residuals $\hat{\epsilon}_{j,m,t}$ that determine the distribution of value functions in the period t conditional on the states of previous two periods are used to predict the expectation in the next period by simulation.

Finally, we are particularly interested in the determinants of the flow utility for homeowners. The parameters in the per period utility function are estimated using $\widehat{\delta}(\Omega_{j,0,m,t})$ backed out from estimated value functions in equation (25). Similar to the literature,[40] the utility of homeownership is decomposed into user cost of owning a property $R_{j,m,t}$ that proportional to house value, observed

[38] Instead of estimate the transition probabilities of state variables, I use a commonly used numerical approximation, treating value functions as a sufficient statistic for the state space, e.g., Gowrisankaran and Rysman (2012), Melnikov (2013), and Bayer, McMillan, Murphy and Timmins (2016). For households, state variables determine the current value function, through which affects the predictions of the distributions of future value functions. This method works well in this problem because of the large number of estimated value functions, and as a result, it largely reduces the computational cost.

[39] In theory, it is conceivable to allow market-specific dynamics of homeownership values based on past house prices and mortgage credit conditions. However, doing so would result in significantly reduced degrees of freedom. To make a balance between flexibility and feasibility, I choose to retain a flexible functional form solely for the value functions.

[40] See e.g.,Bayer, Ferreira and McMillan (2007), Bayer, McMillan, Murphy and Timmins (2016)

property attributes X_j, and market (time) specific factors α^m (α^t) . The user cost is typically approximated by rental cost, which is about 2% of house prices in large Chinese cities during the sample period.[41]

$$\widehat{\delta}(\Omega_{j,0,m,t}) = \alpha^r_{m,t} R_{j,m,t} + \alpha^x X_j + \alpha^m + \alpha^t + \xi_{j,m,t}. \tag{30}$$

Decomposing the utility of homeownership into user and non-user cost components introduces identification challenge, because user cost is determined by house prices, which in turn can be related to unobservables that affect the desirability of owning a property. To address the endogeneity concern, I adopt a similar identification strategy as Bayer, McMillan, Murphy and Timmins (2016), where the estimated $\widehat{\alpha}^y_{m,t}$ from the second stage estimation is utilized to determine $\alpha^r_{m,t}$. This approach assumes that a marginal increase in the user cost has an equivalent impact on the one-period utility as a marginal increase in mortgage repayment, both reflecting the marginal utility of income. The remaining parameters are estimated through an OLS regression

$$\widehat{\delta}(\Omega_{j,0,m,t}) - \widehat{\alpha}^y_{m,t} R_{j,m,t} = \alpha^x X_j + \alpha^m + \alpha^t + \xi_{j,m,t}, \tag{31}$$

where α^x is a vector of parameters measuring the utility generated from different property characteristics; α^m is the market fixed effects; α^t is the time fixed effects. $\xi_{j,m,t}$ is the type-market-time specific unobservable term that quantifies the unobserved quality for different property types.

4.4 Identification and Discussion

This section briefly discusses how the parameters in the model are identified using information from the data and compares the model with alternative modeling frameworks. Overall, property attributes and mortgage credit conditions serve as exogenous variation for identification. Besides, several other sources of data variation help estimate the parameters: (a) the number of likes and visits, (b) the number of home buyers and sellers, (c) transaction prices, (d) homeowners' listing and selling decisions.

First, the number of likes and visits provide important information to identify the arrival rate of potential buyers $\lambda_{j,m,t}$, which is key for determining the distribution of bids received by sellers for each product type in any market-time combination. Since the secondary housing markets work in this listing and waiting format, the number of visits by potential buyers in a given time period directly imply the arrival rate of bids from buyers. Second, the bidding multiplier ψ_m is identified by the observed number of buyers and sellers, together with the arrival rates of bids. The higher ψ_m is, the more bids potential buyers make, the more actively buyers search in the housing market, indicating lower search friction. Third, given the arrival rate of potential buyers, transaction prices identify

[41] The market estimate of the average price-to-rent ratio of large and median size Chinese cities was 46 in 2018, while for first tier cities the ratio was 56. Other studies also find similar magnitudes, see e.g., Wu, Gyourko and Deng (2016), Zhang and Chen (2018).

η_j and σ_m through the variation of transaction prices among and within property types, respectively: the average price of different property attributes determine η_j; the dispersion of transaction prices determines the standard deviation of households' private valuation σ_m. Finally, given the probability of receiving bids and homeowners' listing and selling decisions, parameters in sellers' probability of selling $p_{j,m,t}$ are identified: The marginal utility of wealth $\alpha^w_{m,t}$ and income $\alpha^y_{m,t}$, as well as the psychological cost k_m are identified by the variation in the probability of transaction and listing among different property types under different housing market conditions and mortgage credit conditions. In Appendix A.3.3, Figure A.6 illustrates the estimation steps and Table A.4 summarizes the identification of key model parameters.

This paper develops a framework that combines a dynamic discrete housing choice model with segmented search to study how mortgage conditions affect household decisions and housing market outcomes. While existing studies have examined the role of mortgage credit in shaping housing consumption decisions using life-cycle models (e.g., Ortalo-Magne and Rady 2006, Bajari, Chan, Krueger and Miller 2013, Kaplan, Mitman and Violante 2020), the key advantage of this framework lies in its ability to incorporate a rich set of market frictions, including product heterogeneity, both monetary and non-monetary transaction costs, and search frictions. This allows for an analysis of how mortgage regulations operate in frictional markets and offers insights into the role these frictions play in shaping the transmission and effectiveness of monetary policy.

Another distinguishing feature is the modeling of the buyer-seller interaction using auctions with limited commitment. In this setup, sellers run auctions for competing buyers and retain the option to reject bids. In contrast, much of the real estate literature models transactions in matching through Nash bargaining frameworks (see, e.g., Novy-Marx 2009, Genesove and Han 2012, Ngai and Tenreyro 2014). However, the auction-based approach reflects actual trading mechanisms in many housing markets, where matches do not always result in transactions and buyers may engage in bidding wars. Recent studies show that the coexistence of auctions and bargaining in housing markets can lead to lower price volatility and higher search costs compared to the bargaining-only mechanism (Barkley, Genesove and Hansen 2024), suggesting the important implications for considering different market mechanisms.

While this modeling framework offers several advantages, it also has limitations, including the exclusion of housing construction, immigration, and a detailed characterization of the mortgage market. These simplifications are made for tractability but are worth discussing. Housing construction is excluded due to the relatively short sample period and the focus on large, developed cities where new development is typically restricted. Moreover, new construction takes time and tends to be less responsive to short-run changes in mortgage conditions. As such, omitting construction responses is unlikely to significantly affect the analysis of short-term policies. However, for long-term policy evaluation, incorporating housing construction dynamics could further dampen the price effects of

mortgage regulations. Similarly, immigration is not explicitly modeled, but short-run variation in immigration is relatively small in the sample context and unlikely to drive the main results. The model also abstracts from competition in mortgage markets across banks. Residential mortgage products are largely standardized products with limited variation in credit terms in the sample. Finally, rental choices are simplified to a single outside option to capture the extensive margin of homeownership at the aggregate level. Rental markets and investors' portfolio decisions are abstracted from to the core of the model, which focuses on the interaction between financial frictions, housing market segmentation and search frictions in the ownership market.

5 Results

5.1 Bidding Prices, the Value of Homeownership, and Market Liquidity

I use maximum likelihood estimation to obtain estimates for housing demand, supply, and the per period utility of owning properties. The estimation results, summarized in Appendix Table A.5, include estimates of bidding prices, liquidity from buyers and sellers, market liquidity, and sellers' relative market power across fifteen major Chinese cities. I provide the model performance results in Online Appendix A.4.4, examining the model-predicted house prices, hazard rate, and its implied survival probability. Comparing these predictions with observed data shows that the model generally performs well across cities in the sample.

The estimation results suggest a large heterogeneity in local housing markets. First, the dispersion of buyers' private valuation $\widehat{\sigma}_m$ suggests that a one standard deviation increase in private valuation raises bidding prices by 29% on average, ranging from 23% in Shenzhen to 36% in Xiamen. Second, there is a significant variation in market liquidity measures – the probability of receiving a bid ($\widehat{q}_{j,m,t}$) and the probability of selling once bids are received ($\widehat{p}_{j,m,t}$) – across local markets. The average monthly probability of receiving a bid is 0.71 for all cities, but Beijing has the highest rate, more than three times that of Shanghai and Suzhou. The average probability of selling conditional on receiving a bid is 0.64, with smaller cross-city variation. Multiplying the two probabilities yields overall market liquidity, which correlates with observed time-on-market outcomes as illustrated in Figure A.1. Markets like Beijing show high liquidity and fast sales, while Shanghai exhibits the opposite. Finally, the ratio of $\widehat{q}_{j,m,t}$ to $\widehat{p}_{j,m,t}$ serves as a measure of sellers' market power. A high ratio indicates a stronger position for sellers, reflecting greater ability to hold out for higher offers. This distinction allows us to differentiate between markets with similar liquidity but different market power dynamics. For example, Chongqing and Guangzhou have similar market liquidity, but sellers in Chongqing have higher market power, making it more of a sellers' market. These insights are not apparent from the time on the market and transaction prices shown in Figure A.1.

Besides the large heterogeneity across markets, we also observe dynamics over time. The left panel

in Figure 2 illustrates the average market liquidity of fifteen major cities over time, with the shaded area indicates the 25th and 75th distribution of the variable. In December 2015, during a cold real estate market, the average probability of completing a transaction within a month was 0.29. As many local markets heated up, this probability rose to about 0.4 by late 2016 and surged to 0.49 by April 2017. To cool the overheated markets, the PBOC tightened mortgage credit in March 2017, leading to significant interest rates and higher down payment requirements. This caused market liquidity to drop, stabilizing around 0.4 after July 2017.

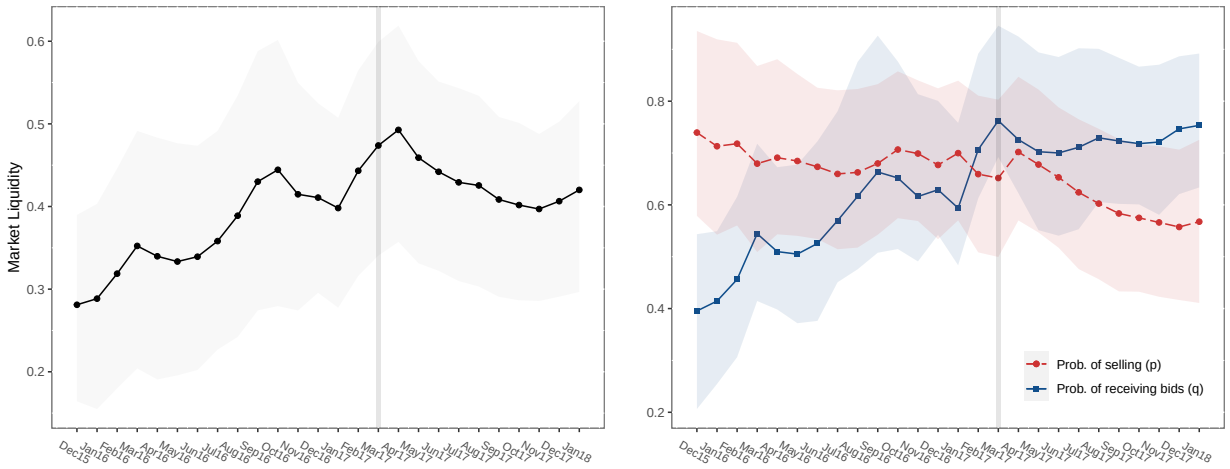


Figure 2: The Probability of Receiving Bids and the Probability of Selling over Time

Note: This figure plots the average market liquidity, the average probability of receiving bids and the probability of selling over time. In the top panel, the market liquidity is determined by the product of $\widehat{p}_{j,m,t}$ and $\widehat{q}_{j,m,t}$. The bottom panel disentangles liquidity between buyers and sellers, i.e., the probability of receiving bids (represented by the blue solid line) and the probability of accepting bids (represented by the red dashed line). The shaded areas indicate the 25th and 75th percentiles of the probability distribution.

Decomposing market liquidity into buyer- and seller-side components further reveals the market power division between buyers and seller over time. The right panel of Figure 2 illustrates market liquidity from buyers, i.e., the probability of receiving bids (the blue solid line), and market liquidity from sellers, i.e., the probability of selling (the red dashed line) over the same time. From December 2015 to September 2016, the probability of receiving bids steadily increased, with a sharp rise between January and March 2017, driving higher market liquidity. This was followed by a decline as mortgage credit tightened. Meanwhile, the probability of selling remained stable before March 2017, and then gradually declined after the credit tightening. Moreover, before January 2017, the probability of receiving bids was lower than the probability of selling, but the gap narrowed, and in February 2017, bids surpassed sales for the first time, indicating a surging demand and a shift from buyers' to a sellers' market. After the mortgage credit tightening, sellers' market power further increased toward the end of the sample period.

These findings have two important implications. First, the decline in market liquidity following mortgage credit tightening is primarily driven by sellers becoming less willing to sell, indicating

that sellers hold a stronger market position in these markets. Second, as shown in the counterfactual analyses in the next section, sellers' responses to regulation depend on their expectations regarding the policy horizon. When sellers believe the policy is temporary and that the market will recover, they are more likely to delay selling, explaining the observed increase in sellers' market power across markets despite tighter credit conditions. Figures A.7 and A.8 in Online Appendix A.4.3 show similar patterns across local housing markets: liquidity declines following mortgage credit tightening. However, the extent of the decline and the relative market power of buyers and sellers vary. The effect is more pronounced in sellers' markets, suggesting that the impact of mortgage regulation is heterogeneous and shaped by underlying market frictions.

5.2 Per Period Utility

Table 2 Panel A summarizes the estimates for the per-period utility of owning a property for homeowners. The first column shows the estimates of marginal utility of liquid wealth and income obtained from the maximum likelihood estimation. These estimates suggest that for households in a market without restrictions on selling and without any saving, a 10,000 CNY (approximately 1,500 USD) increase in liquid wealth increases households utility by $(5.376 \times 0.01) = 0.054$, and the same amount of increase in annual income increase households' flow utility by $(3.930 \times 0.01) = 0.039$. Moreover, the marginal utility of liquid wealth and income decreases with household savings and increases when other real estate regulations are implemented. This suggests that households experience lower marginal utility of income and liquid wealth if they are wealthier or when restrictive real estate policies are in place. Considering all households with different savings and local real estate regulations, a 10,000 CNY increase in liquid wealth results in a 0.7% increase in the median value of homeownership, and the same increase in annual income leads to an 10.7% increase in the median value of homeownership. Table A.7 in Appendix A.4.5 presents the estimated non-monetary cost for sellers, which reflects the non-monetary benefits enjoyed by homeowners compared to renters, such as school admission advantages and weak tenant protections.

Table 2 Panel B reports how property attributes affect the utility of owning a property. I run an OLS regression of equation (31), regressing the model estimated per period utility obtained from equation (25), deducting estimated user costs, on property attributes and market and time fixed effects. Property size types are grouped by their decile, and age types are grouped by their quintile. Districts are classified as either Urban or Suburban, and further distinguished by whether they have a high concentration of schools. To capture households' non-linear preference for property size and age, the quadratic terms of property size and age are included. The estimates suggest that households prefer larger properties. However, they do not always prefer the most recently built houses, as these are often situated farther from the city center and may offer fewer amenities. This preference can be reflected by the observation that houses aged between 12 and 16 years have the highest transaction

Table 2: Parameter Estimates for Utility and Value Function

	Estimate	Std. Err.
Panel A		
Wealth (α^w)		
Constant	5.376	(0.001)
Saving	-0.179	(0.000)
LSP	0.620	(0.003)
Income (α^y)		
Constant	3.930	(0.001)
Saving	-0.122	(0.001)
LSP	0.448	(0.001)
Panel B		
Property attributes (α^x)		
Size	0.002	(0.001)
Size^2	-0.000	(0.000)
Age	0.003	(0.001)
Age^2	-0.0001	(0.000)
Urban	0.063	(0.016)
Schools	0.049	(0.010)

This table presents key estimates for utility and value functions. The first column reports the estimated parameters and the second column reports standard errors. Estimates in Panel A are obtained from maximum likelihood estimation. Two sets of estimates are reported in the table: the impact of liquid Wealth (measured in 1 Million CNY) and Income (measured in 1 Million CNY) on households' utility. Saving is denominated in unites of 10,000 CNY. LSP is a dummy variable taking value of one if restrictive selling policy was implemented, and zero otherwise. Estimates in Panel B are obtained from OLS regression. Size and Age are the median living space of a property type and the median age of a property type, respectively. City fixed effects and time fixed effects are included in the regression.

price compared with other age groups.[42] An average household derives the highest utility from a 12 year-old properties, and the value varies across cities. Moreover, households derive significantly higher utility from living in urban districts and in areas with a high concentration of schools.

A better way to interpret these results is to compute households' willingness to pay for property attributes, defined as the additional user cost to pay per period for an additional unit consumption of property attributes. An average household in Beijing is willing to pay 714 CNY more per month for owning a 10 square meters larger property, and 350 CNY more per month to own a property that is newer by 5 year.[43] An average household in Beijing is willing to pay 3,673 CNY more per month for living in urban districts and 2,850 CNY more per month in districts with numerous schools. The high willingness to pay for owning properties in urban districts and good education resources districts suggests a market segmentation across these markets, as households' demand for urban and education is price inelastic. A small change in house price in urban and good education resources districts will not significantly alter households' housing choices, while the may more likely to change across housing product with different size and age.

On average, a homeowners in Beijing is willing to pay 3,673 CNY more per month to live in an urban district and 2,850 CNY more per month to live in a district with abundant educational resources. This high willingness to pay for properties in urban areas and school-rich districts indicates strong segmentation across these submarkets, as household demand for these attributes is relatively price inelastic. In such submarkets, small changes in house prices are unlikely to significantly alter housing choices. In contrast, households are more responsive to price changes across housing products with different size and age.

Finally, households form extrapolative beliefs about future value of homeownership based on past states. As detailed in Online Appendix A.4.6, past house prices and mortgage interest rates exhibit both momentum and mean-reversion effects on households' beliefs, while past down payment requirements show economically insignificant effect (Table A.8). These relationships are utilized to form expectations in counterfactual analyses.

6 Counterfactuals

This section examines counterfactual mortgage regulations and their impact on housing market outcomes and household welfare, comparing their effects across markets with varying levels of market frictions. To understand the role of household expectations, I compare the baseline scenario with the one without the expectation channel, where the policy affects only flow utility while future expecta-

[42] See Table A.1.

[43] Note that the willingness to pay is a function of savings, selling restrictions, property size, and property age. The average property size in Beijing is 86 square meters and is on average 15 years old. The average household savings in Beijing were 205,500 CNY in the year 2016.

tions remain fixed.[44] To understand the role of market frictions, besides the baseline scenario, I also consider mortgage regulations in scenarios with lower market frictions, such as reduced transaction costs, search friction, and non-monetary cost of selling.

6.1 Mortgage Interest Rates

6.1.1 Market Liquidity and Prices

I start with simulating a 1 percentage point increase in mortgage interest rates. Changes in mortgage interest rates first affect mortgage repayments for homebuyers, which in turn influence the value of home purchases, thereby affecting housing demand and market tightness. This further influences incoming bids and sellers' probability of accepting those bids. Thus, house prices are endogenously determined, which, in turn, affect the value of homeownership and owners' decisions to list their properties in the equilibrium.[45]

Table 3 Panel A summarizes the median percentage changes in housing market outcomes under the counterfactual mortgage policy with the expectation channel. Column (1) reports the overall effects across all housing product types and markets. At the property level, the overall impact of increased mortgage interest rates is relatively small on the probability of listing, the probability of receiving bids, the probability of selling, and the highest bids. At the market level, however, the number of transactions declines by 1.7% due to reduced liquidity, and average transaction prices fall by 6.5%. This larger price effect at the aggregate level is driven by increased borrowing costs, which disproportionately affect more expensive properties, shifting demand toward more affordable ones. In other words, substantial cross-sectional variation across housing product segments dampens effects at the property level but becomes more pronounced when aggregated to the market level.

The cross-sectional effect of mortgage regulation becomes clear when looking at different market segments reported in Columns (2) to (5). Specifically, Columns (2) and (3) distinguish between small and large properties, defined as those below or above the median property size. The increase in mortgage interest rates raises borrowing costs, disproportionately affecting buyers of larger properties. For properties above the median size, the median probability of receiving bids falls by 1.3%, leading to a 0.2% decline in bidding prices. The decrease in housing demand and bidding prices decreases homeowners' probability of listing and increase their probability of accepting bids. In contrast, small properties see an increase in the probability of receiving bids, as well as higher prices

[44] More explicitly, shutting down the expectation channel means the expected continuation value, i.e., the second term on the right-hand side of equations (7) and (10), remains unchanged. In contrast, when the expectation channel is active, the policy affects both current utility and future expected values.

[45] To compute new equilibrium outcomes in the model, I use a nested fixed-point algorithm containing an outer-inner loop structure. The outer loop updates house prices according to equation (37); within each update, the inner loop searches for value functions induced by the given prices by iteratively updating equation (10) until the value functions converge. Thus, we obtain new equilibrium prices and value functions after a policy change by iteratively updating the outer loop until house prices converge.

and a greater likelihood of listing – reflecting a demand shift from large to more affordable small properties. At the market level, this shift results in a larger deterioration in liquidity and transaction prices for large properties compared to small ones. Columns (4) and (5) compare suburban and urban districts. Properties in suburban districts see an increase in the probability of receiving bids and highest bids, while urban districts experience a slight decrease, suggesting a demand shift from expensive urban to cheaper suburban areas. However, the magnitude of substitution across geographic locations is smaller than that across size segments, indicating a higher degree of geographical market segmentation.

Table 3: Counterfactual Increase in Mortgage Interest Rates

	Overall	**Size**		**Location**	
		Small	Large	Suburban	Urban
	(1)	(2)	(3)	(4)	(5)
Panel A: Housing Markets					
Property Type Level					
Prob. of Listing	-0.5	0.4	-2.9	-0.0	-1.3
Prob. of Receiving Bids	0.4	3.7	-1.3	1.9	-0.0
Prob. of Accepting Bids	0.3	0.0	0.7	0.1	0.5
Highest Bids	0.1	0.7	-0.2	0.3	-0.0
Market-Time Level					
Number of Transaction	-1.7	6.1	-7.6	1.5	-2.6
Average Transaction Price	-6.5	-0.2	-6.0	-3.4	-7.3
Panel B: Household Welfare					
Home Owner	0.1	1.2	-0.9	0.8	-0.2
Home Buyer	-123.0	-84.2	-158.0	-114.3	-128.6
Home Seller	0.5	3.3	-1.9	1.8	-0.0

Note: This table summarizes the median percentage changes in market outcomes and household welfare in the counterfactual increase in mortgage interest rates. Panel A reports the counterfactual results for the probability of receiving bids, the probability of accepting bids, the highest bids, the number of transactions, and the market-level transaction prices. Panel B reports the median of welfare changes (in one thousand CNY) for homeowners, buyers, and sellers. Columns (1) corresponds to the overall policy impact on all housing products and markets, while the last four columns correspond to the policy change with different market segments, such as product size (Small vs Large) and geographical location (Suburban vs Urban).

6.1.2 Welfare Implications

Table 3 Panel B summarizes the welfare implications of mortgage policy changes for homeowners, buyers, and sellers for both overall and by housing segment. Household welfare is measured as the one-time transfer needed to keep lifetime utility constant. A negative value indicates a welfare loss, meaning that in the counterfactual scenario, households are worse off and would require a positive transfer to maintain their baseline utility.

As shown in Column (1), a 1 percentage point increase in mortgage interest rates leads to a median

welfare loss of 123.0 thousand CNY (approximately 18.5 thousand USD) for homebuyers, while the impact on homeowners and sellers is minimal. This highlights that tightened mortgage credit incurs higher financing costs that are directly and almost solely borne by homebuyers. Columns (2) to (5) show welfare changes across market segments. Buyers of larger properties experience greater welfare losses (158.0 vs. 84.2 thousand CNY), reflecting higher financing costs. Homeowners and sellers of larger properties also face welfare losses due to a more pronounced decline in liquidity and house prices. In contrast, homeowners and sellers of small properties experience welfare gains, as demand shifts toward smaller, more affordable properties, improving market liquidity and prices. Comparing urban and suburban districts, a similar pattern emerges: participants in urban districts face larger welfare losses, especially homebuyers (128.6 vs. 114.3 thousand CNY). Notably, the cross-sectional welfare disparity is smaller across geographic locations than across property sizes, consistent with the relatively smaller demand substitution across locations.

The counterfactual analysis offers three key insights into the impact of mortgage policies on housing markets. First, while tighter mortgage credit conditions can help cool overheated markets by reducing transactions and lowering house prices, they do so largely at the expense of homebuyers. Second, increasing mortgage interest rates has large cross-sectional effects, shifting demand from more expensive to more affordable properties. In particular, homebuyers substitute toward smaller or suburban properties, which can increase demand and even raise prices in those lower-end segments, which are often targeted by first-time buyers. This crowding-out effect may undermine the policy objective of improving housing affordability for these buyers. Finally, housing segments with more favorable characteristics are more negatively affected by increases in mortgage interest rates. To examine this, I regress the percentage changes in highest bids, market liquidity, and welfare changes for homeowners, buyers, and sellers in the counterfactual increase in mortgage interest rates on housing characteristics. As shown in Table 4, larger, newer, and urban properties experience greater declines in prices, liquidity, and welfare, particularly for buyers and sellers. These results suggest that macroprudential mortgage regulation reduces housing consumption by lowering demand for favorable housing characteristics, adversely impacting market participants in these segments.

6.1.3 The Expectation Channel

To understand the role of household expectations in affecting their housing decisions, I consider a counterfactual mortgage regulation scenario that excludes the expectation channel, keeping the expected continuation utility unaffected by the policy change. In other words, households adopt a short-term perspective, ignoring the long-run impact of mortgage regulation on their valuation of homeownership. The results are reported in Table A.9.

There are three main takeaways regarding the role of expectations. First, in terms of housing market outcomes (Panel A), the effects are generally less pronounced than in the baseline scenario with the

Table 4: The Cross-Sectional Effect of Counterfactual Mortgage Regulation

	Market Variables		**Welfare**		
	Highest Bids	Liquidity	Owner	Buyer	Seller
	(1)	(2)	(3)	(4)	(5)
Size Decile	-0.27^{***}	-1.52^{***}	-2.10^{***}	-24.80^{***}	-3.31^{***}
	(0.04)	(0.27)	(0.68)	(5.44)	(0.56)
Age Quintile	0.09^{***}	0.44^{***}	0.71^{**}	7.18^{***}	1.05^{***}
	(0.01)	(0.07)	(0.26)	(1.21)	(0.18)
Urban	-0.73^{***}	-4.21^{***}	-6.95^{**}	-73.68^{***}	-9.59^{***}
	(0.15)	(0.93)	(2.49)	(17.02)	(1.63)
Schools	0.02	-2.54	-3.28^{**}	-52.57^{*}	-4.61^{**}
	(0.17)	(2.55)	(1.46)	(27.24)	(2.00)
Observations	146,832	146,832	146,832	146,832	146,832
Adjusted R^2	0.53	0.52	0.75	0.79	0.38

Note: This table reports the cross-sectional effect of the counterfactual mortgage regulation, regressing the percentage changes in housing market outcomes (Columns 1 and 2) and changes in household welfare in 1,000 CNY (Columns 3 to 5) on housing characteristics under the counterfactual increase in mortgage interest rates. Size Decile refers to the property's size decile (1 to 10), and Age Quintile refers to its age quintile (1 to 5). Urban is a dummy variable equal to one if the property is located in an urban district. School is a dummy variable equal to one if the property is located in a district with many schools. *p<0.1; **p<0.05; ***p<0.01

expectation channel. Moreover, muting the expectation channel prevents households from accounting for the long-term impact of increased interest rates. As a result, homeowners do not change their listing behavior, and sellers are less likely to accept bids, as they have an incentive to delay sales in anticipation of a market recovery. Second, in terms of welfare (Panel B), homeowners experience smaller welfare changes. This is because they do not actively participate in the housing market unless they sell. When the expected future value of homeownership, through anticipated changes in house prices and market liquidity, is not considered, there is little impact on their welfare or listing behavior. Third, the cross-sectional disparity across market segments is more pronounced when households adopt a longer-term horizon. This suggests that the expectation channel amplifies welfare differences between lower- and higher-end market segments.

6.1.4 The Role of Market Friction

To further examine the role of various market frictions in the transmission of mortgage interest rates, I simulate the same counterfactual under three scenarios with reduced market frictions. First, I set the transaction costs to zero, representing a general reduction in transaction frictions. Second, I analyze a 20% increase in matching efficiency, which can be interpreted as a reduction in search frictions, such as improvements in search technology that buyers find a seller faster. Finally, I consider a 10% decrease in the non-monetary cost of selling, which can be interpreted as a reduction in the

non-monetary benefits of homeownership, such as stronger tenant protections, thereby increasing liquidity provision from sellers.

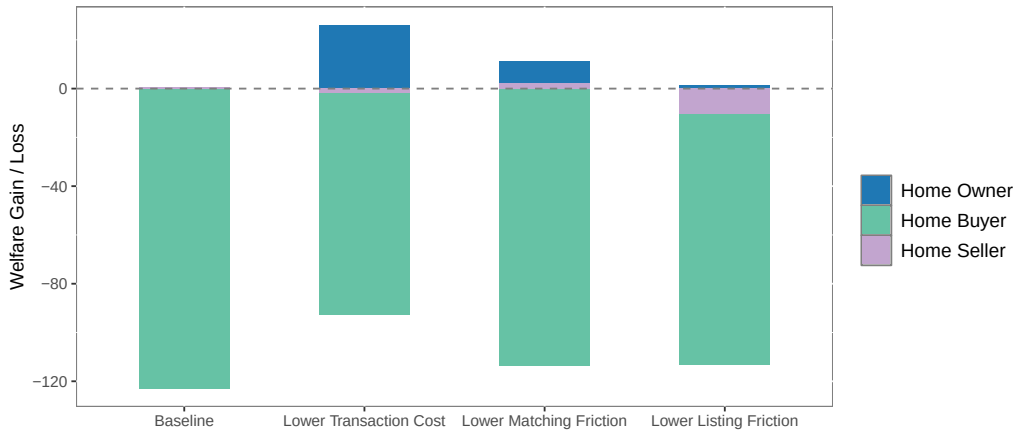


Figure 3: Counterfactual Mortgage Regulation and Market Frictions

Note: This figure plots the median welfare gain/loss for Homeowners (blue), Homebuyers (green), and Homesellers (purple) after a one percentage point increase in mortgage interest rate under four market friction level: the baseline scenario (Baseline), a 100% decrease in transaction costs (Lower Transaction Cost), a 20% increase in matching efficiency (Lower Matching Friction), and a 10% decrease in non-monetary cost of selling (Lower Listing Frictions).

In all three scenarios, lower market frictions mitigate total welfare losses for households, though the distribution of these welfare improvements varies depending on the type of friction and the channels through which they work. Figure 3 shows the welfare changes for homeowners, buyers, and sellers under each counterfactual scenario, while the corresponding housing market outcomes are reported in Table A.10.

In the baseline case (Baseline), homebuyers bear nearly all the welfare loss due to increased financing costs. When transaction costs are eliminated (Lower Transaction Cost), total welfare losses decrease, primarily due to smaller losses for buyers and gains for homeowners. Specifically, the welfare loss for homebuyers decreases by 25.9%, driven by lower house prices and reduced transaction costs. Sellers are almost unaffected, as the decline in house prices and market liquidity is offset by the reduction in transaction costs. Homeowners benefit from increased housing wealth, which is not subject to transaction costs upon sale. Similarly, reducing matching frictions by 20% (Lower Matching Friction) lowers the overall welfare loss, decreasing buyers' welfare losses from 123.0 to 113.6 thousand CNY on average. Improved matching efficiency allows sellers to find buyers with higher private valuations, which raises house prices and liquidity. This, in turn, leads to welfare gains for both homeowners and sellers. Finally, reducing seller-side frictions (Lower Listing Friction) lowers total welfare losses mainly for buyers but results in a significant welfare loss for sellers. Lower non-monetary selling costs increase the likelihood of listing, expanding housing supply and driving down house prices. This highlights the redistributive role of seller-side frictions: reducing them shifts welfare from sellers to buyers.

6.2 Down Payment Requirements

Another mortgage regulation instrument is down payment requirement. I simulate a 10 percentage points increase in down payment requirements, as a temporary and a long-term policy change respectively, and under the baseline market friction scenario as well as reduced market friction scenarios. The counterfactual results on housing market outcomes and household welfare are reported in Table A.11. We find a similar but weaker impact of increasing down payment requirements on housing market outcomes and household welfare compared to an increase in mortgage interest rates. This suggests that down payment requirements are less influential than interest rates for housing decisions in these Chinese housing markets. The reasons for this are as follows: On the one hand, during the sample period, Chinese commercial banks offered long-term fixed-spread mortgages without refinancing options, making it more costly for households to be locked into expensive mortgages. On the other hand, since mortgage interest rates were already high during this period, higher down payment requirements also led to a reduction in future mortgage repayments, contributing to the weaker effects observed under the higher down payment requirement scenario.

7 Conclusion

This paper investigates how mortgage regulation affects housing market outcomes and household welfare in segmented housing markets with search frictions. Using novel data from China, it first documents a mortgage credit tightening by the PBOC that led to increases in mortgage interest rates and down payment requirements in major Chinese cities. The regulation decreased the house price growth rate and reduced transaction volumes, with a stronger impact on more expensive properties, suggesting a cross-sectional effect of mortgage regulation across market segments.

To quantitatively assess the cross-sectional and distributional effect of mortgage regulation, this paper develops a micro-founded structural model of home listing, purchasing and selling, accounting for housing product and demand heterogeneity, search frictions, transaction costs, and financial frictions. Estimating the model decomposes market liquidity from buyers and sellers. During the period of mortgage credit tightening, housing market liquidity decreased, driven by a decrease in both the probability of receiving bids and the probability of selling. Moreover, the estimated willingness-to-pay for property attributes suggests housing consumption substitution patterns, indicating the level of market segmentation.

With counterfactual policy changes, the paper quantifies how mortgage regulation that tightens mortgage credit conditions affects housing markets and participants. Simulating an increase in the mortgage interest rate, I find a larger impact on expensive properties, for instance large and urban area properties, decreasing the demand for those types and pushing buyers towards cheaper properties

resulting in a sizable decrease in the market average transaction price due to the substitution effect. It also results in a large welfare loss for home buyers compared to sellers and owners. An increase in down payment requirements has a similar but smaller impact. Comparing short-term and long-term policies reveals that long-term changes have a stronger effect on market outcomes and household welfare. I further examine the role of market friction in housing market, simulating counterfactuals in three different scenarios of reduced market frictions. The results demonstrate an improvement in total welfare losses and different redistribution patterns depending on the source of friction.

These results highlight the significant role of mortgages in shaping housing market outcomes and household welfare, with policy timing and market frictions also substantially influencing housing decisions and well-being. Regulations on mortgage interest rates and down payment requirements can affect housing market outcomes. However, they may also lead to cross-sectional and distributional effects that are not ideal in some circumstances. For instance, increased mortgage interest rates in segmented markets reduce demand in higher-end segments, shifting it to lower-end segments and further decreasing housing affordability in those areas. Additionally, housing market frictions influence how mortgage regulations affect different participants, shaping the distributional impact through distinct channels.

This paper structurally analyzes the transmission mechanism of mortgage credit policy on housing markets and quantifies the welfare impact of these policy changes. The general framework characterizing home listing, purchasing, selling with financial, search, and transaction frictions, as well as rich housing product heterogeneity, can be applied to other housing markets to evaluate different policy interventions. The model can be extended to account for household heterogeneity if the information on households are available (e.g., Kvaerner, Pavanini and Peng 2023). It can be extended to account for housing supply as Murphy (2018), to combine with life-cycle model such as Fonseca, Liu and Mabille (2024) to capture the rich housing heterogeneity, both of which are promising directions for future research.

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A Online Appendix – Mortgage Credit and Housing Markets

A.1 Additional Motivating Evidence

A.1.1 The Classification of Housing Products

Housing products in the sample are categorized based on the property's size, age, and district location. Size is divided into 10 groups based on deciles, and age is divided into 5 groups based on quintiles. The sample encompasses 145 districts across 15 cities, resulting in a total of 6,112 distinct housing products. Note that the number of product is less than ($10 \times 5 \times 145 =$) 7250 because not every district contains all 50 types of housing products. Table A.1 demonstrates how these housing product classifiers contribute to explaining transaction prices.

A.1.2 Housing Markets in China

Figure A.1 illustrates the average time on the market (red bars) and the average monthly house price growth rate (black line) in the sample. The monthly house price growth rate ranges from 0.5% to 2.5%. Properties in Shanghai on average take as long as 8.7 months to be sold, suggesting a "cold" housing markets with low liquidity, while properties in most other cities stay on the market for 2 to 3 months. In general, cities with higher market liquidity tend to have higher house price growth rates, but some variation still cannot be explained.

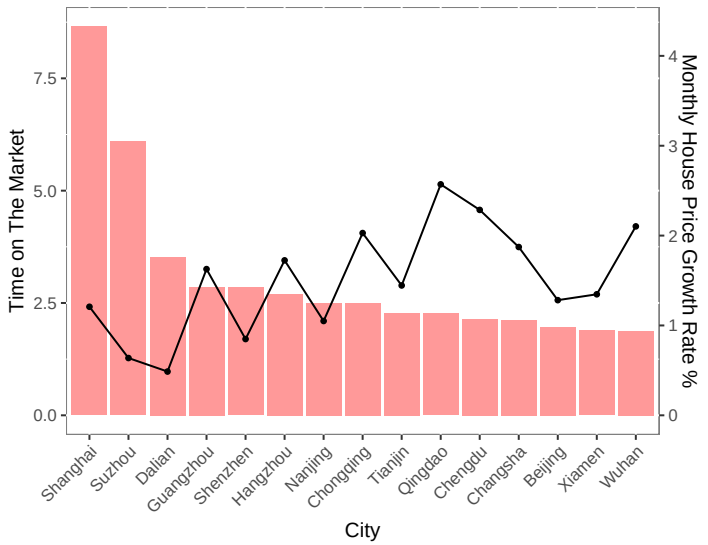


Figure A.1: Time on the Market and House Price Growth Rate

Note: This figure illustrates the housing market conditions for the fifteen major cities in China. The red bars indicate the average time on the market (in months) for properties in that market. The black line indicates the average monthly house price growth rate in percentage points for properties in that market.

Figure A.2 takes Beijing as an example to illustrate how market conditions evolve over time. The top

Table A.1: Housing Product Characteristics and House Prices

	Log(Total Transaction Price)			
	(1)	(2)	(3)	(4)
Age Gr. 2: 5 - 8 years old	-0.05^{***}	-0.02^{***}	-0.07^{***}	0.22^{***}
	(0.002)	(0.002)	(0.001)	(0.003)
Age Gr. 3: 9 - 11 years old	-0.01^{**}	-0.002	-0.09^{***}	0.39^{***}
	(0.003)	(0.002)	(0.002)	(0.003)
Age Gr. 4: 12-16 years old	-0.002	-0.02^{***}	-0.14^{***}	0.50^{***}
	(0.003)	(0.002)	(0.002)	(0.004)
Age Gr. 5: 17 - 30 years old	-0.23^{***}	0.02^{***}	-0.15^{***}	0.60^{***}
	(0.003)	(0.002)	(0.002)	(0.005)
Size Gr. 2: 47 - 56 square meters		0.25^{***}	0.26^{***}	0.24^{***}
		(0.003)	(0.002)	(0.002)
Size Gr. 3: 57 - 65 square meters		0.39^{***}	0.42^{***}	0.39^{***}
		(0.003)	(0.002)	(0.002)
Size Gr. 4: 66 - 74 square meters		0.51^{***}	0.56^{***}	0.52^{***}
		(0.003)	(0.002)	(0.002)
Size Gr. 5: 75 - 82 square meters		0.61^{***}	0.67^{***}	0.62^{***}
		(0.003)	(0.002)	(0.002)
Size Gr. 6: 83 - 88 square meters		0.70^{***}	0.78^{***}	0.72^{***}
		(0.003)	(0.002)	(0.002)
Size Gr. 7: 89 - 95 square meters		0.75^{***}	0.83^{***}	0.77^{***}
		(0.003)	(0.002)	(0.002)
Size Gr. 8: 96 - 110 square meters		0.86^{***}	0.93^{***}	0.86^{***}
		(0.003)	(0.002)	(0.002)
Size Gr. 9: 111 - 132 square meters		1.02^{***}	1.09^{***}	1.00^{***}
		(0.003)	(0.002)	(0.002)
Size Gr. 10: 133 - 300 square meters		1.33^{***}	1.36^{***}	1.21^{***}
		(0.003)	(0.002)	(0.002)
City FE	Yes	Yes	No	No
District FE	No	No	Yes	No
Project FE	No	No	No	Yes
Observations	368,768	368,768	368,768	368,768
Adjusted R^2	0.63	0.81	0.87	0.93

Note: This table illustrates how age groups, size groups, and district, and project fixed effects explain the variation in the logarithm of transaction prices. Age is grouped by quintile, size is grouped by decile. The unit of observation is a transaction, with the total transaction price denominated in 10,000 CNY (approx. 1,500 USD) serving as the dependent variable. Age Groups and Size Groups are dummy variables taking value of one if the observed property falls in that specific age or size group. City fixed effects are included in Columns (1) and (2), District fixed effects are included in Column (3), and Housing Project fixed effects are in Column (4). $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

panel plots the average transaction prices in Beijing during the sample period. House prices started from about 40,000 CNY (approx. 6,000 USD) per square meter in December 2015 and peaked in March 2016 around 67,000 CNY per square meter (approx. 10,000 USD). Moreover, transaction prices seem to log-normally distributed, as illustrated by Figure Figure A.3, where the distribution of transaction prices and the logarithm of transaction prices are presented. The left subfigure depicts the distribution of transaction prices for all property types. Most transaction prices fall in the range of 3 to 5 million CNY, but it is clear to see the distribution of transaction prices is right-skewed, with many houses are sold beyond 10 million CNY. The right figure plots the distribution of the logarithm of transaction prices, which tends to be normally distributed.

The middle panel of Figure A.2 plots the number of transactions (blue bars) and the number of new listings (red bars) in each month. When the red bars overlap with the blue bars, the color becomes darker. Note that the number of transactions surpasses the number of newly listed properties in a month when house prices increase quickly, suggesting that when a housing market is "hot", housing demand is high relative to supply, and the market is liquid.

The bottom panel of Figure A.2 plots the average mortgage interest rate and down payment requirement for households' first home purchases in Beijing. The average interest rate started from around 4.2 percentage points in early 2016, and experienced a sharp increase in the first half of 2017, reaching 5.5 percentage points by the end of 2017. Down payment requirements also increased from 30% in 2016 to 40% by the end of 2017. Along with the mortgage credit tightening, house prices fell and the number of transactions dropped. There were more new property listings than transactions, suggesting an increase in housing supply relative to demand and a decrease in market liquidity. This was not only the case in Beijing: across the fifteen major cities, the average monthly house price growth rate at the residential zone level declined from 2% before March 2017 to 1.1% afterward.

These findings suggest the influential role of mortgage credit but reveal little of the underlying mechanism. To evaluate the effect of mortgage credit conditions on housing market outcomes, it is necessary to analyze the transmission mechanism – how mortgage interest rates and down payment requirements affect households' purchasing and selling decisions, market liquidity, the relative market power, and ultimately house prices. Quantifying the effect of mortgage credit conditions on housing market microstructure is both important and challenging.

A.1.3 Mortgage Credit Conditions

The sharp change in mortgage credit conditions started from March 2017 was a nationwide shock, as all cities responded to the policy. The top panel of Figure A.4 shows the average mortgage interest rate for the 15 cities in the sample. Almost all cities started to increase mortgage interest rates significantly after March 2017. The bottom panel plot how average down payment requirements change over time in the 15 cities. The average down payment requirement increased after March

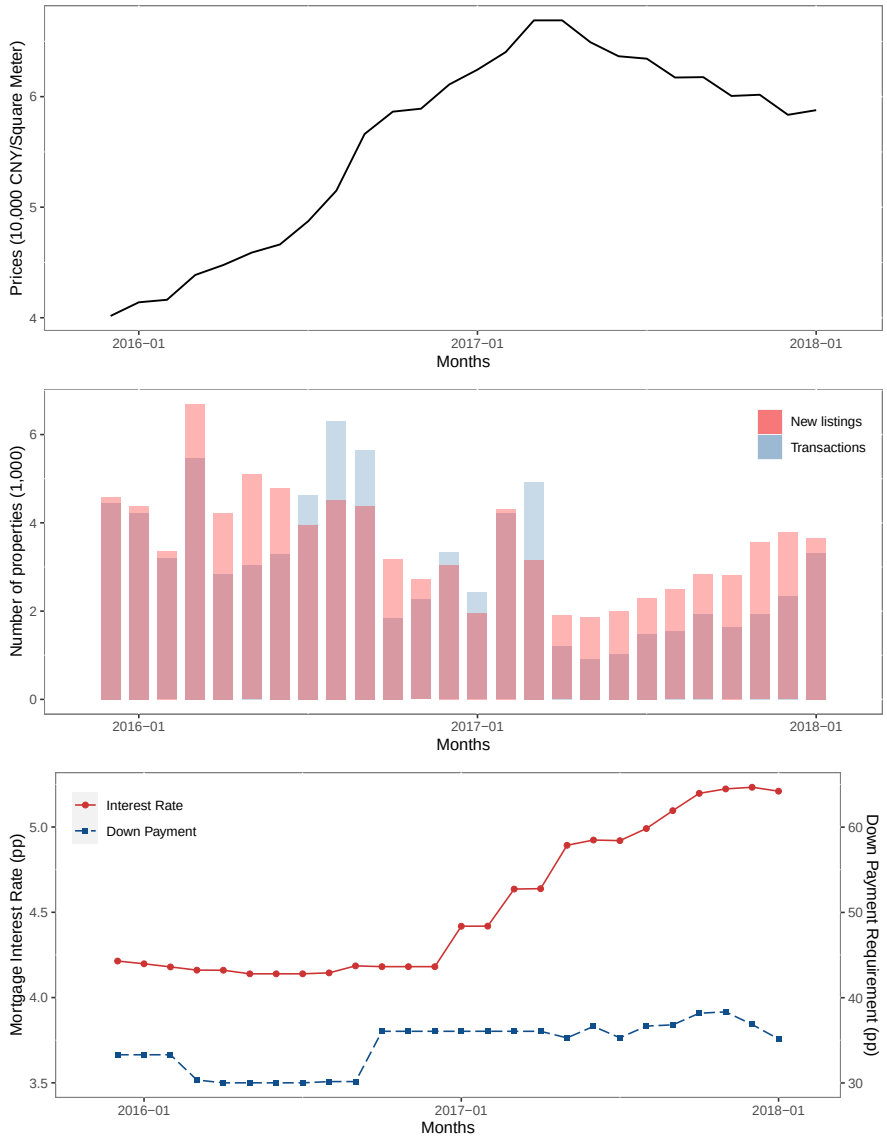


Figure A.2: House Prices, Transaction Volumes, and Mortgage Interest Rates: The Example of Beijing

Note: The top panel plots the average house prices in 10,000 CNY per square meter for Beijing from December 2015 to January 2018. In the middle panel, the red bar indicates the number of new properties (in 1,000) listed in the market in that month, while the blue bar shows the number of transactions (in 10,000) that occurred in that month. The bottom panel illustrates the variation in mortgage market conditions. The red solid line shows the average mortgage interest rate, and the blue dashed line plots the down payment requirements.

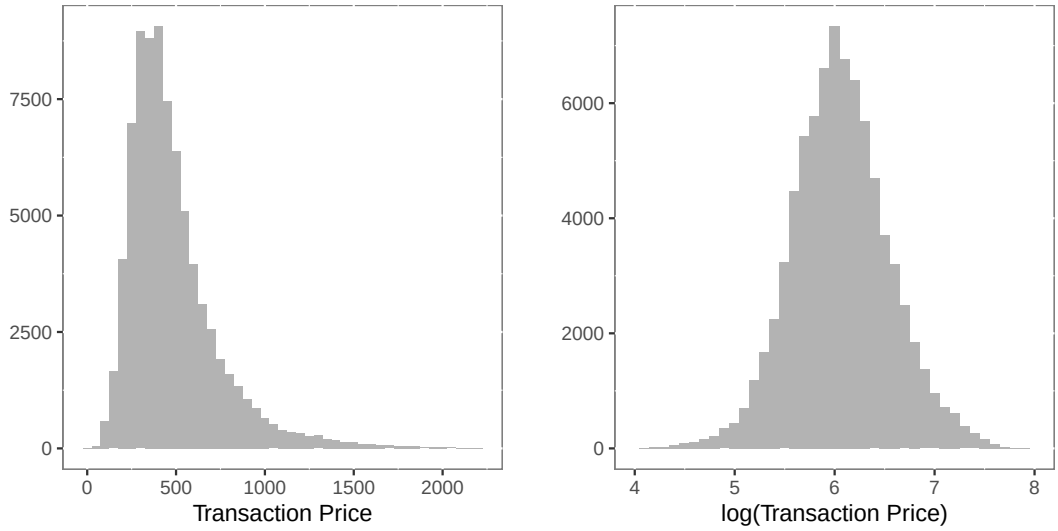


Figure A.3: The Distribution of House Prices: The Example of Beijing

Note: This figure plots the distribution of transaction prices of Beijing during the sample period. The left subfigure illustrates the distribution of transaction prices (in 10,000 CNY) for all property types. The right subfigure plots the distribution of the logarithm of transaction prices for all property types.

2017 in almost all cities at different levels. Moreover, almost all banks responded to the policy. As shown in Figure A.5, in March 2017, almost all banks offer a discount on mortgage interest rates, i.e., below 4.9%, in the 15 cities, while in June 2017 most banks increased their mortgage interest rate above the benchmark rate.

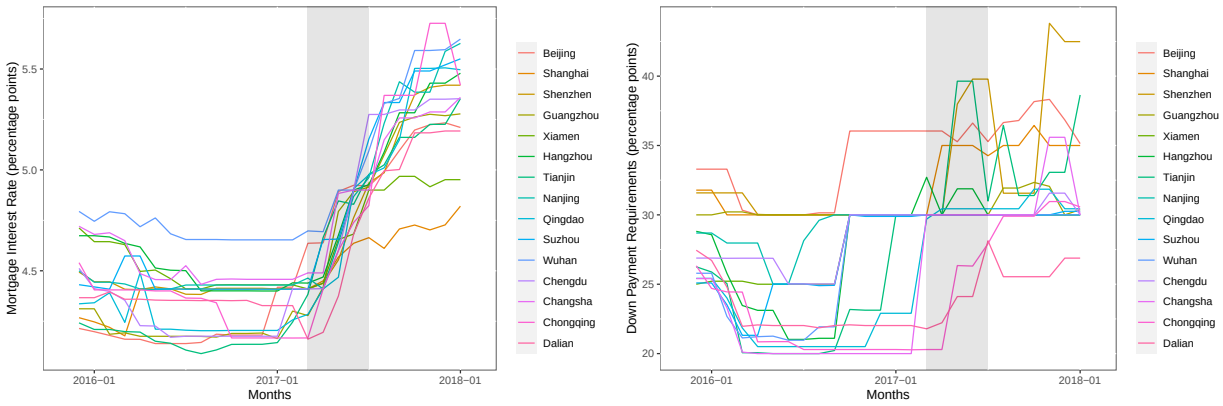


Figure A.4: Mortgage Credit Conditions over the Sample period

Note: This figure documents how mortgage credit conditions change over the whole sample periods for the 15 cities. The left panel is for the average mortgage interest rate, and the right panel is for the average down payment requirements.

A.1.4 Other Regulations in Real Estate Markets

Besides mortgage credit interventions, other policies have been implemented in Chinese local real estate markets in response to an over-heated market, for example, the limited purchase policy and limited sale policy. The limited purchase policy, introduced between 2010 and 2011, aimed to curb

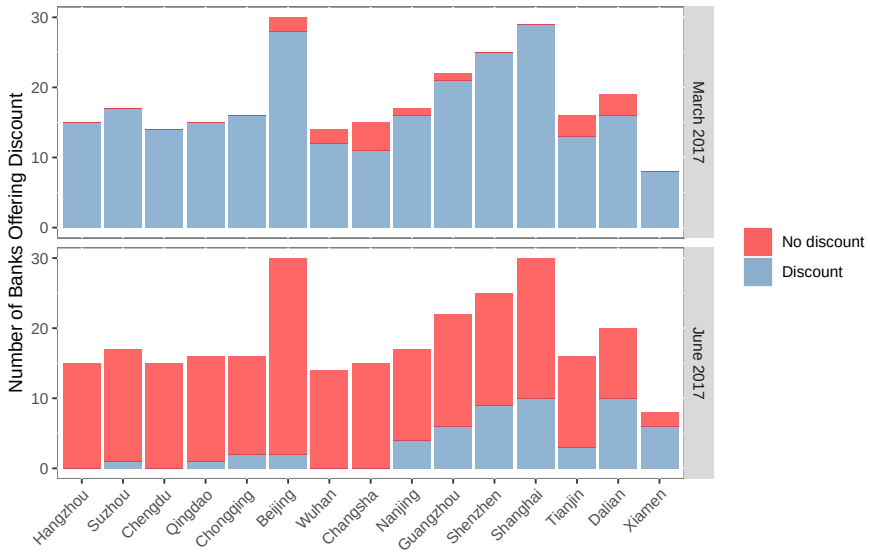


Figure A.5: The Number of Banks Offering Discount on Mortgage Interest Rates in March and June 2017

Note: This figure shows the number of banks that offer discount on mortgage interest rates, that is, mortgage interest rates below 4.9 percentage points in April 2017 and in June 2017.

speculative home purchasing by prohibiting households from buying a second or third residential property. Meanwhile, the limited sale policy, which requires a minimum holding period before selling the property, was introduced in 2017 in some cities. Table A.2 reports the cities that introduced the policy, the time of introduction, and the minimum required holding period.

Table A.2: The Introduction of the Limited Sales Policy

City	**Introduction of the LSP**	**Minimum Years**
Xiamen	2017.3	2
Guangzhou	2017.3	2
Qingdao	2017.3	2
Beijing	2017.3	3
Hangzhou	2017.3	3
Chengdu	2017.4	3
Changsha	2017.5	2
Nanjing	2017.5	3
Chongqing	2017.9	2

Note: This table reports the introduction of the limited sale policy in major cities in China. Data are collected from the websites of the Housing and Urban-Rural Development Commission of each cities.

A.2 Expected Value Functions

A.2.1 Assumptions

To simplify the model, I follow the regular assumptions of Conditional Independence (CI) and i.i.d. unobservables $\varepsilon_{i,t}$ (IID). The standard Conditional Independence (CI) assumption assumes that conditional on the current values of decision and observable state variables, next period's unobservable state variables do not depend on current unobservables. CI and IDD assumptions of $\varepsilon_{i,t}$ lead to

$$F(\Omega_{j,t+1}, S_{i,t+1}, \varepsilon_{i,t+1} \mid \Omega_{j,l,t}, S_{i,t}, \varepsilon_{i,t}, d_{i,t}) = F_{\varepsilon}(\varepsilon_{i,t+1}) F(\Omega_{j,t+1}, S_{i,t+1} \mid \Omega_{j,l,t}, S_{i,t}, d_{i,t}).$$

Since $S_{i,t}$ is also an unobservable state variable, I make another conditional independence assumption that whether there exists a bid in the next period $S_{i,t+1}$ do not depend on that of the current period $S_{i,t}$ conditional on the current state $\Omega_{j,l,t}$, that is,

$$F(\Omega_{j,t+1}, S_{i,t+1} \mid \Omega_{j,l,t}, S_{i,t}, d_{i,t}) = F_S(S_{i,t+1} \mid \Omega_{j,t+1}) F_{\Omega}(\Omega_{j,t+1} \mid \Omega_{j,l,t}, d_{i,t}).$$

This assumption implies that the incidence of an incoming bid is only determined by property attributes and current market conditions. Finally, assuming that individual households' action cannot affect macroeconomic conditions, $F_{\Omega}(\Omega_{j,t+1} \mid \Omega_{j,l,t}, d_{i,t}) = F_{\Omega}(\Omega_{j,t+1} \mid \Omega_{j,l,t})$. As a result, the conditional probability of the state variables can be divided into three parts:

$$F(\Omega_{j,t+1}, S_{i,t+1}, \varepsilon_{i,t+1} \mid \Omega_{j,l,t}, S_{i,t}, \varepsilon_{i,t}, d_{i,t}) = F_{\varepsilon}(\varepsilon_{i,t+1}) F_S(S_{i,t+1} \mid \Omega_{j,t+1}) F_{\Omega}(\Omega_{j,t+1} \mid \Omega_{j,l,t}). \quad (32)$$

A.2.2 Expected value functions in waiting and decision states

Denote $V(\Omega_{j,l,t}, \varepsilon_{i,t}, d_{i,t-1})$ the choice specific value function of choosing a type j property ownership in time period t, that is

$$V(\Omega_{j,l,t}, \varepsilon_{i,t}, d_{i,t-1}) \;=\; u^A(\Omega_{j,l,t}, \varepsilon_{i,j,l,t}, d_{i,t-1}) + \beta \mathbb{E}\left[V(\Omega_{t+1}, \varepsilon_{i,t+1}, d_{i,t}) \;\middle|\; \Omega_t, S_{i,t}, \varepsilon_{i,t}, d_{i,t} = \{j, l\} \right].$$

It has a similar form as the value function defined in equation (4). The only difference is that we know the the utility of in time period t is generated by the type j property ownership. Therefore,

$$V(\Omega_t, \varepsilon_{i,t}, d_{i,t-1}) = \max_{\{j,l\} \in \mathcal{D}_{i,t}} V(\Omega_{j,l,t}, \varepsilon_{i,t}, d_{i,t-1}).$$

Given the probability structure in equation (32), we can easily take the expectation of the choice-specific value function with respect to $\varepsilon_{i,t}$. Denote the the expected choice specific value function

by

$$\begin{aligned}\overline{V}(\Omega_{j,l,t}, j^-, l^-) &= \delta(\Omega_{j,l,t}) + \mathbb{1}_{\{l^- \neq l \wedge j^- \neq j\}} k + \mathbb{1}_{\{j^- \neq j\}} \chi(\Omega_{j,l,t}, h_{i,t-1}) + \\ &\quad \beta \mathbb{E}\left[\mathbb{E}_\varepsilon[V(\Omega_{t+1}, \varepsilon_{i,t+1}, d_{i,t} = \{j,l\})] \,\middle|\, \Omega_t, S_{i,t}\right], \end{aligned} \tag{33}$$

where

$$\mathbb{E}_\varepsilon[V(\Omega_{t+1}, \varepsilon_{i,t+1}, d_{i,t} = \{j,l\})] = \mathbb{E}_\varepsilon\left[\max_{\{j^+,l^+\} \in \mathcal{D}_{i,t+1}} V(\Omega_{j^+,t+1}, \varepsilon_{i,t+1}, d_{i,t} = \{j,l\})\right] \tag{34}$$

$$= \mathbb{E}_\varepsilon\left[\max_{\{j^+,l^+\} \in \mathcal{D}_{i,t+1}} \left\{\overline{V}(\Omega_{j^+,t+1}, j, l) + \varepsilon_{i,t+1}\right\}\right] \tag{35}$$

$$= \ln\left(\sum_{\{j^+,l^+\} \in \mathcal{D}_{i,t+1}} \exp\left(\overline{V}(\Omega_{k^+,t+1}, j, l)\right)\right). \tag{36}$$

The last equality comes from the type I extreme value distributed ε_{it}, which has the probability density function $f(\varepsilon) = e^\varepsilon \exp(-e^\varepsilon)$.

A.2.3 Notations for the choice-specific expected value functions

Table A.3: Table of Notation for Expected Value Functions

Agent Type	Action	Value Function	Description
Owner	Stay	$v^{j,0}_{j,0,t}$	Expected value of staying in property
Owner	List	$v^{j,0}_{j,1,t}$	Expected value of listing the property
Seller	Hold	$v^{j,1}_{j,1,t}$	Expected value of holding the listing
Seller	Sell	$v^{j,1}_{0,0,t}$	Expected value of selling the property
Non-owner	Stay	$v^{0,0}_{0,0,t}$	Expected value of continuing to rent
Non-owner	Search	$v^{0,0}_{0,1,t}$	Expected value of entering the buyer pool
Buyer	Rent	$v^{0,1}_{0,1,t}$	Expected value of continue renting and searching
Buyer	Purchase	$v^{0,1}_{j,0,t}$	Expected value of purchasing property j

A.3 Model Estimation

A.3.1 Estimating the Normalized Value Function

Instead of using the empirical probability $\widehat{\pi}_{jmt}$ that gives the same weight to each property type, the substitutability of other types is considered by weighting the similarity of other types to type j. The empirical probability is approximated by

$$\widehat{\widehat{\pi}}_{jmt} = \frac{\sum_{i=1}^{N_{mt}} 1_{[d_{imt}=j]} \cdot W_i^j}{\sum_{i=1}^{N_{mt}} W_i^j},$$

where N_{mt} is the number of all transactions in market m at time t, and W_i^j is the kernel weight that specifies how close the property type of each transaction i is to type j in the type space. If transaction i's property type is far away from type j, then observation i is less informative for the popularity of type j, and thus the weight should be lower. The weight is defined as a product of three normal kernel weights

$$W_i^j = \prod_{l=1}^{L} \frac{1}{b_l} \psi \left(\frac{X_{i,k(l)} - X_{j(l)}}{b_l} \right),$$

where L is the dimension of X_j (i.e., age, size, and district). For each standard normal kernel ψ, b_l is determined by cross validation. The lth attribute of a type j property and the lth attribute of a property i is denoted by $X_{j(l)}$ and $X_{i,k(l)}$ respectively.

A.3.2 The Probability of Winning Bids

To be the highest bid among n bids, the bidder's private valuation must be higher than the other $n-1$ bidders. According to the nth order statistics, the density of the nth highest bid is

$$f^{(n)}(\nu; \sigma_m) = n\Psi(\frac{\nu}{\sigma_m})^{n-1}\psi(\frac{\nu}{\sigma_m}), \text{ for } n \geq 1,$$

where $\Psi(\cdot)$ and $\psi(\cdot)$ are the cumulative and density probability function of the standard normal distribution. Notice that the nth order density is well-defined for $n \geq 1$. The probability density that a bidder with private valuation ν wins a type j property equals the sum of nth order densities $f^{(n)}(\nu, \sigma_m)$ weighted by the probability of receiving n bids, conditional on having received at least one bid $n \geq 1$,

$$f(\nu; \sigma_m, \lambda_{j,m,t}) = \sum_{n=1}^{\infty} \underbrace{\frac{{\lambda_{j,m,t}}^n e^{-\lambda_{j,m,t}}}{q_{j,m,t} n!}}_{\text{prob(n bids } \mid n \geq 1)} \underbrace{f^{(n)}(\nu; \sigma_m)}_{\text{prob}(\nu \text{ wins } \mid n \geq 1 \text{ bids})}.$$

After maximum likelihood estimation obtaining the estimates for $\{\widehat{\eta}_j, \widehat{\sigma}_m\}$, house prices of a property type are determined as the expected highest bid,

$$\widehat{P}_{j,m,t} = \int \exp(\widehat{\eta}_j X_j + \widehat{\phi}_\lambda + \nu) f(\nu, \widehat{\sigma}_m, \widehat{\lambda}_{j,m,t}) \mathrm{d}\nu = \sum_{n=1}^{\infty} \frac{\widehat{\lambda}_{j,m,t}^n e^{-\widehat{\lambda}_{j,m,t}}}{\widehat{q}_{j,m,t} n!} \int \exp(\widehat{\eta}_j X_j + \widehat{\phi}_\lambda + \nu) f^{(n)}(\nu, \widehat{\sigma}_m) \mathrm{d}\nu. \tag{37}$$

The integral is computed via simulation, considering a maximum of 50 bids, as the empirical probability of receiving more than 20 bids is very low.

A.3.3 Data Variation, Estimation Steps, and Identification

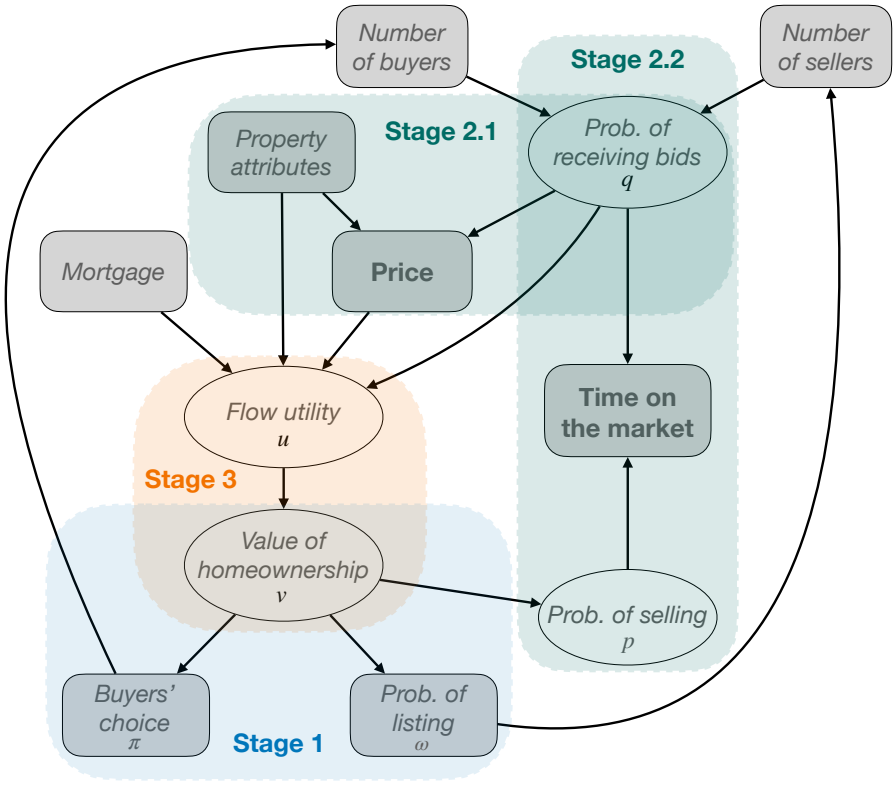


Figure A.6: Estimation Steps and Key Variables

Note: This figure illustrates the steps involved in estimating the model and highlights the key variables used for identification. The grey boxes indicate variables that are observable in the data, while the white ovals represent model variables that are not directly observable. The model is estimated in three stages.

Table A.4: Key Model Parameters and Sources of Identification

Parameter	**Definition**	**Source of Identification**
$\lambda_{j,m,t}$	Arrival rate of potential buyers	Number of likes and visits for a listed property per period
ψ_m	Bidding multiplier	The relationship between the arrival rates of potential buyers and the observed number of buyers and sellers
η_j	Valuation of housing attributes	Distribution of average transaction prices across property types
σ_m	Dispersion of private valuations	Distribution of transaction prices within property types
k_m	Non-monetary cost of selling	Homeowners' decisions of listing across different markets
$\alpha^w_{m,t}$	Marginal utility of wealth	Given the arrival rate of buyers, sellers decision of selling across different type of houses, market conditions, and mortgage conditions (in particular down payment requirements)
$\alpha^y_{m,t}$	Marginal utility of income	Given the arrival rate of buyers, sellers decision of selling across different type of houses, market conditions, and mortgage conditions (in particular mortgage interest rates)
α^x	Marginal utility of property attributes	Given the user cost, households' demand for properties with certain characteristics.

A.4 Additional Estimation Results

A.4.1 Bidding Prices and Market Liquidity

Table A.5 summarizes the estimates for bidding prices and liquidity from buyers and sellers, market liquidity and sellers' relative market power. The first row reports the weighted average estimates of the fifteen major cities, and the subsequent rows report the estimates for each local market. The first column presents the variation of bidders' private valuation of properties $\widehat{\sigma}_m$. A standard deviation increase in household private valuation raises the bidding price by 29% on average. Buyers in Shenzhen have the lowest variation in idiosyncratic valuation, where a standard deviation increase in private valuation leads to a 23% increase in bidding prices, whereas those in Xiamen have the highest, resulting in a 36% increase.

The second and third columns report the mean and standard deviation of the probability of receiving bids and the probability of selling, which indicate housing market liquidity from buyers and sellers, respectively. On average, the probability of receiving bids in a month is 0.71 in the fifteen cities, and there is a large variation across cities. For example, sellers in Beijing have the highest probability of receiving bids, which is more than three times higher than that of sellers in Shanghai and Suzhou. The average probability of selling if bids are received is 0.64, with a relatively smaller variation across cities compared with the probability of receiving bids. The product of the two probabilities represents the probability of having a transaction for a listed property in each time period, a measure for market liquidity, which is reported in the fourth column of Table A.5. The last column reports the relative magnitude of the probability of receiving bids $\widehat{q}_{j,m,t}$ to the probability of selling to bidders $\widehat{p}_{j,m,t}$, which serves as a measure of sellers' relative market power.

A.4.2 Alternative Assumption on Outstanding Mortgage Debt

Table A.6 presents the estimates of utility and value functions under the alternative assumption that sellers have no remaining mortgage debt at the time of sale. Overall, the estimates are similar to those in Table 2, with the estimated wealth effect being slightly lower under this assumption. Under the alternative assumption, a 10,000 CNY increase in liquid wealth results in a 0.6% increase in the median value of homeownership, and the same increase in annual income leads to an 11.3% increase in the median value of homeownership.

A.4.3 Market Liquidity Dynamics for Local Housing Markets

Figure A.7 illustrates the market liquidity overtime for the 15 major local housing markets, and Figure A.8 decomposes the dynamic of market liquidity provision from buyers and sellers.

Table A.5: Estimation Results: House Prices and Market Liquidity

	Variation of Bids ($\widehat{\sigma}_m$)	Liquidity from Buyer ($\widehat{q}_{j,m,t}$)	Liquidity from Seller ($\widehat{p}_{j,m,t}$)	Market Liquidity ($\widehat{q}_{j,m,t}\widehat{p}_{j,m,t}$)	Sellers' Market Power ($\widehat{q}_{j,m,t}/\widehat{p}_{j,m,t}$)
Overall	0.29	0.71	0.64	0.44	1.35
Beijing	0.28	0.86	0.65	0.54	1.76
	(0.00)	[0.17]	[0.24]	[0.19]	[1.59]
Changsha	0.26	0.68	0.66	0.44	1.19
	(0.01)	[0.21]	[0.22]	[0.18]	[0.59]
Chengdu	0.32	0.78	0.61	0.47	1.39
	(0.00)	[0.19]	[0.17]	[0.17]	[0.53]
Chongqing	0.26	0.70	0.59	0.40	1.39
	(0.00)	[0.17]	[0.18]	[0.13]	[0.87]
Dalian	0.24	0.57	0.58	0.32	1.18
	(0.00)	[0.18]	[0.19]	[0.13]	[0.73]
Guangzhou	0.31	0.62	0.66	0.40	1.05
	(0.00)	[0.19]	[0.20]	[0.17]	[0.50]
Hangzhou	0.31	0.60	0.63	0.38	1.06
	(0.00)	[0.19]	[0.17]	[0.15]	[0.57]
Nanjing	0.27	0.71	0.61	0.43	1.30
	(0.00)	[0.11]	[0.17]	[0.13]	[0.54]
Qingdao	0.27	0.58	0.66	0.35	1.52
	(0.00)	[0.28]	[0.24]	[0.17]	[3.64]
Shanghai	0.30	0.23	0.83	0.19	0.30
	(0.02)	[0.16]	[0.16]	[0.13]	[0.26]
Shenzhen	0.23	0.65	0.56	0.36	1.33
	(0.00)	[0.13]	[0.20]	[0.14]	[0.62]
Suzhou	0.30	0.23	0.75	0.16	0.36
	(0.07)	[0.13]	[0.18]	[0.08]	[0.36]
Tianjin	0.32	0.69	0.69	0.47	1.08
	(0.00)	[0.14]	[0.18]	[0.15]	[0.42]
Xiamen	0.36	0.67	0.66	0.43	1.10
	(0.02)	[0.17]	[0.16]	[0.14]	[0.48]
Wuhan	0.29	0.76	0.61	0.46	1.40
	(0.00)	[0.18]	[0.18]	[0.17]	[0.62]

This table summarizes the estimation results for the variation of biding prices, liquidity from buyers, from sellers, market liquidity, and sellers' relative market power for each city. The first column reports the estimates for the variation of incoming bids ($\widehat{\sigma}_m$) with standard errors reported in parentheses. The second and third columns report the mean and the standard deviation (in brackets) of the estimated liquidity from buyer $\widehat{q}_{j,m,t}$ and from seller $\widehat{p}_{j,m,t}$. The last two columns report the estimated average market liquidity ($\widehat{q}_{j,m,t}\widehat{p}_{j,m,t}$) and sellers' market power ($\widehat{q}_{j,m,t}/\widehat{p}_{j,m,t}$) with standard deviation in brackets for each city.

Table A.6: Estimates for Utility and Value Function under Alternative Assumption

	Estimate	Std. Err.
Panel A		
Wealth (α^w)		
Constant	4.630	(0.001)
Saving	-0.158	(0.000)
LSP	0.053	(0.002)
Income (α^y)		
Constant	4.709	(0.001)
Saving	-0.155	(0.000)
LSP	0.033	(0.002)
Panel B		
Property attributes (α^x)		
Size	0.002	(0.001)
Size^2	-0.000	(0.000)
Age	0.003	(0.001)
Age^2	-0.0001	(0.000)

This table presents key estimates for utility and value functions under the assumption that sellers have no remaining mortgage debt at the time of selling. The first column reports the estimated parameters and the second column reports standard errors. Estimates in Panel A are obtained from maximum likelihood estimation. Two sets of estimates are reported in the table: the impact of Wealth (measured in 1 Million CNY) and Income (measured in 1 Million CNY) on households' utility. Saving is denominated in unites of 10,000 CNY. LSP is a dummy variable taking value of one if restrictive selling policy was implemented, and zero otherwise. Estimates in Panel B are obtained from OLS regression. Size and Age are the median living space of a property type and the median age of a property type, respectively. City fixed effects and time fixed effects are included in the regression.

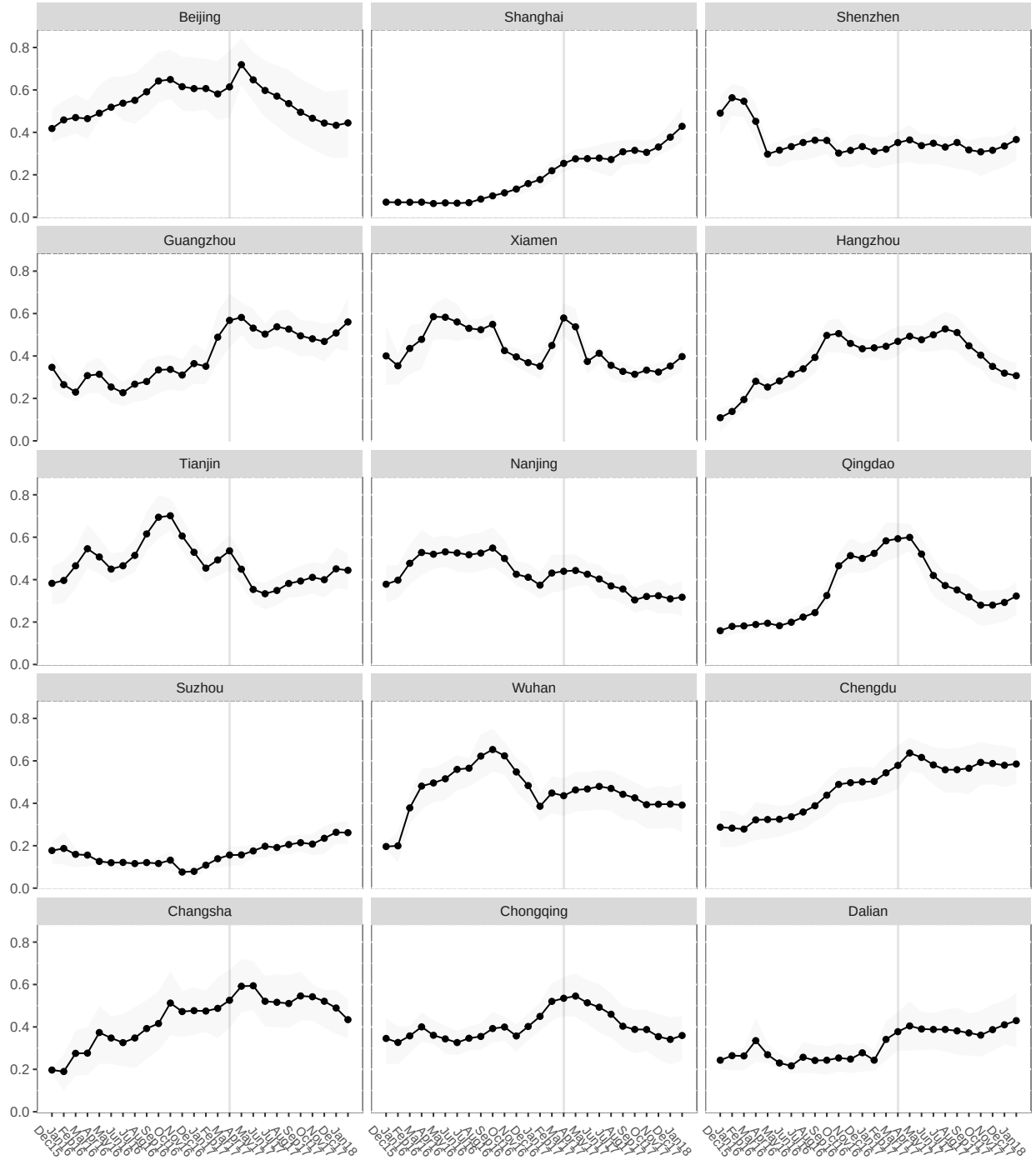


Figure A.7: Market Liquidity for Each Market

Note: This figure plots the dynamics of market liquidity, defined as the product of the probability of receiving bids from buyers and the probability of selling conditional on receiving bids. The shaded area corresponds to the 25th and 75th percentiles.

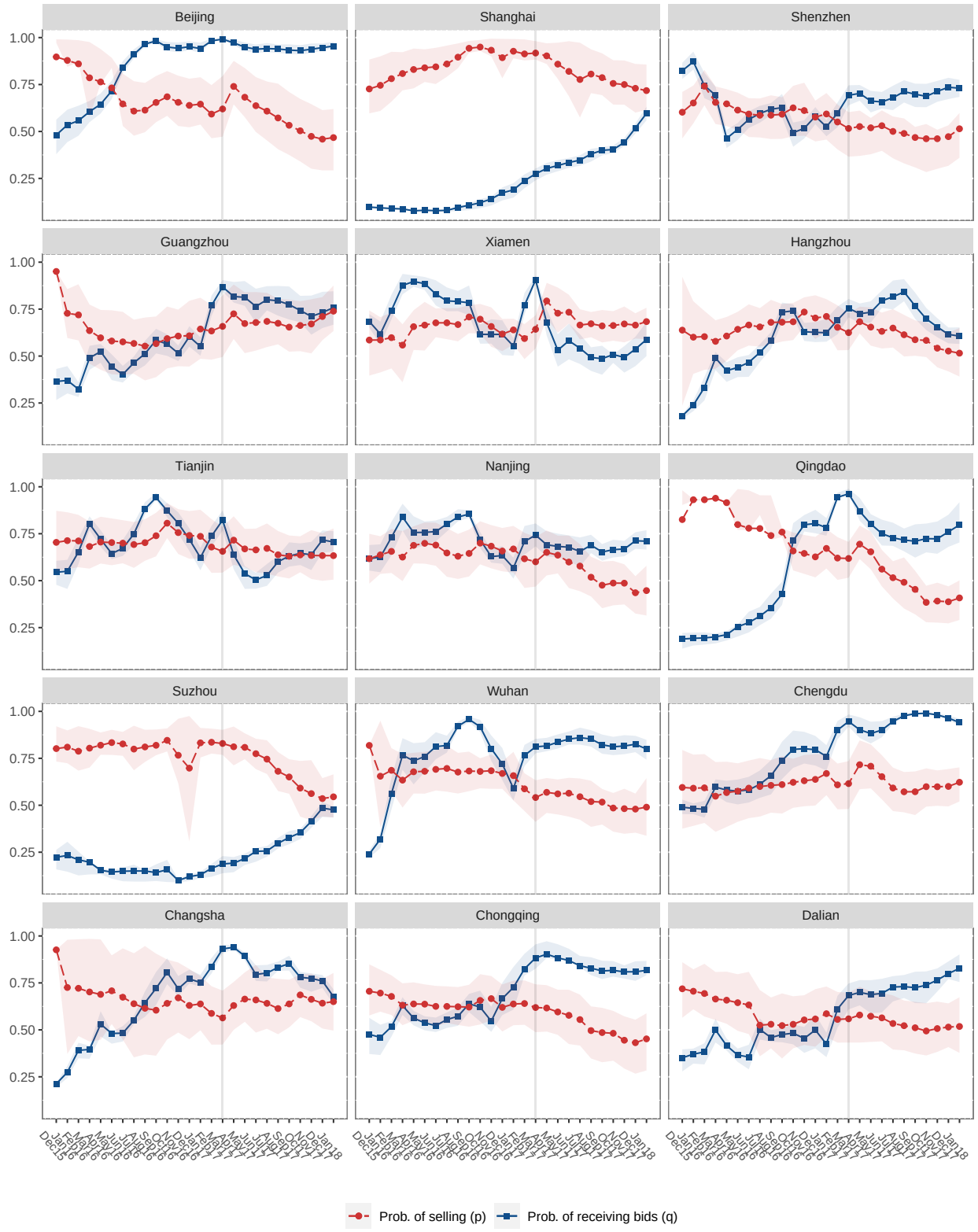


Figure A.8: Liquidity from Buyers and Sellers for Each Market

Note: This figure plots the probability of receiving bids from buyers and the probability of selling conditional on receiving bids, corresponding to the liquidity from buyers and sellers respectively. The shaded area corresponds to the 25th and 75th percentiles.

A.4.4 Model Fit

This section presents the model performance by comparing the model predicted house price $\widehat{P}_{j,m,t}$, hazard rate and its implied survival probability using the estimated $\widehat{q}_{j,m,t}$ and $\widehat{p}_{j,m,t}$. The hazard rate of property i that belongs to type j in market m after s months since listing is obtained from $\widehat{h}_i(s) = \widehat{q}_{j,m,t_{i,0}+s} \times \widehat{p}_{j,m,t_{i,0}+s}$. The survival probability is

$$\widehat{S}_i(s) = \prod_{\tau=1}^{s} (1 - \widehat{q}_{j,m,t_{i,0}+\tau} \times \widehat{p}_{j,m,t_{i,0}+\tau}).$$

Figure A.9 shows the distribution of observed and predicted house prices for the 15 major cities. The horizontal axis is the logarithm of house prices in 1 Million CNY. Blue dashed lines stand for observed prices, while red solid lines stand for predicted prices. Figure A.10 plots the average hazard rate of selling a property by the time on the market, i.e., the probability of having a transaction in that time period given that the property is still on the market. The horizontal axis is the number of months that have passed since the listing. The blue dashed line is for observed hazard rates, while the red solid line is for model predicted hazard rates. Figure A.11 shows the average survival probability, i.e., the probability that a property has not been sold after several months. The blue dashed line is for observed survival probability while the red solid line is for the model prediction. Comparing the model estimated hazard rate and survival probability with their respective data suggests that the model provides a good fit in general. For hazard rate, model predictions are less volatile than actual data, but with similar magnitudes. For the survival probability, the model estimation is very close to the actual realization.

A.4.5 Non-Monetary Cost of Selling

The estimates for the non-monetary cost of selling a property range from 2.46 in Suzhou to 4.47 in Qingdao, which corresponds to 39.6% and 77.9% of the average value of homeownership in these two cities. The substantial non-monetary costs are reflected in the relatively small fraction of homeowners who choose to list their properties for sale. This aligns with the high non-monetary benefits of homeownership in China, such as school admission advantages, an underdeveloped rental market, and weak tenant protections.

A.4.6 Extrapolative Beliefs

Table A.8 reports the final set of estimates for households' belief about future states, as defined in equation (29). Households' beliefs about the future value of homeownership are based on past value functions, as well as house prices and mortgage conditions. The transition weights for these past value functions are allowed to be market-specific. The average estimate for the one-period lagged coefficient on value functions is 0.208 for homeowners (with a standard deviation of 0.184) and

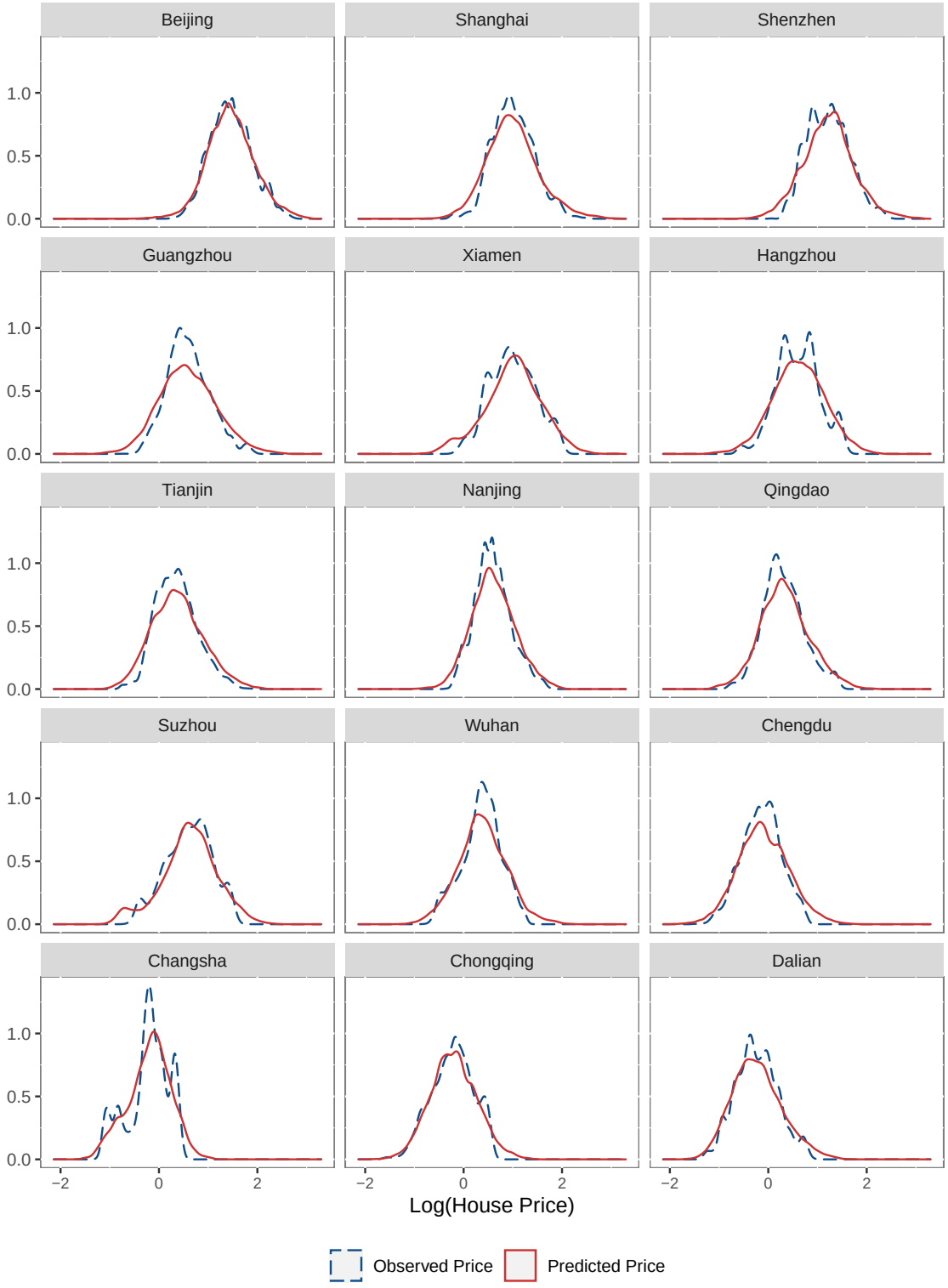


Figure A.9: House Prices

Note: This figure plots the observed and estimated house prices for the 15 major cities. The horizontal axis is the logarithm of house prices (in 1 Million CNY). Blue dashed lines stand for observed results. Red solid lines stand for model estimated results.

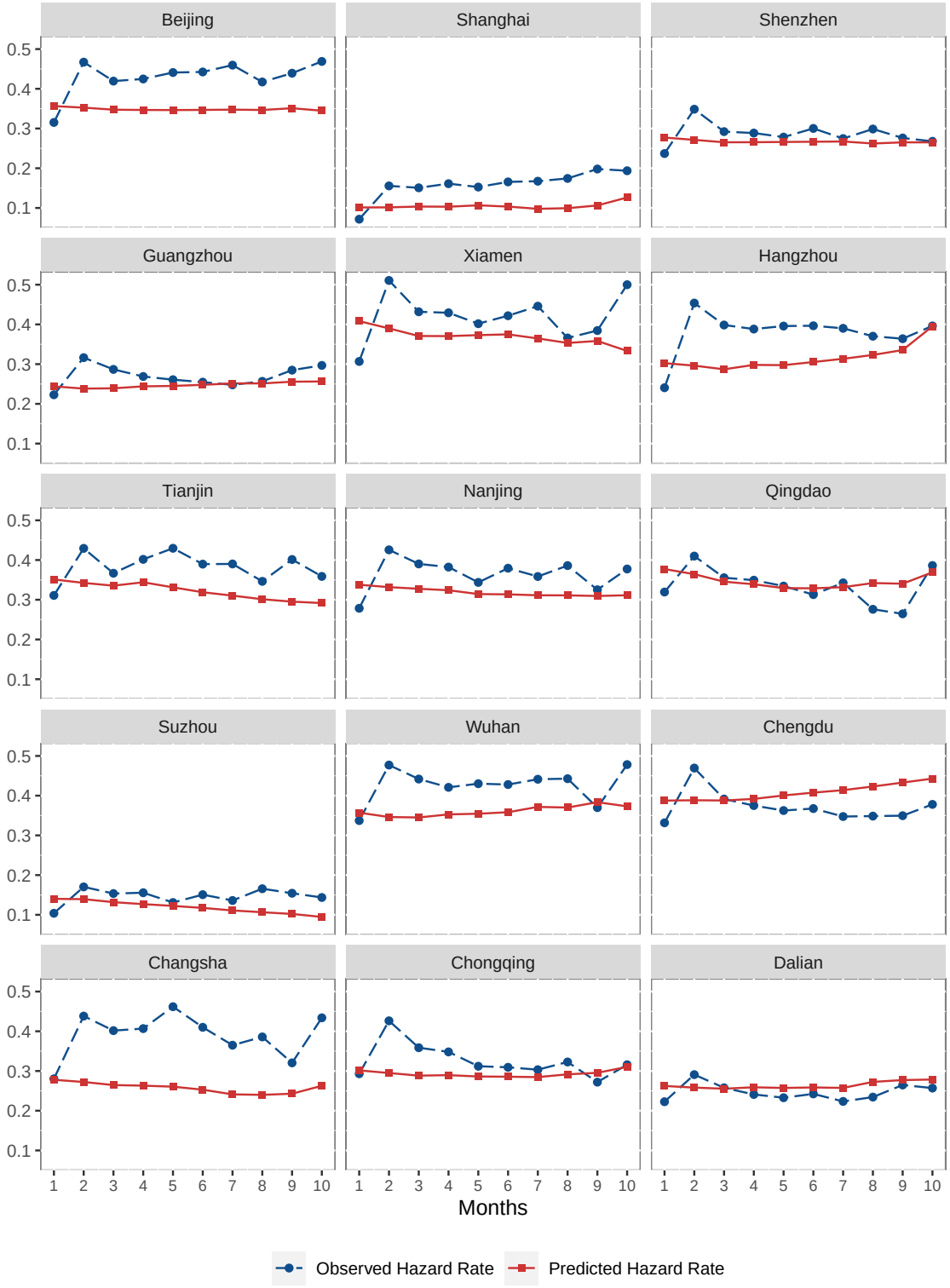


Figure A.10: Hazard Rate

Note: This figure plots the observed and estimated hazard rate for the 15 major cities. The horizontal axis is the number of months that has been past since listing. Blue dashed lines stand for observed results. Red solid lines stand for model estimated results.

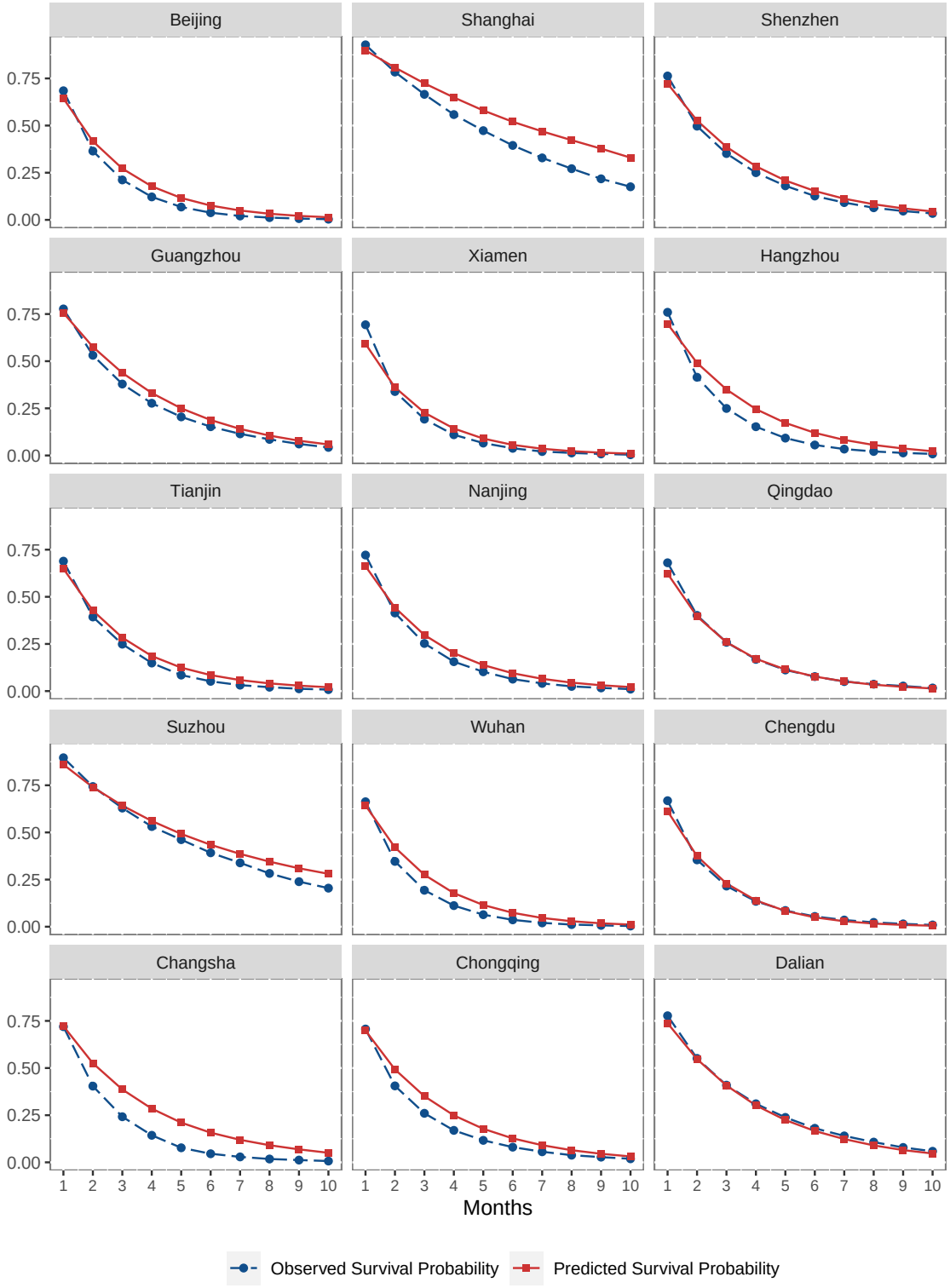


Figure A.11: Survival Probability

Note: This figure plots the observed and estimated survival probability for the 15 major cities. The horizontal axis is the number of months that has been past since listing. Blue dashed lines stand for observed results. Red solid lines stand for model estimated results.

Table A.7: Estimates for Non-Monetary Cost of Selling

	Estimate	Std. Err.
Non-Monetary Cost (k)		
Beijing	3.556	(0.007)
Changsha	3.260	(0.022)
Chengdu	4.382	(0.003)
Chongqing	3.533	(0.009)
Dalian	3.977	(0.003)
Guangzhou	3.649	(0.002)
Hangzhou	4.019	(0.016)
Nanjing	4.164	(0.013)
Qingdao	4.526	(0.019)
Shanghai	3.379	(0.002)
Shenzhen	4.157	(0.011)
Suzhou	2.509	(0.002)
Tianjin	3.957	(0.010)
Wuhan	4.076	(0.014)
Xiamen	4.707	(0.041)

This table presents the estimates of sellers' non-monetary costs of listing in each city. The first column reports the estimated parameters and the second column reports standard errors.

0.231 for sellers (with a standard deviation of 0.201). The mean of the two-period lagged coefficient estimate is 0.076 for homeowners and 0.101 for sellers. Past house prices and mortgage interest rates exhibit both momentum and mean-reversion effects on households' extrapolative beliefs regarding the future value of ownership, while past down payment requirements show economically insignificant effect. These relationships are utilized to form expectations in counterfactual analyses.

Table A.8: Extrapolative belief on Expected Value Function

	Value Function		House Price		Interest Rate		Down Payment	
	$\zeta_m^{v,t-1}$	$\zeta_m^{v,t-2}$	$\zeta^{P,t-1}$	$\zeta^{P,t-2}$	$\zeta^{I,t-1}$	$\zeta^{I,t-2}$	$\zeta^{D,t-1}$	$\zeta^{D,t-2}$
Panel A: Home Owners								
Coefficient	0.208	0.076	1.625	-1.104	0.560	-0.345	0.003	0.009
S.D./S.E	[0.184]	[0.128]	(0.024)	(0.023)	(0.018)	(0.017)	(0.001)	(0.001)
Panel B: Home Sellers								
Coefficient	0.231	0.101	1.764	-1.489	0.513	-0.412	-0.009	0.006
S.D./S.E	[0.201]	[0.134]	(0.025)	(0.025)	(0.019)	(0.019)	(0.001)	(0.001)

Note: This table reports the estimated determinants of how house prices and mortgage conditions in the past two periods affect the expected value of homeownership for homeowners (Panel A) and sellers (Panel B), as defined in equation (29). These coefficients form the basis on which households form expectation of the future value of homeownership. Standard deviation are shown in brackets while standard errors are shown in parentheses.

A.5 Additional Counterfactual Results

Table A.9: Counterfactual Increase in Mortgage Interest Rates: No Expectation Channel

	Overall	**Size**		**Location**	
		Small	Large	Suburban	Urban
	(1)	(2)	(3)	(4)	(5)
Panel A: Housing Markets					
Property Type Level					
Prob. of Listing	0.0	0.0	0.0	0.0	0.0
Prob. of Receiving Bids	0.1	3.7	-2.9	1.5	-0.8
Prob. of Accepting Bids	0.0	0.3	-0.3	0.1	-0.1
Highest Bids	0.0	0.8	-0.4	0.3	-0.1
Market-Time Level					
Number of Transaction	-1.7	6.0	-7.5	1.3	-2.7
Average Transaction Price	-6.3	-0.2	-5.7	-3.4	-7.1
Panel B: Household Welfare					
Home Owner	0.0	0.1	-0.1	0.0	-0.0
Home Buyer	-123.3	-87.9	-152.5	-116.5	-127.6
Home Seller	0.1	3.3	-4.7	1.9	-1.2

Note: This table summarizes the median percentage changes in market outcomes and household welfare in the counterfactual increase in mortgage interest rates without the expectation channel at work. Panel A reports the counterfactual results for the probability of listing, probability of receiving bids, the probability of accepting bids, the highest bids, the number of transactions, and the market-level transaction prices. Panel B reports the median of welfare changes (in one thousand CNY) for homeowners, buyers, and sellers. Columns (1) corresponds to the overall policy impact on all housing products and markets, while the last four columns correspond to the policy change with different market segments, such as product size (Small vs Large) and geographical location (Suburban vs Urban).

Table A.10: Counterfactual of Mortgage Interest Rates with Various Market Frictions

	Overall	**Size**		**Location**	
		Small	Large	Suburban	Urban
	(1)	(2)	(3)	(4)	(5)
Panel A: Transaction Costs					
Property Type Level					
Prob. of Listing	3.4	4.9	2.6	4.6	2.9
Prob. of Receiving Bids	-1.5	1.1	-4.7	0.0	-2.7
Prob. of Selling	-3.2	-2.4	-3.9	-2.4	-3.8
Highest Bids	-0.2	0.3	-0.6	0.0	-0.4
Market-Time Level					
Number of Transaction	-5.3	2.3	-11.0	-1.1	-6.7
Average Transaction Price	-6.3	-0.9	-5.5	-3.8	-7.0
Panel B: Matching Efficiency					
Property Type Level					
Prob. of Listing	-5.3	-1.9	-9.3	-3.6	-6.7
Prob. of Receiving Bids	3.5	7.5	1.2	5.8	2.4
Prob. of Selling	1.1	0.4	1.9	0.7	1.4
Highest Bids	0.4	0.9	0.1	0.6	0.3
Market-Time Level					
Number of Transaction	-2.3	5.9	-7.9	0.8	-3.4
Average Transaction Price	-6.7	-0.2	-5.7	-3.5	-7.4
Panel C: Selling Friction					
Property Type Level					
Prob. of Listing	27.2	32.9	20.9	30.2	25.0
Prob. of Receiving Bids	-9.6	-6.3	-12.1	-7.7	-10.6
Prob. of Selling	-7.4	-8.3	-6.6	-6.5	-8.1
Highest Bids	-1.6	-1.3	-1.8	-1.4	-1.8
Market-Time Level					
Number of Transaction	-3.2	8.1	-10.6	3.2	-5.6
Average Transaction Price	-9.7	-3.1	-7.9	-7.0	-10.0

Note: This table summarizes the average percentage changes in the probability of listing, the probability of receiving bids, the probability of selling, the highest bids, the number of transactions, and the market-level transaction prices in the counterfactual increase in mortgage interest rates. Panel A reports the counterfactual results for a temporary policy change; Panel B reports the results for a permanent policy change. Columns (1) corresponds to the policy change in the baseline scenario, while the last three columns correspond to the policy change with lower market frictions, that is a 10% lower transaction costs (Column (2)), a 10% higher bidding frequency from buyers (Column (3)), a 10% lower cost of selling (Column (4)).

Table A.11: Counterfactual Increase in Down Payment Requirement

	Overall	**Size**		**Location**	
		Small	Large	Suburban	Urban
	(1)	(2)	(3)	(4)	(5)
Panel A: Housing Markets					
Property Type Level					
Prob. of Listing	-0.1	0.1	-0.7	0.0	-0.2
Prob. of Receiving Bids	0.2	1.1	-0.2	0.5	0.0
Prob. of Selling	0.1	0.0	0.2	0.0	0.1
Highest Bids	0.0	0.2	-0.0	0.1	0.0
Market-Time Level					
Number of Transaction	-0.5	2.0	-2.1	0.4	-0.7
Average Transaction Price	-1.9	-0.0	-1.5	-1.0	-1.9
Panel B: Household Welfare					
Home Owner	0.1	0.3	-0.1	0.2	-0.0
Home Buyer	-29.8	-19.8	-38.2	-25.7	-32.5
Home Seller	0.2	0.8	-0.3	0.5	0.0

Note: This table summarizes the median percentage changes in market outcomes and household welfare in the counterfactual increase in down payment requirements. Panel A reports the counterfactual results for the probability of receiving bids, the probability of accepting bids, the highest bids, the number of transactions, and the market-level transaction prices. Panel B reports the median of welfare changes (in one thousand CNY) for homeowners, buyers, and sellers. Columns (1) corresponds to the overall policy impact on all housing products and markets, while the last four columns correspond to the policy change with different market segments, such as product size (Small vs Large) and geographical location (Suburban vs Urban).