Mortgage Credit and Housing Markets*

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Abstract

This paper investigates how mortgage credit conditions affect housing markets and the demand for homeownership. Using unique data on homeowners' listings and transactions from the largest Chinese real estate brokerage company, and exploiting policy-driven changes in mortgage credit conditions in China, I provide empirical evidence that higher mortgage interest rates and down payment requirements have a negative effect on housing demand and prices. Estimating a structural model of households' demand and supply of residential properties, I find that mortgage interest rates and down payment requirements negatively affect households' willingness to pay and the value of owning residential properties. With counterfactual experiments, I quantify how mortgage credit policies influence housing demand, supply, price, market liquidity, bargaining power and study the role of expectation in determining housing market outcomes.

JEL-classification:

Keywords: mortgage credit, housing markets, structural estimation, forward-looking expectations, market liquidity, bargaining power

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1 Introduction

Residential property is an important component of households' wealth, and its purchase largely relies on mortgage credit. In the United States, real estate assets constitute 27% of households' net wealth in 2018, and outstanding home mortgages account for about two-thirds of households' total debt.[1] It is however an empirical question whether changes in mortgage market conditions can affect housing demand and prices and by how much; this is crucial to understand housing market responses to monetary policies and regulatory changes in lending markets. There are two main challenges in answering these questions. First, since credit terms and availability are generally endogenously determined by credit demand and the value of houses serving as collateral (Bemanke and Gertler 1989, Kiyotaki and Moore 1997), causality is hard to prove. Even with unchanged credit conditions, the actual credit supply is higher when housing price grows. As noted by Glaeser, Gottlieb and Gyourko (2012), credit conditions in the United States over the last two decades lack sufficient variation to account for the large movement in house prices, casting doubts on identification issues. Second, the durability of residential properties requires a dynamic consideration. The belief of future prices can affect housing demand and hence affect price changes today. Households can form expectation not only of housing markets, but also of monetary and regulatory policies, making forward-looking behavior essential to determine housing demand and prices.

This paper investigating how mortgage credit affect housing markets addresses these challenges. Instead of relying on exogenous changes in mortgage credit conditions, I build a dynamic structural model, which takes the expectation of future prices and market conditions into account. There are four benefits of the structural model. First, by explicitly modelling households' housing demand and supply, the model delivers key measures of the microstructure of housing markets, such as market liquidity and the relative bargaining power of sellers and buyers, which are not directly observable. Second, by estimating how mortgage credit conditions affect the utility of homeownership, the model estimates households' willingness to pay for property attributes under different mortgage credit conditions. Third, by incorporating expectations of future house prices into the value of homeownership, the model sheds light on the role of expectations in determining equilibrium outcomes. Finally, structural models are especially suitable for estimating causal effect with counterfactual experiments. By simulating a policy change in mortgage credit conditions, with and without the expectation channel, the model quantifies the direct causal effect of mortgage credit conditions on housing and evaluates the importance of forward-looking expectations.

I use novel hand-collected data from the largest Chinese real estate brokerage company Lianjia to estimate the model. Such data has never been examined before. Lianjia's online platform provides detailed listing and transaction information on all of their successful transactions. China provides an ideal setting to study the effectiveness of mortgage credit policies, as mortgage conditions are often regulated to intervene in housing markets. As the second largest economy in the world, China has been experiencing a real estate boom since the 1990s; this has raised concerns that a downturn in the real estate sector may have spillover effects both

[1] See Federal Reserve Statistical Release, Second Quarter 2018, Board of Governors of the Federal Reserve System, September 20, 2018. In the United States, the 2018 second quarter statistics show that households' direct holdings of real estate reached 28.8 trillion USD, which accounts for 82.5% of their total nonfinancial assets and 26.9% of their total net wealth. The outstanding home mortgage amounts to 10.2 trillion USD, almost 66% of the total outstanding debt of households and 20% of the nonfinancial sector.

domestically and globally. To cool down the housing markets, mortgage credit policies, such as increasing mortgage interest rates and down payment requirements, have been commonly used in China through the governments' strong influential power in the banking system. Therefore, sharp changes in mortgage interest rates and down payment requirements exist and mostly reflect policy makers' intention rather than banks' profit maximization motivates; this relieves the concern that banks endogenously set mortgage interest rates and down payment requirements based on house prices.

In the model, I consider a city as a housing market, where agents are forward-looking households who choose homeownership to maximize their lifetime expected utility. Agents can be either property buyers or property owners. Property buyers search properties in the market, choosing the type of property (location, size, and age) that yields the highest lifetime utility among all available types in the market, and make a take-it-or-leave-it bid.[2] In the spirit of Bayer, McMillan, Murphy and Timmins (2016), conditional on buyers' purchase decision, buyers face a discrete choice problem, where valuable properties are more likely to be chosen. Thus, more valuable property types tend to have higher market share. The market share of each property type, reflecting buyers' valuation for that type, is used to estimate households' value functions in a computationally light way.

Property owners instead list their properties and have the option to sell only if there exists a potential buyer's bid in that period; otherwise they have to keep owning the property, waiting for bids in the future. The expectation of future market conditions and the probability of receiving bids affect the value of homeownership. In each period, owners need to make an optimal decision whether to accept or reject bids by comparing the value of owning and selling. Therefore, overly optimistic beliefs of future prices would increase the value of owning property, and thus encourage buyers to rush into purchase and sellers to withhold their properties in the current period. The probability of receiving bids and the probability of accepting bids reflect housing demand and supply for housing market participants. Modelling the two probabilities not only disentangles the equilibrium market outcome into supply and demand, but also provides measures of market liquidity and bargaining power – the product of the two probabilities determines the likelihood of a transaction, that is a measure for market liquidity, while the ratio of the two probabilities determines the relative bargaining power of property buyers and sellers.

Based on the estimates of the structural model, I conduct two counterfactual policy experiments to study the effectiveness of different policies and the role of the expectation channel. I simulate changes first in mortgage interest rates and then in down payment requirements to calculate the new equilibrium outcome of housing demand, supply, highest bidding price, market liquidity, and relative bargaining power. In each counterfactual, two scenarios are considered. One scenario without the expectation channel, which only accounts for the impact of policy changes on direct utilities, keeping households' expectations constant. The other scenario with the expectation channel, which accounts for the impact on both utilities and households' expectations. Comparing the results in counterfactuals with the baseline cases suggests the causal effect of

[2]The utility of owning property depends on property attributes, as widely confirmed by hedonic models. See the survey by Sirmans, Macpherson and Zietz (2005) which examined 125 empirical studies for hedonic pricing models in real estate markets and find that property attributes, such as size, age, number of bathrooms, number of bedrooms, and location, have clear impact on house prices, while some other attributes, such as garage, basement, and time on the market, differ in magnitude and direction among different studies.

mortgage credit policies, while comparing the difference between the two scenarios suggests how much of the effect can be explained by the expectation channel.

I first provide reduced-form empirical evidence that house price growth rate decreased after large increases in mortgage interest rates and down payment requirements. After the nationwide large increase in mortgage interest rates in May 2017, monthly house price growth rates dropped by 3.8% on average. The drop was larger for cities that were more affected by the policy change and for properties no more than 20 years old, the threshold above which mortgage credit are almost unattainable in China. Moreover, compared with weakly affected cities, strongly affected cities had a larger increase in the number of listed properties and a larger drop in transaction volume, suggesting that housing demand decreased relative to housing supply. Similarly, larger than 15% increases in down payment requirements reduces the house price growth rate, and vice versa. However, the reduced methods fail to provide a clean identification for the causality and insights on the underlying mechanism, suggesting the need for a structural model.

I use a micro-founded structural model, showing that housing markets are localized with very different features. Buyers' housing markets, with low housing demand relative to supply, tend to have low market liquidity and house price growth rate. While sellers' housing markets, with high housing demand relative to supply, tend to be more liquid. Households prefer larger and younger properties. House prices have a negative impact on the utility of holding a property, which corresponds to the opportunity cost of not selling for the property owner, and the cost of purchase for potential buyers. Higher mortgage interest rates and down payment requirements, corresponding to higher financing costs for mortgages and down payments, increase households' price sensitivity and decrease their willingness to pay for property attributes. On average, households are willing to pay 407,000 CNY (approx. 57,400 USD) more for properties in the larger size decile and 360,500 CNY (approx. 50,800 USD) more for properties in the younger age quintile. The willingness to pay for both the larger size and the younger age type will drop by 4% if the mortgage interest rate increases from 5 to 6 percentage points, when the minimum down payment requirement is 30% of the property value. Similarly, increasing the down payment requirements from 30% to 40% decreases the willingness to pay for both the larger size and the younger age type by 12% when the mortgage interest rate is 5 percentage points. Moreover, the effects of mortgage interest rates and down payment requirements may counteract each other. When the down payment requirement is very high, increasing mortgage interest rates cannot decrease the willingness to pay. Intuitively, higher down payment requirements decrease the amount of mortgage loan, decreasing the total financing cost for mortgages. This finding is also in line with the liquidity constraint argument by Stein (1995) and Ortalo-Magne and Rady (2006). When down payment requirements are so high for home buyers to be constrained for mortgages, increasing mortgage interest rates leads to lower house prices and more affordable down payment, which encourages home purchases.

Combining the estimates of housing demand, supply, utility and value functions, I conduct two sets of counterfactual experiments. I simulate a 1 percentage point increase in mortgage interest rate, finding that the probability of receiving bids (i.e. housing demand) drops by 17%, the probability of selling to bidders (i.e. housing supply) increases by 20%, the highest bidding price decreases by 17%, the market liquidity decreases by 5%, and seller's relative bargaining power decreases by 69%. The expectation channel, explaining about 25% to 45% of the counterfactual outcomes, amplifies (attenuates) the effect of increasing mortgage interest rates in buyers' and balanced (sellers') housing markets. The other exercise is to increase down payment requirements by 10 percentage points. I find similar results: higher down payment requirements lead to lower demand, higher supply, lower prices, lower liquidity, and lower bargaining power for sellers. I also find that mortgage credit policies are more effective for expensive, old, small, and illiquid properties, suggesting that properties with unfavourable attributes are more affected by policy interventions.

This paper contributes to four strands of literature. First, it contributes new empirical evidence to the growing body of empirical work examining the impact of mortgage credit on housing markets and real economic activities.[3] Various changes in credit supply have been employed in extant work. For example, Mian and Sufi (2009) argue that ZIP codes with a high fraction of subprime borrowers experienced an expansion in mortgage credit due to the increase in securitization of subprime mortgages. Adelino, Schoar and Severino (2012) exploite the changes in conforming loan limits to show that houses eligible for cheaper finance experienced an increase in house prices. Favara and Imbs (2015) use deregulation in bank branches across US states to identify the impact of an exogenous change in credit supply on house prices. They find that credit expansion can explain a significant share of the increase in house prices. The causal interpretation of the results in these papers relies on the exogeneity of changes in mortgage credit conditions, that is the increase in credit supply is not caused by high housing demand in booming real estate markets. The unique feature of China's mortgage credit policies mitigate this concern, because credit tightening occurred during booming periods aiming at cooling the overheated housing markets. More importantly, exogenous credit supply changes are not ubiquitous. In this paper, causality is inferred through a more general approach, a structural model and subsequent counterfactual analyses.

Second, the paper contributes to the strand of research in industrial organization that applies dynamic discrete choice models with multi-step estimation approach (Rust 1987, Hotz and Miller 1993). These methods have been applied to various problems, including the dynamic demand for durable and storable goods where intertemporal effects affect forward-looking agents' behavior (Hendel and Nevo 2006, Gowrisankaran and Rysman 2012, Melnikov 2013).[4] Housing shares similar features with durable goods in these models. As a significant component of households' financial portfolio, housing price fluctuation has an important impact on future households' wealth; this reinforces households' intertemporal consideration.

Closely related work considering the dynamic feature in real estate is Bayer, McMillan, Murphy and Timmins (2016), which studies the neighborhood choice of households in the San Francisco metropolitan area over households' life cycle to address the demand for non-marketed amenities. Using a similar estimation strategy, this paper adopts on another perspective – the demand for property ownership under different mortgage market conditions, which explains the purchasing and selling behavior of property buyers and sellers in the market. Murphy (2017) in contrast emphasizes the supply side, but focuses instead on landowners' con-

[3] 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, Ludvigson and Van Nieuwerburgh 2017), and mortgage credit expansion (Mian and Sufi 2009, Adelino, Schoar and Severino 2012, Favara and Imbs 2015, Landvoigt, Piazzesi and Schneider 2015). The housing net worth can have real effect on economic activities, such as employment and entreupership (Mian and Sufi 2014, Adelino, Schoar and Severino 2015, Di Maggio and Kermani 2017, Greenwald 2018).

[4] Other topics see e.g., patent renewal (Pakes 1986), investment models of machine replacement (Kennet 1993, 1994), models of retirement decision (Rust and Phelan 1997, Karlstrom, Palme and Svensson 2004).

struction decision while taking into account expectations about future prices and costs. The setting of this paper is more suitable for large cities where land is scare and the secondary market is paramount. Therefore, optimistic beliefs over house prices in an inelastic housing supply environment are likely to have stronger effect on sellers' behavior than the case of Murphy (2017).

Third, this paper relates to work on the liquidity and market structure of housing markets. As high transaction, search, and opportunity costs are important determinants of purchasing decisions, residential properties need a spell of time on the market before they are sold. Thus, how quickly a property can be sold under the optimal selling strategy in a search and matching process reflects its liquidity – the inverse of the time on the market or the probability of sale in a unit of time (Lippman and McCall 1986, Kluger and Miller 1990, Krainer 2001, Head and Lloyd-Ellis 2012). Previous studies have focused on time on the market for property buyers and sellers separately.[5] It is hard however to analyze liquidity as an equilibrium outcome without considering both buyers and sellers. Genesove and Han (2012) build a random matching model to study how a demand shock affects the housing market liquidity, and employ survey data on home buyers and sellers to provide empirical evidence consistent with their model. Instead of relying on reduced-from analyses by aggregating micro data, this paper presents a structural model that considers the liquidity of real estate properties for market players who adopt optimal strategies to maximize their lifetime utility. Estimating the structural model not only provides a measure for liquidity, but also disentangles the liquidity provision between buyers and sellers for each individual transaction, linking policy changes and agents' reactions. To the best of my knowledge, the two driving forces of the housing market have never been empirically analyzed jointly in a structural model before.

Last but not least, this paper contributes to recent studies on the role of expectations in housing markets. Considerable evidence that households form extrapolative beliefs in housing markets based on recent trends has been documented 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). Theoretically, those inaccurate beliefs, often excessively optimistic during booms, can stimulate large fluctuations in house prices, as the recent price growth raises agents' forecasts of future prices and increases demand even when prices have deviated from fundamentals (Piazzesi and Schneider 2009, Glaeser and Nathanson 2017, Barberis, Greenwood, Jin and Shleifer 2018). However, empirical evidence from the field instead of lab experiments or surveys is scarce. This paper fills the gap based on a micro-founded behaviour model with extrapolative beliefs. Rather than using a rule of thumb or calibrating the parameters in the expectation, they are fully estimated from the data, providing direct evidence on how the expectation affecting housing market outcomes in the real world.

The rest of the paper is organized as follows. Section 2 provides a data description and institutional details. Section 3 presents reduced form evidence on the effect of mortgage market conditions on housing markets. In Section 4, I present the structural model. Section 5 describes the econometric framework, including price

[5]For the time on the market for proper buyers, see e.g., Baryla and Ztanpano (1995), Anglin (1997), Elder, Zumpano and Baryla (1999), Baryla, Zumpano and Elder (2000). For the time on the market for proper sellers, see e.g., Haurin (1988), Glower, Haurin and Hendershott (1998), Anglin, Rutherford and Springer (2003), Genesove and Mayer (2001, 1994), Levitt and Syverson (2008), Hendel, Nevo and Ortalo-Magné (2009).

prediction and identification strategies. The estimation results are presented in Section 6. Section 7 presents the counterfactuals, and Section 8 concludes.

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, is a serious problem. In the past decade, house prices of major Chinese cities have grown at more than 10 percent annually, and the annual rate for newly-built house prices 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 house purchases, with a house price to income ratio of 28.2, much higher than that of the UK (9.3), the US (3.4), and other comparable countries.[6] The situation in large cities is even worse, with that ratio reaches 45.5 in Beijing, 45.4 in Shanghai, 42.5 in Shenzhen, 28.7 in Guangzhou.

There are a number of stylized facts about Chinese housing markets. First, despite a large construction boom in many cities, there is still a demand-supply imbalance, with substantial heterogeneity among cities.[7] While many cities experienced hot markets, with housing demand outpaced supply, a few cities have experienced cold markets, with housing supply outpaced demand (Wu, Gyourko and Deng 2016). Second, high house prices go together with a high vacancy rate, and the proportion of households with vacant houses increases with household income.[8] The high vacancy rate in China is likely to be a signal of a speculative investment behavior. Following the numerous years of boom, real estate assets are an attractive investment alternative, as holding real estate properties gives the owners the option to sell at higher prices in the future. In other words, optimistic expectations of future house prices are an important feature of housing markets in China. Third, the government controls the supply of land and hence new houses. In China, the nation legally owns the land and the government decides the amount and time of the distribution by land use conveyance. Real estate firms can acquire land use rights from public auction and tender, using acquired land to develop real estate projects. Most residential properties in large cities are developed by real estate firms, such that units in one real estate project are very similar in quality, location, and amenities. The limited chance of

[6]Data from NUMBEO, the house price to income ratios in 2018 for some other countries are Brazil 16.3, South Korea 14.1, Japan 12.6, Russia 11.4, France 9.9, India 9.7, Germany 8.0, Australia 7.4, Canada 6.1.

[7]The housing construction increased significantly in China. Between 2003 and 2014, 9.3 billion square meters of living space was built, almost 7 square meters for every person in China (Glaeser, Huang, Ma and Shleifer 2017)

[8]The vacancy rate is calculated as the proportion of homeowner inventory that is vacant and for sale. The vacant housing units does not include housing units that are newly built but not yet sold. There is a debate about the vacancy rate in China. According to the China Household Finance Survey in 2013 by Southwestern University of Finance and Economics, in 2013 the vacancy rate was 22.4 percent for the national average, and 21.2, 21.8, and 23.2 percent for the first-, second-, and third-tier cities in China respectively. At the household level, 35.1 percent of entrepreneurial households and 39.7 percent of top decile income households own vacant houses. Estimation by China International Capital Corporation based on the aggregated data from the National Population Census suggests a vacancy rate of 17.7% in 2013. Wu, Gyourko and Deng (2016) find a much lower vacancy rate in China of 9.7% in 2014.

(re)constructing own homes makes households largely rely on the second-hand housing market to change their residence in large cities where the majority of the urban area has been developed. Finally, the rate of homeownership is high in China. Before the late 1970s, most urban households in China were living in state-owned housing. A series of housing reforms since the late 1980s that privatized state-owned housing to existing residents increased the homeownership rate to over 80% in urban areas (Wang 2011). On the one hand, the long tradition of valuing family in Asian culture encourages homeownership. On the other hand, the underdeveloped rental markets keep households preferring owning to renting, albeit low rent-to-price ratios in China.

To study real estate markets, I use hand-collected data from the largest Chinese real estate brokerage company Lianjia, which provides both online and offline real estate services.[9] The offline offices provide traditional purchasing advice service and ensure the reliability of property information, as an important role of the real estate agents in an offline office is to collect and integrate property information into their data system by visiting sellers and properties.[10] 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 will be available online for households who are interested in buying to find the best match. 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 arrange an appointment for advice and a visit. There is no monetary cost for services unless a transaction takes place. In a transaction, the commission fee is about 3% of the price; this is usually paid by buyers. Potential buyers offer a bidding price for the property in a first come first served way. In other words, whenever there is a bid by a potential buyer, the seller needs to decide whether to sell the property to this buyer or decline.

Besides information on listed properties, all historical transaction records are available. For the transactions, there is detailed information about the property, e.g., the asking price, the date of listing, living space, year of construction, number of rooms, location, decoration, type of property, builder's name, etc. There is also information about the transaction, e.g., the date of the transaction, transaction price, the number of people who liked the property, etc. In addition to many details for historical transactions, listed properties that have not been sold out on the platform have more information such as the number of visits by potential buyers, visiting history in the past 30 days, properties' blueprints, professional advisors' comments, etc. However, those unsold properties lack the key information of the final transaction price. The estimation will mainly focuses on sold properties, while the properties on the market are used to construct the number of new listings and the number of alternative properties in each markets.

[9]Established in 2001, Lianjia has become the largest company in the real estate service industry in China. Until the end of 2016, Lianjia owned more than 8,000 service offices and employed more than 150,000 real estate agents in 28 metropolitan cities in China. As the market leader, Lianjia has the largest market share in the first-tier cities and outperforms many other competitors. In 2016, Lianjia had the largest market share in Beijing, Shanghai, Guangzhou, Shenzhen, Tianjin, Chengdu, Qingdao, Dalian, Wuhan, Chongqing. In 2017, its market share in Beijing was 46.39%, with the second largest player at 12.28%, while its market share in Shanghai was 18.38%, with the second largest player at 6.08%.

[10]A common problem in many online real estate platforms without careful screening is the fraud for commission or deposit using fake property information. Lianjia states that over 97% of their real estate properties are authentic and not fake, because of their offline services.

Table 1: Summary Statistics

	Transactions			On The Market		
Statistic	N	Mean	St. Dev.	N	Mean	St. Dev.
Panel A: Properties						
Listing Price	338,789	29,098.4	23,478.5	110,822	40,473.6	23,818.2
Total Listing Price	338,789	243.2	229.0	110,822	389.4	320.4
Total Transaction Price	338,789	235.9	220.5			
Time On The Market	338,789	2.4	3.0	110,822	7.9	3.6
Number of Likes	338,789	46.9	69.3	110,822	44.0	60.9
Size	338,789	86.4	35.3	110,822	96.4	43.6
Age	338,789	11.4	6.7	110,822	12.9	6.9
Decor	338,789	2.6	1.3	110,822	2.3	1.3
Elevator	338,789	0.7	0.5	110,822	0.6	0.5
Subway	338,789	0.5	0.5	110,822	0.4	0.5
Number of Bedrooms	338,789	2.2	0.9	110,822	2.4	1.0
Number of Living Rooms	338,789	1.4	0.6	110,822	1.5	0.6
Number of Bathrooms	338,789	1.3	0.5	110,822	1.4	0.6
Management Fee	338,789	1.8	2.6	110,822	1.9	2.4
Total Number of Apartments	338,789	1,600.5	1,038.6	110,822	1,496.1	991.8
Number of Alternatives	338,789	90.4	115.1	110,822	131.4	174.2
Panel B: Mortgage Markets						
Number of Banks	390	18.4	5.9			
Number of Branches	390	1,518.1	956.6			
Average Interest Rate	390	4.6	0.4			
Down Payment Requirement	390	0.3	0.1			
Interest Rate Discount	390	0.6	0.4			

Note: Panel A presents summary statistics for Historical transactions and properties on the market. Listing Price is the property listing price in CNY per square meter. 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. Size is the living space in square meters. Age is the number of years since construction. Decor is a variable from one to four indicating the interior style of decoration is attractive, simple, raw, or others. Elevator is a dummy variable taking value of one if elevators are available and zero otherwise. Subway is a dummy variable taking value of one if there are subway stations close to the property and zero otherwise. Number of Bedrooms / Living Rooms / Bathrooms are variables representing the number of different rooms of a property. Management Fee is in CNY per square meter per month. 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 city month level. Number of Banks is the number of active banks in a city month combination. Number of Branches is the total numberof 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. Interest Rate Discount is the fraction of banks in a market that set mortgage interest rate below the benchmark interest rate. Credit Rationing is the fraction of banks that stop granting mortgage loans.

Table 1 Panel A summarizes real estate properties listed on Lianjia from 15 major cities in China from December 2015 to January 2018.[11] There are 338,789 observations of historical transactions and 110,822 unsold properties on the market. For historical transactions, the average listing price is 29,098 CNY (approx. 4,400 USD) per square meter. The average total listing price is 2.43 million CNY (approx. 0.37 million USD) and the average total transaction price is 2.35 million CNY (approx. 0.36 million USD). On average, a property is sold out after 2.4 months. Properties that are still on the market by the end of the sample period tend to have a higher listing price and (naturally) longer time on the market compared with sold properties. A valuable piece of information from the online platform is the record of how many people have liked a property, a direct measure of the demand for each property.[12] On average, a sold property has 47 likes, while an unsold property has 44 likes. For an average historical transaction, the construction size is 86.4 square meters and it has been 11.4 years since it was built, while properties on the market are larger and older. Four levels of interior decor, numbered from one to four, are attractive, simple, raw, and other. 70 percent of sold properties have an elevator and 50 percent are close to a subway station. On average, there are 2.2 bedrooms, 1.4 living rooms, 1.3 bathrooms for a sold property.

Further information on real estate projects includes the common charge, the project scale, and the address of the project. The average common charge is 1.8 CNY (approx 0.26 USD) per square meter per month. There are 1,600 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. Since we have information on the listing date and transaction date, it is possible to construct the number of available properties on the platform at the time of transaction within the same zone; this captures the level of competition. On average, there are 90 alternative properties on the online market from the same zone when a transaction occurs.

2.2 The Booming Housing Market

The fast-growing real estate market has few reliable metrics for prices other than the official average price index of newly build homes in 70 large and medium-sized cities, released by the National Bureau of Statistics of China, according to which house prices 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). In fact, as the sample suggests, house prices grow at a surprisingly fast pace: The transaction price (per square meter) increased by 18.2 percent annually on average in the major cities. Chengdu is among the fastest growing cities with annual growth rates of 27.4 percent. Beijing experienced a booming period in the year 2016, during which the average listing price surged from about 40,000 CNY (approx. 5,600 USD) per square meter in December 2015 to 65,000 CNY (approx. 9,100 USD) per square meter in the last quarter of the year 2016.

Despite the high house price growth overall, each market's situation differs. Figure 1 illustrates the average

[11] The four largest cities are commonly classified as the first-tier cities, which are Beijing, Shanghai, Shenzhen, Guangzhou. The rest large cities commonly classified as the second-tier cities, including Xiamen, Hangzhou, Nanjing, Qingdao, Suzhou, Wuhan, Chengdu, Chongqing, Changsha, Dalian

[12] By clicking the "follow" button, a property will be saved for comparison and review in the future. Any updates of the property will be delivered to its followers timely. Since properties are not ranked by popularity, there is little benefit from manipulating the number of likes.

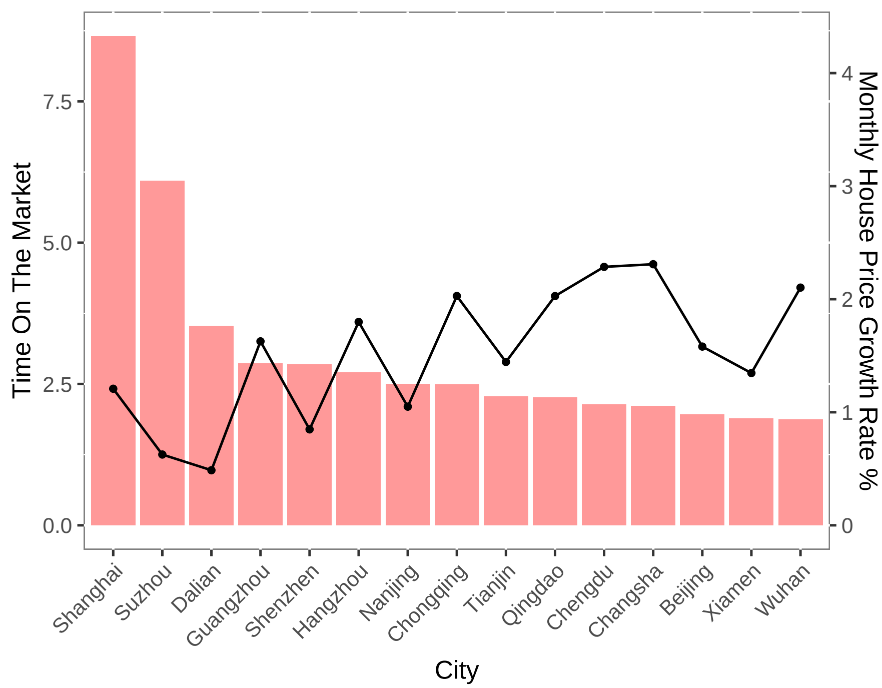

Figure 1: Time on the Market and House Price Growth Rate

Note: This figure illustrates the housing market conditions for the 15 major cities in China. The red bars indicates the average time on the market (in months) for properties in that market. The black line indicates the average of monthly house price growth rate in percentage points for properties in that market.

time on the market (red bars) and the average monthly house price growth rate (black line) in the sample period. Properties in Shanghai on average need as long as 8.7 months to be sold. Similarly, in Suzhou and Dalian, housing markets with low house price growth rate in the sample period, the average time on the market is 6.1 and 3.5 months respectively. The long waiting time and low house price growth rate suggest that they are "cold" housing markets with low liquidity. However, the house price growth rate cannot be fully explained by the time on the market. For example, Shanghai and Nanjing have similar growth rate in house prices but the time on the market for Shanghai is 3.5 times higher than Nanjing; with similar house price growth rate, the time for sale in Guangzhou is 45% longer than that in Beijing. The housing market conditions cannot be thoroughly analyzed without a model that delves into the driving forces of market outcomes.

The top panel of Figure 2 plots key housing market outcomes for three representative large cities. Beijing is one of the four largest cities that are often referred to as first-tier cities, while Tianjin and Chengdu are among the so-called second-tier cities, which are provincial capital cities or metropolitan cities with a strong regional economy.[13] For each city, the dashed line shows the average listing price of all properties listed at the beginning of the month. The solid line is the average price of transactions that occurred in each month. The red bars are the number of new properties listed in each month, while the blue bars are the number

[13]First Tier group contains Beijing, Shanghai, Shenzhen, Guangzhou, where house prices largely surpass the Second Tier group. Within the Second Tier group, there is a clear difference in the prices: Cities located close to the coast (such as Hangzhou, Nanjing, Qingdao, Suzhou, Tianjin, Xiamen) tend to outperform interior cities (such as Changsha, Chengdu, Chongqing, Dalian, Wuhan).

of transactions occurred in that month. When the red bars overlap with the blue bars, the color become darker.

Two interesting facts emerge from these figures. First, when the number of transactions surpasses the number of newly listed properties in a month, housing demand is high, which coincidently occurs when house prices grow up fast. This observation is intuitive, as high housing demand can drive up house prices when the supply is inelastic, while the less obvious channel is that a high price growth rate can change the market expectation and hence further increase current housing demand. The second fact is that listing prices are higher than transaction prices, especially when the market has a low demand. The listing price to a large extent reveals sellers' reservation price, as unreasonably high listing prices decrease the pool of potential bidders. The high asking price compared to the transaction price in low demand periods implies that property sellers are optimistic, which is in line with the well-documented phenomenon that in housing markets agents form adaptive or extrapolative beliefs based on recent trends.

2.3 Mortgage Credit

China used to have a wholly state-owned mono-banking system before the year 1978. In recent decades, the authorities have taken a series of reforms to make the banking system more market-oriented and competitive, but the large banks are still mainly state-owned or state holding.[14] The government's strong influence in banks helps the implementation of the central bank's credit policy through window guidance, that is, direct instructions to commercial banks concerning their specific lending activities. For example, to dampen the surging housing demand in booming markets, mortgage interest rates may be instructed to increase. As a result, the government's objective in real estate markets can be implemented through mortgage credit policies, without incurring general monetary policy changes, which makes the mortgage interest rate a flexible direct measure for the financing cost of mortgages.

After experiencing surging house prices in many cities during the year 2016, in the Central Economic Work Conference held at the end of that year, the annual meeting where China's central government set the national agenda for financial and banking sectors in the coming year, the willingness to regulate housing markets by financial tools was emphasized. Following that, the central bank People's Bank of China (PBOC) and the China Banking Regulatory Commission released their intention to control credit for the real estate sector. On March 23, 2017, the State Council distributed government work guidance to provincial governments to emphasize controlling mortgage credit based on local real estate market conditions. In the following months, all provinces adopted a tight mortgage credit policy, while the response of each city was allowed to vary according to local market conditions.

[14] China's banking system reform includes ownership diversification, the introduction of a board of directors and a board of supervisors, and more autonomy in the senior management's decision-making process, but the main market players are still mainly or partially state-owned. The five largest state-owned commercial banks account for about 40% of the banking system's assets, and their senior managers are appointed or approved by the government. There are twelve joint stock commercial banks whose shares are wholely or partially held by the central government, by local governments, or by state-owned enterprises. Since 2003, city commercial banks and rural commercial banks have been established through the restructuring and consolidation of regional credit cooperatives, mainly held by local governments. More discussions, see e.g. Lin and Zhang (2009), Dong, Meng, Firth and Hou (2014), Hung, Jiang, Liu, Tu and Wang (2017).

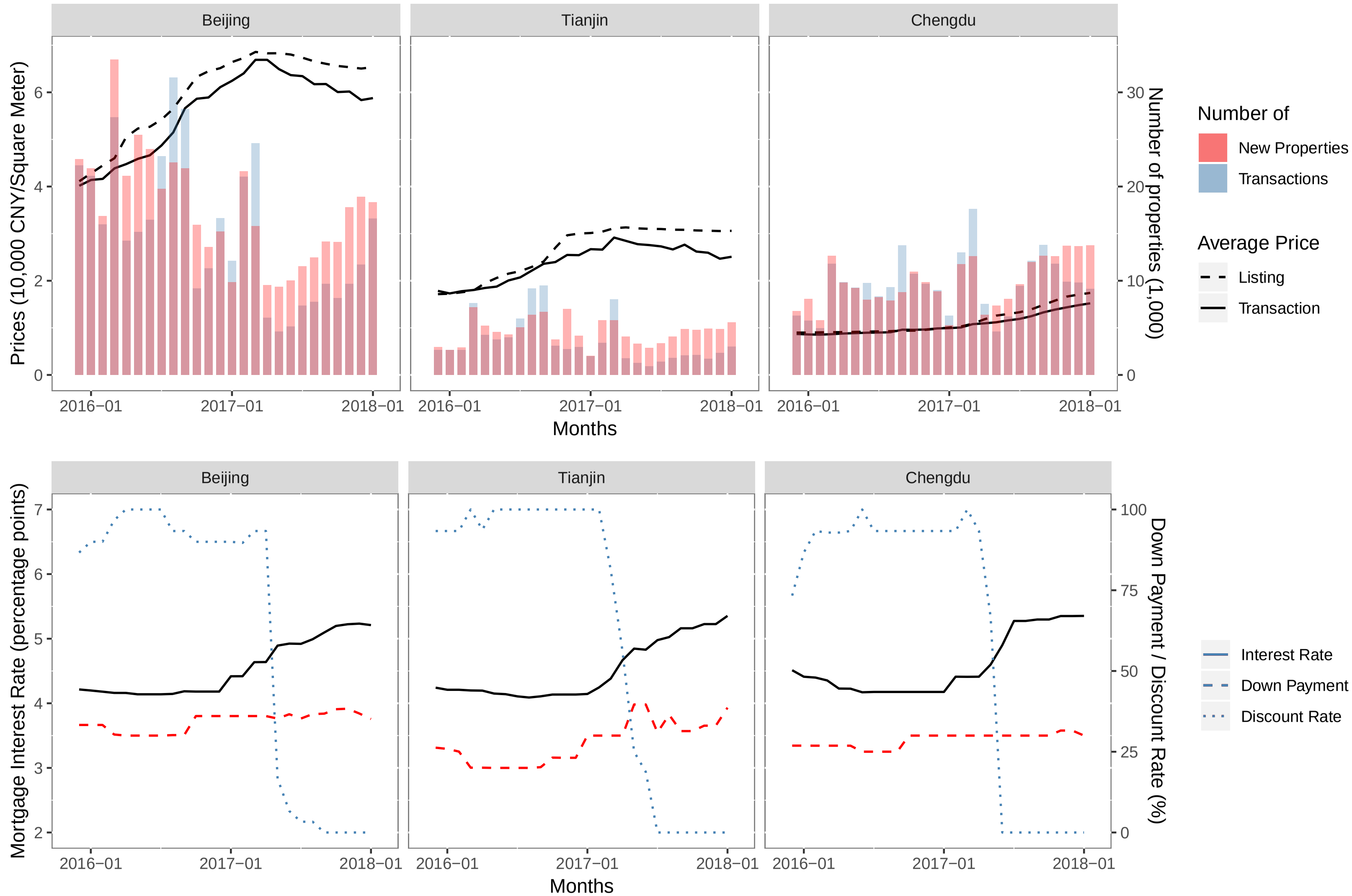

Figure 2: House Prices, Transaction Volumes, and Mortgage Market Conditions

Note: The top three figures plot house prices and transaction volumes for three representative cities from December 2015 to January 2018. The solid line is city level average transaction prices in 10,000 CNY per square meter. The dashed line is the city level average listing price of all properties listed in the market at the beginning of the month. Red bar shows the number of new properties (in 1,000) listed in the market in that month, while blue bar shows the number of transactions (in 10,000) occurred in that month. The bottom three figures illustrate the variation in mortgage market conditions. The black solid line shows the average mortgage interest rate for the first mortgage in each city. The red dashed line represents the down payment requirement for the first mortgage in each city. The dashed blue line plots the fraction of banks that are giving discount on mortgage interest rate in each city.

The monthly city level mortgage market information summarized in Table 1 Panel B is obtained from Rong360, a leading fintech company in China providing data service in finance. The sample contains the actual month-city level mortgage interest rates, down payment requirements, and credit rationing information 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 share, and calculate the average mortgage interest rate and down payment requirement of each city and month weighted by bank's market share. On average, there are 18 lending banks and 1,518 operating branches in each city. In China, commercial banks set their mortgage interest rates referring to the benchmark interest rate set by the central bank, which has been anchored at 4.9 percentage points for long-term lending since October 2015. Banks adjust their actual interest rates by setting a spread relative to the PBOC benchmark rate.[15] The average annual mortgage interest rate for purchasing first residential property in the sample is 4.6 percentage points. The average down payment requirement for the first mortgage is 30%, i.e., 70% the loan-to-value ratio. On average, there are 60% of banks that set interest rates below the benchmark rate.

The bottom panel of Figure 2 plots the mortgage market variables for households' first residential property purchase in the three cities. The solid line is the average mortgage interest rate in each month for a city. The average interest rate started from around 4.2 percentage points in early 2016, and experienced an increase in the first half of 2017, reaching 5.5 percentage points by the end of 2017. The dashed line indicates down payment requirements as a percentage of the collateral value. There was a drop in down payment requirements in 2016 for all three cities, while in 2017 down payment requirements recovered to the previous level or to an even higher level. The dotted line is the percentage of banks in the city that provided a discount on the interest rate. The mortgage market experienced a sharp change during May 2017. Before May 2017, almost all banks were offering a discount on interest rate compared to the central bank benchmark interest rate, while after that almost all banks stopped offering a discount on the interest rate. The sharp change in lending conditions suggests a turning point in the mortgage market environment, as the central government's target switched from stimulating housing markets in 2016 to preventing overheated markets in 2017.

Comparing the two markets as shown in Figure 2, the booming periods in the real estate market, with fast-growing house prices and a high transaction volume, coincide with loose mortgage market conditions. At the same time, after tightening mortgage credit in May 2017, house price growth rates slowed down. Other cities show similar patterns; graphical illustrations of those cities' market conditions are provided in Appendix A.1.

3 Motivating Evidence

In this section, I present reduced form evidence of mortgage market conditions' impact on housing markets, taking advantage of the policy-oriented changes in China's mortgage markets. I first exploit the nationwide

[15] A negative spread corresponds to a proportional fixed discount on interest rate relative to the benchmark rate, while a positive spread corresponds to a surcharge. It is expressed in a proportional form. For example, a 10% discount relative to the PBOC rate means that the actual interest rate is 90% of the PBOC benchmark rate (i.e., 4.41%). The discount or surcharge rate is fixed over the lifespan of the mortgage loan, typically 20 or 30 years in China, and the actual interest rate changes accordingly once PBOC rate changes.

large increase in mortgage interest rates in May 2017 to study the impact of tightened mortgage market conditions on housing prices and demand. Then, using variations in average down payment requirements larger than 15 percent across cities, I compare house price growth rate before and after the changes. I further examine the effect at the 20-year-old threshold, as properties older than 20 years are almost always not eligible for mortgage credit in China.

3.1 Mortgage Interest Rates

The sharp rise in mortgage interest rates in May 2017 served as a nationwide shock to mortgage credit markets. Even though the average mortgage interest rates increased in all cities after the event, the number of banks that increased the mortgage interest rate in that month varied, reflecting the level of policy stringency. Cities where lots of banks increased the interest rate simultaneously were strongly affected by the policy, while cities with fewer responding banks are considered as the control group.

I use regression model (1) to study the impact of tightening mortgage market conditions in May 2017. The dependent variable is the logarithm of the transaction (listing) price of property i in city m at the time of the transaction (listing) t. Properties in cities where the percentage of banks that increased their mortgage interest rate in May 2017 above the median (60%) are assumed to the treatment group with the dummy variable $Policy_i$ taking the value of one. Otherwise, properties in cities where fewer banks responded, indicating a weaker implementation of the policy, are classified with the $Policy_i$ indicator equal zero. $Post_i$ is a dummy variable taking the value of one if the transaction (listing) of property i occurs between June and August 2017, and zero if the transaction (listing) occurs between February and April 2017. Other control variables are denoted as $\mathbf{W}_{imt}$. Since t indicates the monthly timeline, the coefficient a_1 captures the average monthly house price growth rate. The coefficient a_2 of the time index and post-event indicator captures how much the house price growth rate changed on average after May 2017, and the coefficient a_3 of the interaction between the time index and the policy indicator captures the difference in house price growth rate between the treated and the control group. The impact of increasing mortgage interest rate is identified by a_4, which compares house price growth rate three months before and after the event, and between the group of cities with a high and low percentage of responding banks.

$$\begin{aligned}\log(Price_{imt}) &= a_0 + a_1 t + a_2 t \times Post_i + a_3 t \times Policy_i \\ &\quad + a_4 t \times Post_i \times Policy_i + \mathbf{a}_5 \mathbf{W}_{imt} + \epsilon_{imt}. \end{aligned} \tag{1}$$

Table 2 reports regression results of how housing price, demand, and supply are affected by tightening mortgage markets comparing observations 3 months before and after the event. In all regressions in this section, standard errors are clustered at the district level to account for unobserved correlation structures in residuals.[16] The dependent variable of the first two columns is the logarithm of transaction price per square meter. Column 1 suggests that after controlling for property attributes (i.e., age, living space, elevator availability, subway, project scale, management fee, number of bedrooms, decor) and district fixed effects,

[16]The main concern here is that observations in the same districts are correlated over time or with each other, e.g., serial correlation. Clustering at the district level resolves this problem by allowing the properties in the same district have any unobserved correlation structure.

Table 2: Housing Price Growth, Demand, and Mortgage Market Condition

	log(Transaction Price)		log(Listing Price)		Alternatives	Transaction	Like
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
T	0.037***	0.038***	0.024***	0.031***			
	(0.003)	(0.004)	(0.004)	(0.005)			
T×Post	−0.038***	−0.025***	−0.020***	−0.018**			
	(0.006)	(0.007)	(0.004)	(0.007)			
T×Policy		−0.002		−0.012*			
		(0.006)		(0.007)			
T×Post×Policy		−0.029***		−0.007			
		(0.011)		(0.009)			
Post					32.995	−72.882***	−0.244
					(28.053)	(15.432)	(0.180)
Policy					19.175	473.771***	1.655***
					(25.717)	(44.160)	(0.135)
Post×Policy					178.961**	−200.338*	−0.382
					(71.207)	(121.091)	(0.381)
Constant	0.472**	0.447**	9.702***	9.527***	711.847***	178.141***	0.761**
	(0.218)	(0.226)	(0.123)	(0.160)	(11.694)	(7.033)	(0.355)
Attributes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	76,544	76,544	73,568	73,568	73,568	73,568	73,568
R^2	0.924	0.924	0.922	0.923	0.953	0.677	0.182

Note: This table presents the changes in house prices and demand after tightening mortgage market. The results are obtained using OLS regressions for property transactions occurred three months before and after May 2017. The dependent variable is the logarithm of transaction price (CNY per square meter) in Column 1 to 3, and the logarithm of listing price (CNY per square meter) in Column 4 to 6. In Column 7 to 9, the dependent variable is the number of alternatives, total number of transactions in the market, and the number of likes per listing day. T is the number of month had past since April 2017. Post is a dummy variable taking value one if the transaction occurs during June and August 2017, and zero if transaction occurs between February and April 2017. First Tier is a dummy variable taking value of one if the transaction is in a first tier city. Attributes include property attributes of Age, Size , Elevator, Subway, Total Number of Apartments, Management Fee. Standard errors are clustered at the district level. *p<0.1; **p<0.05; ***p<0.01

the average monthly housing price growth rate between February and April 2017 was 3.7%, while after the tightening of the mortgage market, the growth rate of transaction prices dropped by 3.8%, to an almost zero growth rate. Column 2 shows that the effect is stronger in cities with a widespread impact of the policy. Before the policy change, house prices grew at 3.8% every month, and there is almost no difference between the control and treated group. Whereas after the policy change, the housing price growth rate dropped 2.5% and (2.5% + 2.9% =) 5.4% for the control and the treatment group cities. In other words, house prices were still growing at a slower level in cities that were weakly affected by the policy, but dropped in heavily affected cities. This result persists if we consider zone fixed effect.

Columns 3 and 4 of Table 2 consider the mortgage market conditions on the expectation of house prices by comparing the listing prices of properties that enter into markets three months before and after the policy change. The dependent variable is the logarithm of listing prices. As suggested by the results in Column 3, the average growth rate of listing prices before the policy change was 2.4% and dropped by 2% after that. The growth in listing prices before the policy is mainly driven by cities that are less affected in the event, as in Column 4 the listing price growth rate before the policy change was 1.2% lower in treated cities relative to the control group. And we cannot conclude that more affected cities experienced larger drop in the growth rate of listing prices, as the triple interaction term has an economically small and statistically insignificant coefficient. These results imply that credit policies have a weaker impact on listing prices than on transaction prices, an evidence for households' optimism. An alternative interpretation is the predictability of policy changes, such that households have adjusted their expectation before the policy implementation.

To study how housing supply and demand were changed after the event, I use the following regression model focusing on the level of demand and supply.

$$\log(Dep_{imt}) = a_0 + a_1 Post_i + a_2 Policy_i + a_3 Post_i \times Policy_i + \mathbf{a}_4 \mathbf{W}_{imt} + \epsilon_{imt}. \tag{2}$$

The dependent variables include housing supply measures (the number of alternatives in the district at the time of listing), market liquidity measure (the number of transactions in the district), and housing demand measures (the number of likes per listing-day). As before, $Post_i$ is a dummy variable that equals one if the observation is after the policy change and zero otherwise. $Post_i \times Policy_i$ equals one if the observation is in a treated city after May 2017, and zero otherwise. Table 2 Columns 7 to 9 display the regression results. For less affected cities, there were 33 more available listed alternatives per district after the mortgage market tightening, and for heavily affected cities the number was $(33 + 179 =)$ 212 more. Since the number of alternative properties is determined by the supply of new properties and the demand from buyers who just purchased properties, the result implies that housing supply increased after the policy change relative to the housing demand. On the contrary, there was a decrease in the number of transactions, a proxy for market liquidity, after the policy change. The number of transactions per district was smaller by 73 unites after the policy change for cities in the control group, while the effect was stronger for treated cities where $(73 + 200 =)$ 273 fewer transaction happened on average. The effect on demand is negative – the number of likes per listing-day decreased by 0.24 for the control group and 0.38 more for the treated group after the policy change – but statistically insignificant.

Preceding results raise the concern that the policy stringency in those treated and control cities may depend

Table 3: Discontinuity at the 20-Years-Old Threshold

	log(Transaction Price)		
	Linear	Quadratic	Local Linear
T×Post×New	-0.108^{***}	-0.048^{***}	-0.048^{**}
	(0.019)	(0.015)	(0.019)
T×Post	0.070	-0.015	0.081
	(0.077)	(0.022)	(0.077)
T	0.012	0.046^{***}	0.063
	(0.039)	(0.011)	(0.039)
Constant	1.223	0.326	0.007
	(1.140)	(0.379)	(1.140)
$f(Age)^l$	Yes	Yes	Yes
Attributes	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Observations	76,544	76,544	16,674
R^2	0.926	0.926	0.928

Note: This table reports the regression of discontinuity design. The dependent variable is the logarithm of transaction prices. Linear (quadratic) specification includes linear (quadratic) term of property age and its interaction term with the month index and the post event indicator. Local linear specification only considers property between 16 and 25 years old with a linear functional form. T is the number of month had past since December 2015. $Post$ is a dummy variable taking value of one if the transaction occurs three months after an event. New is a dummy variable taking value of one if the property is less than 20 years old. Attributes include property attributes of Size , Elevator, Subway, Total Number of Apartments, Management Fee. Standard errors are clustered at the district level. *p<0.1; **p<0.05; ***p<0.01

on their housing market conditions. To further examine the effect of increasing mortgage interest rates, I use the fact that in China banks avoid granting mortgage loans for properties that are older than 20 years to study the different effect at the threshold.[17] Properties older than 20 years are almost always not eligible for mortgage loans and hence should be less affected by changes in mortgage market conditions. Hence, the variable Age_i has a cutoff between 20 and 21 in the following specification.

$$\log(Price_{imt}) = a_0 + a_1 t + a_2 t \times Post_i + a_3 t \times Post_i \times New_i + f^L(Age_i) + \mathbf{aW}_{imt} + \epsilon_{imt}. \quad (3)$$

where $f^L(Age_i)$ is a polynomial function of property age and its interactions with the month index and the after event indicator.[18] The dummy variable New_i equals one if the property is not more than 20 years old since the construction, and zero otherwise. The coefficient a_3 captures how changes in house price growth rate differ across the 20-years-old threshold.

Table 3 reports the regression results for the discontinuity in property age. The first column considers the linear functional form of age. The results suggest that after increasing mortgage interest rates the house price growth rate decreased 10.8 percentage points more for properties below their 20th year of construction compared with properties just above that. The second column further includes quadratic terms of age, providing more flexibility for the impact of property age. In this case, the price growth rate for 20-year-old properties dropped 4.8% more than that for 21-year-old counterparts. The last column only consider properties between 16 and 25 years old, and allow a linear functional form of age within the truncated range of age, which confirms the results in the quadratic specification.

3.2 Down Payment Requirements

For down payment requirements, there was no such nationwide change as the mortgage interest rate. Hence, I exploit large changes in average down payment requirements in each city at different time. An event of an increase (a decrease) in down payment requirements is defined as a larger than 15% increase (decrease) in down payment requirements compared with that in the previous month. Using a similar setting, the following regression model compares the growth rate of transaction prices three months before and after the events:

$$\log(Price_{imt}) \quad = \quad a_0 + a_1 t + a_2 t \times Event_i + a_3 t \times Event_i \times Post_i + \mathbf{aW}_{imt} + \epsilon_{imt}. \quad (4)$$

The dependent variable is the logarithm of transaction prices of property i in market m sold t months after December 2015. Since large changes in down payment requirements occur at different time in different cities, the dummy variable $Event_i$ indicates the event of a large change in down payment requirements, taking the value of one if the transaction of property i occurred three months before or after an event and zero otherwise. The dummy variable $Post_i$ indicates that the transaction of property i happened three

[17] Property ownership in China is legally using right for 50 to 70 years. As risk and uncertainty after the legal usage right expiration are much higher, banks stop providing mortgage loans if the underlying property is too old. In practice, the property age above 20 years is a commonly adopted threshold.

[18] More specifically, its functional form is $f^L(Age_i) = \sum_{l=1}^{L} \left(a_4^l Age_i^l + a_5^l t \times Age_i^l + a_6^l t \times Post_i \times Age_i^l \right)$. When the function takes a linear form, $L = 1$; when it takes a quadratic form $L = 2$.

Table 4: The Impact of Changes in Down Payment Requirements

	Down Payment Requirement Increases				Down Payment Requirement Decreases			
	(1)	Linear	Quadratic	Local Linear	(5)	Linear	Quadratic	Local Linear
T	0.018***	0.018***	0.018***	0.017***	0.021***	0.021***	0.036***	0.020***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
T×Event	0.028***	0.033***	0.018***	0.055***	−0.011***	−0.005	−0.053***	0.024
	(0.004)	(0.005)	(0.006)	(0.014)	(0.003)	(0.005)	(0.018)	(0.015)
T×Event×Post	−0.030***	−0.021*	−0.007	−0.090***	0.014***	−0.008	0.047*	0.085*
	(0.003)	(0.012)	(0.012)	(0.029)	(0.003)	(0.013)	(0.028)	(0.052)
New		−0.103***	−0.042***	−0.030**		−0.108***	−0.052***	−0.026***
		(0.018)	(0.010)	(0.012)		(0.018)	(0.015)	(0.010)
T×Event×Post×New		−0.017***	−0.008	−0.004		0.015	0.004	−0.019
		(0.006)	(0.005)	(0.006)		(0.010)	(0.025)	(0.012)
Constant	1.033***	1.166***	1.134***	1.210***	1.000***	1.135***	0.803***	1.135***
	(0.031)	(0.035)	(0.035)	(0.076)	(0.035)	(0.033)	(0.235)	(0.069)
$f(Age)^l$	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Attributes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Event FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	338,789	338,789	338,789	73,825	338,789	338,789	139,201	73,825
R^2	0.911	0.912	0.913	0.905	0.909	0.910	0.919	0.904

Note: This table presents OLS regression results of house prices with large increases (Column 1 to 4) and decreases (Column 5 to 8) in down payment requirements. Column 2 and 6 include all linear term of property age and its interaction term with the month index, the event indicator, and post event indicator. Column 3 and 7 include all quadratic term of property age and its interaction with the month index, the event indicator, and post event indicator. Column 4 and 8 only considers property between 16 and 25 years old with linear specification. T is the number of month had past since December 2015. $Event$ is a dummy variable taking value one if the transaction occurs three months before and after an event, and zero otherwise. $Post$ is a dummy variable taking value of one if the transaction occurs three months after an event. New is a dummy variable taking value of one if the property is less than 20 years old. Attributes include property attributes of Age, Size , Elevator, Subway, Total Number of Apartments, Management Fee. Standard errors are clustered at the district level. *p<0.1; **p<0.05; ***p<0.01

months after a large down payment requirement change. And $\mathbf{W}_{imt}$ stands for property attributes including district fixed effects and event fixed effects.

As shown in Column 1 of Table 4, the monthly house price growth rate was 1.8% in the sample period. Shortly before an increase in down payment requirements the monthly house price growth rate was as high as ($1.8\% + 2.8\% =$) 4.6%, while after the event the rate slowed down by 3.0%. In events with lower down payment requirements, as shown in Column 5, the result is the opposite: Before the decrease in down payment requirements monthly house price growth rate was 1.1% lower than the average, while after the event house prices grew 1.4% faster than shortly before those events. The results suggest that higher down payment requirements slow down the house price growth rate, while lower down payment requirements stimulate the growth of house prices. However, as the increase in down payment requirements tends to happen in booming housing markets, and decreases happen in sluggish housing markets, it reminds us of the endogeneity concern of credit policy changes.

I employ again the 20-years-old threshold in mortgage loan availability to analyse the effect of down payment requirements. Most results confirm that young properties are more affected by credit policy changes, but the results are not all statistically significant. As shown in Columns 2 to 4 in Table 4, the quadruple intersection term compares properties just above and below the 20-years-old threshold. In the linear form specification, newer properties' prices grew 1.7% slower after an increase in down payment requirement, meaning that down payment requirements are more effective for new properties, while in the other two specifications, the effect is smaller and no longer statistically significant. On the other hand, the effect of a decrease in down payment requirements is more ambiguous, as we cannot reject the hypothesis that decreases in down payment requirements have the same impact on properties above and below the threshold.

3.3 The Need for a Model

Preceding results suggest that tight mortgage credit conditions can slow down the house price growth rate, increase housing supply relative to demand, and decrease housing demand and market liquidity. However, we need stronger evidence for making causal statements. More importantly, these findings say little of the underlying mechanism. To fully evaluate the effect of mortgage credit conditions on housing markets, it is necessary to analyse the transmission mechanism – how mortgage credit conditions affect financing costs for mortgages and down payments, which affect the value of homeownership, households' purchasing and selling decision, and ultimately house prices. This may be difficult for several reasons. First, as econometricians, we may observe equilibrium outcomes but lack direct measures of demand and supply, making the disentanglement of the two driving forces nontrivial. For example, observing that the number of alternative properties increased after tightening mortgage credit can not tell whether demand decreased or supply increased, but only that supply increased relative to demand. Second, mortgage credit variables are endogenously determined by housing markets. Exogenous changes in mortgage credit conditions are rare because even policy interventions can be predictable. As implied by the results in section 3.2, down payment requirements are increased in hot housing markets to cool those markets, and vice versa. Therefore, we are short of a clean way to identify the causal effect with reduced form methods. Furthermore, forward-looking expectations play an important role in housing markets. The comparison between transaction prices and listing prices in section 3.1 revealed households' optimism.

To address these issues, in the rest of the paper I present a structural model of housing demand and supply which incorporates households' expectations of future house values. This model allows me to quantify the mechanism of how mortgage credit conditions affect the housing market through housing demand, supply, and expectations.

4 The Model

The model considers each city as a market and each month as a time period, where property buyers and sellers in a market and time period make decisions to maximize their lifetime expected utility. Sellers decide when to sell their property, while buyers choose which type of property to purchase conditional on the decision to purchase in that period. Sellers and buyers are forward-looking households with an adaptive expectation of the value of property ownership. They are intrinsically not different so that once a property buyer has purchased a property, he becomes the property owner and has the option to sell the property, and vice versa for property sellers. This assumption implies that property buyers and sellers share the same valuation for the utility generated by the same set of property attributes.

In a real estate market m, each seller has a property i to sell and ends up selling it to a buyer. Suppose that the owner of property i posts an advertisement for a sale at time $t_{i,0}$, after which buyers may approach her to visit the property, and offer the seller a price for the property. At each time period $t > t_{i,0}$ with a coming bid, the seller needs to decide whether to sell the property at the bid price or reject the offer. If the seller rejects, she retains the opportunity to sell in the next period $t+1$. Each property is classified as of type j, $j \in \{1, 2, \cdots, J_m\}$, based on characteristics X_j, such as its age, size, and location. Buyers enter into the market for the type of property that yields the highest utility and bid for that type until their offer is accepted. A potential buyer is willing to pay the market valuation of the property P_{jmt} plus an idiosyncratic term that reflects the buyer's specific preferences. The market valuation P_{jmt} is the equilibrium price for the property of type j under mortgage credit conditions Y_{mt}, which include mortgage interest rates and down payment requirements.

4.1 The Seller's Problem

When sellers make their optimal decision to sell the property, there are two sources of uncertainty. First, market conditions may change over time, driving prices up and down. Second, real estate properties are heterogeneous and illiquid, making any transaction possible only when there is a buyer willing to bid for the property. Assume that for each property type j buyers arrive according to a Poisson process with rate λ_{jmt}, capturing the likelihood that there will be bidders arriving in one period.

Let S_{ijmt} indicate whether there exist buyers' bids for property i in time t. If $S_{ijmt} = 1$, there is at least one buyer arriving in that period and the seller can make the decision to sell or to hold.[19] When no buyer arrives,

[19] I assume that there may be more than one bids in a period. In this case, sellers will focus on the bid with the highest bidding price. When she chooses to sell, she will accept the highest bid. When she chooses to decline the highest bid, she will decline all other bids in this period.

$S_{ijmt} = 0$ and the seller can only hold the property. I focus on whether there exists at least one bid in one period, because the binary setting can capture the illiquidity feature while keeping the size of the state space tractable. Denote the probability of S_{ijmt} by

$$F_S(S_{ijmt}) = \begin{cases} q_{jmt} & \text{if } S_{ijmt} = 1; \\ 1 - q_{jmt} & \text{if } S_{ijmt} = 0, \end{cases}$$

where

$$q_{jmt} = 1 - e^{-\lambda_{jmt}} \tag{5}$$

is the probability of having buyers in one period. A high q_{jmt} means that this property type is popular and the demand for the property type is high. It further indicates a high market liquidity provided by buyers, where sellers can easily find a buyer. On the contrary, a low q_{jmt} corresponds to low liquidity provided by buyers due to weak demand.

Given the realization of S_{ijmt}, denote the seller's decision by $d^s_{ijmt} \in D^{S_{ijmt}}$. The superscript of d^s_{ijmt} indicates seller. If the seller decides to sell the property i in time period t, $d^s_{ijmt} = 1$; if she decides to keep holding the property, $d^s_{ijmt} = 0$. According to the definition, $D^0 = \{0\}$ and $D^1 = \{0, 1\}$. I assume that the selling decision is irreversible, namely the seller faces an optimal stopping problem to choose the selling time $t_{i,1} > t_{i,0}$ such that $d^s_{ijmt_{i,1}} = 1$ and $d^s_{ijmt} = 0$ for all $t \in (t_{i,0}, t_{i,1})$.

The utility of owning a property per period is denoted by $u(\Omega_{jmt}, S_{ijmt}, \varepsilon_{ijmt,d}, d^s_{ijmt})$, where $\Omega_{ijm} = \{X_j, Y_{mt}, P_{jmt}, \xi_{jmt}\}$ and ξ_{jmt} is the unobserved quality of the property type, for instance, the congestion in the neighborhood. The state variables are Ω_{ijm} and S_{ijmt}, that is property characteristics, mortgage credit conditions, house prices, unobserved quality, and the coming bids. The idiosyncratic unobservable utility $\varepsilon_{ijmt,d}$, which is assumed to be an independently and identically distributed (i.i.d.) type I extreme value term, depends on the current decision d^s_{ijmt}. No matter whether there is a potential buyer's bid, the seller can keep holding the property and enjoy the utility generated by the property, either through living there or through rental income. Only when there are potential buyers arriving in a given period, can the seller decide to sell the property for price P_{jmt} and stop enjoying the flow of utility. Following the assumption in Rust (1987) that the per period utility function is additively separable, and normalizing the average flow utility of selling to zero, the utility of owning a property is

$$u(\Omega_{jmt}, S_{ijmt}, \varepsilon_{ijmt,0}, 0) = \delta(\Omega_{jmt}) + \varepsilon_{ijmt,0} \tag{6}$$

and the utility of no property is $u(\Omega_{jmt}, S_{ijmt}, \varepsilon_{ijmt,1}, 1) = \varepsilon_{ijmt,1}$. The decomposition implies that the utility function can be divided into the property type specific part $\delta(\Omega_{jmt})$ and the idiosyncratic part of owning and selling a property, i.e., $\varepsilon_{ijmt,0}$ and $\varepsilon_{ijmt,1}$.

In every period, the seller observes the realization of Ω_{jmt} and S_{ijmt}. Based on their historical realizations, she forms expectations of future states and chooses d^s_{ijmt} to maximize her expected utility. The seller's problem is

$$\max_{d^s_{ijmt} \in D^{S_{ijmt}}} \mathbb{E}\left\{ \sum_{t=t_{i,0}+1}^{\infty} \beta^{t-t_{i,0}} u(\Omega_{jmt}, S_{ijmt}, \varepsilon_{ijmt,d}, d^s_{ijmt}) | \Omega_{jmt_{i,0}}, S_{ijmt_{i,0}}, \varepsilon_{ijmt_{i,0},d}, d^s_{ijmt_{i,0}} \right\},$$

where $\beta \in (0,1)$ is households' discount factor. Using $V(\Omega_{jmt}, S_{ijmt}, \varepsilon_{ijmt,d}, d^s_{ijmt})$ to denote the value function of the owner, the value function of holding the property is the utility generated by the property in the current period plus the expected value of owning it in the next period discounted by the discount factor, that is

$$\begin{aligned} V(\Omega_{jmt}, S_{ijmt}, \varepsilon_{ijmt,0}, 0) &= \delta(\Omega_{jmt}) + \varepsilon_{ijmt,0} \\ &+ \beta\mathbb{E}\left\{V(\Omega_{jmt+1}, S_{ijmt+1}, \varepsilon_{ijmt+1,d}, d^s_{ijmt+1})|\Omega_{jmt}, S_{ijmt}, \varepsilon_{ijmt,d}, d^s_{ijmt}=0\right\}. \end{aligned} \tag{7}$$

Under regular assumptions of Conditional Independence and i.i.d. unobservables $\varepsilon_{ijmt,d}$, the expected value functions have closed-form expressions. Detailed discussions and the derivation are in Appendix A.2. Denoting $\overline{V}(\Omega_{jmt}, S_{ijmt})$ as the expected value function with respect to $\varepsilon_{ijmt,d}$, the dynamic programming logit model implies Bellman equations in waiting state and decision state respectively as:

$$\overline{V}(\Omega_{jmt}, 0) = \delta(\Omega_{jmt}) + \beta\mathbb{E}\left[q_{jmt+1}\overline{V}(\Omega_{jmt+1}, 1) + (1-q_{jmt+1})\overline{V}(\Omega_{jmt+1}, 0)|\Omega_{jmt}\right]; \tag{8}$$

$$\overline{V}(\Omega_{jmt}, 1) = \ln\left(1 + \exp\left(\overline{V}(\Omega_{jmt}, 0)\right)\right). \tag{9}$$

In the waiting state, sellers can only hold the property and hence the expected value function is the expectation of value functions in equation (7) over the idiosyncratic term. In the decision state, sellers can choose between the selling and holding, and hence there are two components in the logarithm: the exponential value of selling, which equals 1, and the exponential value of holding, which is the same as that in the waiting state.

In the decision making stage, denoting the probability of selling a type j property in market m at time t given that there exist bids as $p^s_{jmt}(\Omega_{jmt}) := \Pr(d^s_{ijmt} = 1|\Omega_{jmt}, S_{ijmt} = 1)$, the conditional probability of selling has the logit form

$$p^s_{jmt} = \frac{1}{1 + \exp\left(\overline{V}(\Omega_{jmt}, 0)\right)}. \tag{10}$$

That is, the probability of accepting bids equals the exponential value of selling compared to the exponential value in the decision state. The higher the value of owning properties $\overline{V}(\Omega_{jmt}, 0)$, the less likely sellers will sell, and hence the value in the decision state is closer the value of owning properties. It constitutes a measure of the market liquidity provided by sellers. A high p^s_{jmt} means that sellers are willing to sell the property when a buyer bids, while a low p^s_{jmt} suggests that sellers are reluctant to sell. In fact, the probability of receiving bids q_{jmt} and the probability of selling p^s_{jmt} provide a way to measure the overall market liquidity provided by buyers and sellers. If both probabilities are high, it suggests a liquid real estate market; whereas, if both probabilities are low, it suggests an illiquid market. If q_{jmt} is high while p^s_{jmt} is low, the demand is high and sellers have high bargaining power, corresponding to a sellers' market; if q_{jmt} is low while p^s_{jmt} is high, coming bids are rare and sellers are eager to sell, indicating a buyers' market.

As a result, for property i the probability of observing that it was listed in $t_{i,0}$ and sold in period $t_{i,1}$ is

$$\begin{aligned} &\Pr(d_{it_{i,0}+1} = 0, \cdots, d_{it_{i,1}-1} = 0, d_{it_{i,1}} = 1|\Omega_{jmt_{i,0}}) \\ =& \left\{\prod_{t=t_{i,0}+1}^{t_{i,1}-1}\left(1 - q_{jmt}p^s_{jmt}\right)F_\Omega(\Omega_{jmt}|\Omega_{jmt-1})\right\} \times q_{jmt_{i,1}}p^s_{jmt_{i,1}}F_\Omega(\Omega_{jmt_{i,1}}|\Omega_{jmt_{i,1}-1}), \end{aligned} \tag{11}$$

where $F_\Omega(\cdot|\cdot)$ denotes the transition probability of state variable Ω_{jmt}.

4.2 The Buyer's Problem

Buyers are forward-looking households similar to sellers, in the sense that once buyers purchase a property they switch to property owners who can enjoy the utility of living there and have the option to sell in the future. Even though, for each transaction there must be a buyer, the data source does not keep track on buyers' behavior over time on the platform. Given such limitation of the data, I focus on buyers' static decision on which type of property to buy conditional on purchasing a residential property at time t. Conditional on purchasing, buyers can choose among all types of properties in the market, whose characteristics and prices are observable by buyers.[20] Housing preferences are mainly based on their life status (e.g., place of work, family size, marriage or retirement). For example, a household consisting of a couple and a preschool-age child would prefer a residential property with three rooms located in the same district as the couple's workplaces with good kindergartens to buying a one-room property in a commercial center. Therefore, a buyer faces a discrete choice problem of choosing a property type j determined by property attributes (age, size, and location) which yield the highest value of owning compared to all other available property types k in the market, i.e.,

$$\overline{V}(\Omega_{jmt}, S_{ijmt}) + \varepsilon_{ijmt,0} > \max_{k \in \{1,2,\ldots,J_m\}} \overline{V}(\Omega_{kmt}, S_{ikmt}) + \varepsilon_{ikmt,0}, \ \forall k \neq j.$$

Notice that once a buyer purchases a property, he becomes the property owner with the same value function as in the seller's problem. The expected value function $\overline{V}(\Omega_{jmt}, S_{ijmt})$ is the same as that in equation (9) and (8). The buyer searches properties in the market focusing on the most desirable type and his final choice of i is of type j. Denoting the type decision of buyer of property i by d^b_{imt} (the superscript indicates buyers), the probability of choosing type j for any buyer $p^b_{jmt} := \Pr(d^b_{imt} = j)$ has a closed form expression due to the Type I extreme value distributed $\varepsilon_{ijmt,0}$, that is,

$$p^b_{jmt} = \frac{\exp(\overline{V}(\Omega_{jmt}, 0))}{\sum_{k=1}^{J_m} \exp(\overline{V}(\Omega_{kmt}, 0))}. \tag{12}$$

As the probability of choosing a type increases with households' valuation for that type, the higher is the expected value function, the higher is the market share of that type in the aggregate level. This suggests that p^b_{jmt} can be approximated by the proportion of buyers that chose type j in market m at period t; this will be helpful for identifying the type average value function as shall see in the next section.

5 Econometric Model

I follow the estimation strategy of Bayer, McMillan, Murphy and Timmins (2016), which is computationally light. I estimate the model in two 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 in each time period. In the second stage, I use sellers' decision on when to sell a property to estimate the liquidity of real estate markets, and recover the estimates of the per period utility based on a set of observable characteristics.

[20] In other words, buyers have discretion to buy any type of property. In fact, there are always more listed property than number of transactions for every type of properties in a market and time combination, avoiding the situation where buyers wish to buy but no lists for a certain type.

5.1 First Stage: Property Type Decision and Expected Value Function

In this stage, I focus on buyers' property type decision. In each market and time period, the total number of transactions for each property type through Lianjia is observable. The empirical proportion of buyers in a given market-period combination who decided to purchase a type j property provides us an estimate for the expected lifetime value of holding it. Since we do not observe buyers' outside options, i.e., no purchase or purchase through another platform in that period, the expected value of property ownership is identifiable up to an additive constant and requires a normalization. The value functions in each market-period combination are normalized by their mean μ_{mt}, such that the normalized value functions $\widetilde{V}(\Omega_{jmt}, 0) = \overline{V}(\Omega_{jmt}, 0) - \mu_{mt}$ have mean zero. Maximizing the likelihood of observed buyers' property type decisions in equation (12) yields a closed-form expression for the normalized value function.

$$\widehat{\widetilde{V}}(\Omega_{jmt}, 0)) = \log(\widehat{p}^b_{jmt}) - \frac{1}{J_m} \sum_{k=1}^{J_m} \log(\widehat{p}^b_{kmt}), \tag{13}$$

where $\widehat{p}^b_{jmt}$ is the empirical probability of 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 reduce 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 Appendix A.3.

5.2 Second Stage: Market Liquidity and Per Period Utility

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 and the probability of selling to the buyer to construct the likelihood function. Maximizing the likelihood function delivers the estimates for the market liquidity, which can be used to calculate the per period utility.

5.2.1 Market Liquidity

After obtaining $\widehat{\widetilde{V}}(\Omega_{jmt}, 0)$ from (13), the seller's probability of selling in a period can be calculated according to equation (10) as follows:

$$\widehat{p}^s_{jmt} = \frac{1}{1 + \exp(\widehat{\widetilde{V}}(\Omega_{jmt}, 0) + \mu_{mt})}, \tag{14}$$

where the normalization term μ_{mt}, the average value of homeownership, is the parameter to be estimated. What remains to be estimated is the rate λ_{jmt} at which bids arrive from potential buyers, which determines the probability of having a bid in one period.

I use the observed information on transactions to model potential buyers' bidding rate. For each listed property, the potential buyers' bidding rate λ_{jmt} is closely related to the probability of transaction per listed property, denoted by γ_{jmt}, because each transaction occurs only when there exists a bid. The higher is the number of transactions, the higher is the probability of receiving bids. I model the number of coming bids proportionally to the number of transactions per period at the rate ϕ_m, that is $\lambda_{jmt} = \phi_m \gamma_{jmt}$. In other words, ϕ_m is the parameter that maps the number of transactions per listed property to the number of received bids per listed property for market m. Since each transaction must correspond to a bid, whereas for each bid the seller can choose to reject, ϕ_m should be larger than one. A larger ϕ_m indicates higher bidding frequency and hence higher housing demand in the market.

I use two other pieces of information to identify the probability of transaction per listed property – the number of total transactions in that market and month, denoted by N_{mt}, and the total number of listed properties of a property type, denoted by A_{jmt}. Both of them are equilibrium outcomes determined by the state variables and only observable ex post, making it hard for households to utilize them as state variables. But the two variables provide extra source of variation in the extensive properties of supply and demand, which help identify key parameters in the model. Together with the buyers' probability of choosing that type p^b_{jmt}, the number of total transaction determines the demand for that type, while the total number of listed properties of that type A_{jmt} gives us supply-side information, that is how many alternatives buyers have. Combining the demand and the supply channels, the rate of transaction per listed property is

$$\gamma_{jmt} = \frac{p^b_{jmt} N_{mt}}{A_{jmt}}. \tag{15}$$

The probability of choosing type j property for each potential buyer can be estimated from equation (12) using the estimated value functions $\widehat{\widetilde{V}}(\Omega_{jmt}, 0)$. In other words, γ_{jmt} is a function of Ω_{jmt}.

Expressing $\widehat{q}_{jmt} = 1 - \exp(-\phi_m \widehat{\gamma}_{jmt})$ according to equation (5) and $\widehat{p}^s_{jmt}$ according to equation (14), the log-likelihood function can be derived from equation (11), where ϕ_m and μ_{mt} are the parameters to be estimated.[21]

$$L_{Sellers}(\phi_m, \mu_{mt}) = \sum_{i=1}^{N} \log \widehat{p}^s_{jmt_{i,1}} + \sum_{i=1}^{N} \log \widehat{q}_{jmt_{i,1}} + \sum_{i=1}^{N} \sum_{t=t_{i,0}+1}^{t_{i,1}-1} \log\left(1 - \widehat{q}_{jmt} \widehat{p}^s_{jmt}\right). \tag{16}$$

The estimates $\widehat{\phi}_m$ and $\widehat{\mu}_{mt}$ can pin down the probability of receiving bids from potential buyers $\widehat{q}_{jmt}$ and the probability of selling given a bid $\widehat{p}^s_{jmt}$, which provide us with estimates of liquidity in housing markets.

5.2.2 Prices and Identification

To estimate the per period utility, I still need to predict house prices for each property type P_{jmt}. As the final transaction price for each property is observable, I can predict the average price for each property type using this information. One concern is that the observed transaction prices may be endogenously determined by factors that affect the value of owning a property, for instance local housing regulations, leading to an estimation bias. To address the price endogeneity issue, I use instrumental variables that are directly related to the prices of property types in a market-time combination, but not related to the utility of owning properties in that market.

[21]Following Rust (1987) and Hotz and Miller (1993), the log-likelihood function can be divided into two parts and estimated separately. One part includes the transition probability of state variables and the other part includes the choice probabilities given the state variables. Here the log-likelihood function is the latter part.

The instrumental variables include 1) the average of the house price index for the second-hand residence of neighboring cities, 2) the average of the house price index for the new residences of neighboring cities, 3) newly constructed residences in current month compared with those of last year, and 4) newly constructed residences in the last month compared with those of last year. The first two variables satisfy the exclusion restrictions due to the strict household-registration system in China, known as *Hukou*, and purchase restriction for non-local registered households, making Chinese housing markets highly segmented in terms of demand. Therefore, price indexes in other markets can hardly impact households' utility of enjoying residence properties in their own market, but asset prices in neighboring markets are closely related (e.g., Beijing and Tianjin). For the last two variables, the newly constructed residences represent a shock to housing supply because houses need some time to be built such that the number of completed constructions is not a result of the current market conditions, but it affects current house prices through an increase in housing supply.

Assume that the final transaction price is log-normally distributed with the following functional form:

$$\log(P_{ijmt}) = \eta_0 + \eta_1 Z_{mt} + \eta_j + \eta_t + \eta_m + \nu_{ijmt}. \tag{17}$$

where P_{ijmt} is the observed transaction price of property i. Z_{mt} denotes the instrumental variables, while η_j, η_t, η_m stand for property type fixed effects, time fixed effects and market fixed effects. ν_{ijmt} is the normally distributed idiosyncratic valuation. The regression estimates $(\hat{\eta}_0, \hat{\eta}_1, \hat{\eta}_j, \hat{\eta}_t, \hat{\eta}_m)$ provide us with the predicted market price for properties with type j as:

$$\widehat{P}_{jmt} = \exp(\hat{\eta}_0 + \hat{\eta}_1 Z_{mt} + \hat{\eta}_j + \hat{\eta}_t + \hat{\eta}_m), \quad \forall\, t_{i,0} \leq t \leq t_{i,1}.$$

Table 5 reports the first-stage results for house prices, with the four instrumental variables. The coefficients are highly significant, suggesting that the instruments are very relevant. As expected, the second-hand house price index in neighboring cities has a positive coefficient, while as substitutes for second-hand houses, the new house price index has a negative coefficient. Similarly, a large number of newly constructed residences in the current and last month increase housing supply and hence has negative coefficients. By including type fixed effects, time fixed effects, and market fixed effects, the model captures a large fraction of the variation in house prices (the R-squared is 0.91).

5.2.3 Per Period Utility

The estimated lifetime value function, together with the estimated probability of receiving bids, are used to recover the per period utility function as suggested by equation (8), that is,

$$\begin{aligned}\widehat{\delta}(\Omega_{jmt}) \;&=\; \widehat{\widehat{V}}(\Omega_{jmt}, 0) - \beta\Big(\mathbb{E}\left[\widehat{q}_{jmt+1} \ln\left(1 + \exp\left(\widehat{\widehat{V}}(\Omega_{jmt+1}, 0)\right)\right) |\Omega_{jmt}\right] \\ &\qquad + \mathbb{E}\left[(1 - \widehat{q}_{jmt+1})\widehat{\widehat{V}}(\Omega_{jmt+1}, 0)|\Omega_{jmt})\right]\Big),\end{aligned} \tag{18}$$

where $\widehat{\widehat{V}}(\Omega_{jmt}, 0) = \widehat{\widetilde{V}}(\Omega_{jmt}, 0) + \widehat{\mu}_{mt}$, and $\widehat{q}_{jmt+1}$ denotes the expected probability of having a potential buyer for type j property in market m at time $t+1$, which depends on Ω_{jmt+1}. The discount factor β is set

Table 5: First Stage Results for House Prices

	log(Transaction Price)
Second-Hand House Price Index in Neighbouring Cities	0.013^{***}
	(0.0002)
New House Price Index in Neighbouring Cities	-0.005^{***}
	(0.0003)
Newly Constructed Houses (Current Month)	-0.001^{***}
	(0.00003)
Newly Constructed Houses (Last Month)	-0.0003^{***}
	(0.00003)
Constant	-0.862^{***}
	(0.019)
Type Fixed Effect	Yes
Time Fixed Effect	Yes
Market Fixed Effect	Yes
Observations	338,789
R^2	0.912

Note: This table presents the first-stage results for house prices. The dependent variable is the logarithm of transaction prices (in 1 Million CNY). Second-Hand (New) House Price Index in Neighbouring Cities is the average of house price index for second-hand (new) houses of other major cities in the same province, or in neighbouring provinces for province level cities. Newly Constructed Houses (Current /Last Month) is the square meters of newly constructed residence in current/last month of the province compared with that of the last year in the same month. The data of house price index for other cites and newly constructed houses is from National Bureau of Statistics of China. *p<0.1; **p<0.05; ***p<0.01

equal to 0.95. To calculate the expectations on the right side of the equation above, we need to estimate the transition probabilities of $F_V(\overline{V}(\Omega_{jmt+1}, 0)|\Omega_{jmt})$.[22]

Based on the estimated house prices and value functions, I can estimate the transition probability of the value functions assuming that the value function evolves as an autoregressive process, such that:

$$\widehat{\overline{V}}(\Omega_{jmt}, 0) = \zeta_{jm}^0 + \sum_{l=1}^{L} \zeta_v^l \widehat{\overline{V}}(\Omega_{jmt-l}, 0) + \sum_{l=1}^{L} \zeta_p^l \widehat{P}_{jmt-l} + \sum_{l=1}^{L} \zeta_y^l Y_{mt-l} + \zeta_{jm}^t t + \epsilon_{jmt}. \tag{19}$$

Here ζ_{jm}^0 and ζ_{jm}^t are type specific constants and time trends for the value functions. The estimates $\hat{\zeta}_v^l, \hat{\zeta}_p^l, \hat{\zeta}_y^l$ denote the average effect of the lagged value function, the equilibrium price, and mortgage credit conditions on the current value function. For each explanatory variable, I consider two lagged periods, i.e., $L = 2$, to allow the state variables in the two most recent months affect the value functions. The residuals $\hat{\epsilon}_{jmt}$ determine the distribution of value functions in the next period conditional on the current states, which allows me to calculate the expectations in equation (18) by simulation.

Finally, I estimate the determinants of the per period utility function using the estimated $\widehat{\delta}(\Omega_{jmt})$ that is backed out from the estimated value functions in equation (18). As the per period utility is a function of the state variables, I model the utility of owning a type j property in market m at time t as a linear function:

$$\widehat{\delta}(\Omega_{jmt}) = \overline{\alpha} + \alpha_P \widehat{P}_{jmt} + \alpha_X X_j + \alpha_Y \widehat{P}_{jmt} Y_{mt} + \alpha_{mt} + \xi_{jmt}. \tag{20}$$

Here α_P is expected to be negative, capturing the opportunity cost of not selling the property. When housing prices are high, the utility of holding the property becomes smaller compared with selling it for cash. α_X is a vector of parameters measuring the utility generated from different property characteristics. Mortgage credit variables are denoted by $\widehat{P}_{jmt} Y_{mt}$, including the interaction terms of property price, mortgage interest rates, and down payment requirements.[23] The coefficient α_Y estimates the the impact of total debt financing cost and required down payment on the utility of owning property, as well as how mortgage credit variables affect price sensitivity within a market-time segment; α_{mt} is the market-time fixed effects; ξ_{jmt} is the type-market-time specific unobservable term that quantifies the unobserved quality for different property types. The estimates $(\widehat{\overline{\alpha}}, \widehat{\alpha}_P, \widehat{\alpha}_X, \widehat{\alpha}_Y, \widehat{\alpha}_{mt}, \widehat{\xi}_{jmt})$ are obtained by ordinary least square regressions.

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[22] For households, Ω determines the current value function, through which affects the predictions of the distributions of future value functions. It is sufficient to form expectation of future value functions conditional on current value functions and state variables. More discussion, see e.g., Gowrisankaran and Rysman (2012), Melnikov (2013).

[23] The intersection of property price and the city-month average mortgage interest rate is a proxy for total financing cost for debt. The interaction of property price and the city-month average down payment requirement is a proxy for total required equity. The triple intersection of property price, mortgage interest rates, and down payment requirements account for the substitution effect between the two instruments.

6 Results

6.1 Estimates for Housing Demand, Supply, and Market Liquidity

I use maximum likelihood estimation to obtain estimates for housing demand, supply, and then back out per period utility of owning properties. Table 6 summarizes the estimates for housing supply and demand. The first column presents the estimated $\widehat{\phi}_m$, measuring how frequently buyers bid in each real estate market, with standard errors in the brackets. For the average of value functions, the estimates $\widehat{\mu}_{mt}$ are at the city-month level. Therefore, for each city, I present the mean, median, and standard deviation of the estimates. Based on those estimates, the statistics of the probability of receiving a bid $\widehat{q}_{jmt}$ and the probability of selling $\widehat{p}^s_{jmt}$ given a bid are presented; these indicate housing demand and supply respectively. Among all cities, Tianjin has the highest frequency of incoming bids, where buyers on average bid 19.1 times before a transaction. The high demand makes sellers almost certain to receive a bid from potential buyers. At the same time, the value of owning a property is high, making sellers unwilling to sell their property. The median of $\widehat{\mu}_{mt}$ for Tianjin is 0.01, and thus the median seller's probability of selling is only 0.34. Taking the relative magnitude of demand to supply as a measure of seller relative bargaining power, a high ratio of the two probabilities suggests a sellers' market, for example, Tianjin and Shenzhen. While for buyers' markets such as Suzhou and Shanghai, the situation is the opposite. In Shanghai, with a 24% probability, a seller will receive a bid in a given month, and with a 60% probability the seller will accept, as the low demand from buyers makes sellers eager to sell.

Figure 3 plots the market liquidity and seller's relative bargaining power for each city. Market liquidity is the product of $\widehat{p}^s_{jmt}$ and $\widehat{q}_{jmt}$, which represents the probability of having a transaction for a listed property in each time period. The relative bargaining power of sellers compared to buyers is the ratio of sellers' probability of receiving bids $\widehat{q}_{jmt}$ to sellers' probability of selling to bidders $\widehat{p}^s_{jmt}$, presented in logarithm. For each city, the median of $\widehat{p}^s_{jmt}$ and $\widehat{q}_{jmt}$ are used to calculate market liquidity and relative bargaining power. Comparing with Figure 1, the markets with lower market liquidity tend to have a longer time on the market, the common notion of liquidity in the real estate literature, for example Suzhou and Shanghai, while liquid markets need shorter time to sell properties, for example Wuhan. However, focusing on equilibrium outcomes of supply and demand, such as time on the market, quantity and prices, is not enough to understand the fundamentals of housing markets.

The added value of the structural model is that we can disentangle housing supply and demand in each local housing market from an agent optimization perspective, providing a new method to examine supply-demand in real estates markets. Given the same market liquidity, markets with high bargaining power for sellers relative to buyers (i.e., sellers' markets) are located in the upper region, while markets where sellers have low bargaining power relative to buyers (i.e., buyers' markets) are located in the lower region. The markets with balanced housing supply and demand (i.e., balanced markets) are located in the middle. Cities with similar liquidity can be different types of market. For example, Shenzhen and Chongqing are similar in market liquidity level, but in Shenzhen housing demand is much larger than supply due to high value of property ownership and thus sellers are unwilling to sell their property, making a transaction unlikely. On the contrary, in Chongqing, sellers are less likely to receive bids, decreasing the chance of a transaction. By

Table 6: Estimation Results: Housing Supply and Demand

	Bidding Freq. $\widehat{\phi}_m$	Homeownership Value $\widehat{\mu}_{mt}$			Prob. of Having Bids $\widehat{q}_{jmt}$			Prob. of Selling $\widehat{p}^s_{jmt}$		
		Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
Beijing	3.92	-2.04	-1.46	1.41	0.57	0.58	0.27	0.61	0.61	0.21
	(0.00)									
Shanghai	3.33	-2.12	-1.80	1.20	0.24	0.17	0.22	0.62	0.60	0.20
	(0.00)									
Shenzhen	12.53	0.09	0.09	0.50	0.81	0.87	0.18	0.33	0.29	0.15
	(0.04)									
Guangzhou	4.41	-1.21	-1.11	0.58	0.48	0.46	0.22	0.54	0.51	0.17
	(0.00)									
Xiamen	6.80	-1.14	-1.02	0.63	0.57	0.56	0.24	0.65	0.63	0.14
	(0.19)									
Hangzhou	5.69	-0.76	-0.56	0.53	0.55	0.55	0.25	0.54	0.54	0.16
	(0.00)									
Tianjin	19.10	-0.23	0.01	0.61	0.87	0.96	0.18	0.38	0.34	0.21
	(0.00)									
Nanjing	6.65	-0.48	-0.43	0.29	0.66	0.66	0.22	0.48	0.47	0.16
	(0.00)									
Qingdao	5.42	-2.41	-0.85	3.38	0.55	0.59	0.29	0.60	0.58	0.19
	(0.08)									
Suzhou	2.53	-2.57	-2.30	2.04	0.16	0.12	0.14	0.78	0.80	0.14
	(0.01)									
Wuhan	6.05	-0.85	-0.68	0.51	0.66	0.68	0.23	0.56	0.55	0.14
	(0.00)									
Chengdu	6.94	-0.52	-0.46	0.33	0.75	0.79	0.20	0.48	0.47	0.16
	(0.00)									
Changsha	7.62	-1.17	-1.02	0.79	0.66	0.69	0.24	0.51	0.48	0.16
	(0.01)									
Chongqing	2.88	-1.48	-1.39	0.34	0.43	0.40	0.20	0.67	0.67	0.15
	(0.00)									
Dalian	1.85	-2.06	-1.98	0.26	0.29	0.27	0.14	0.78	0.79	0.12
	(0.00)									

Note: This table summarizes the estimation results for market liquidity parameters. The the estimates of ϕ_m and standard errors are displayed in the bracket. For estimates of μ_{mt}, q_{jmt}, and $\widehat{p}^s_{jmt}$, their mean, median, and standard deviation are displayed respectively. *p<0.1; **p<0.05; ***p<0.01

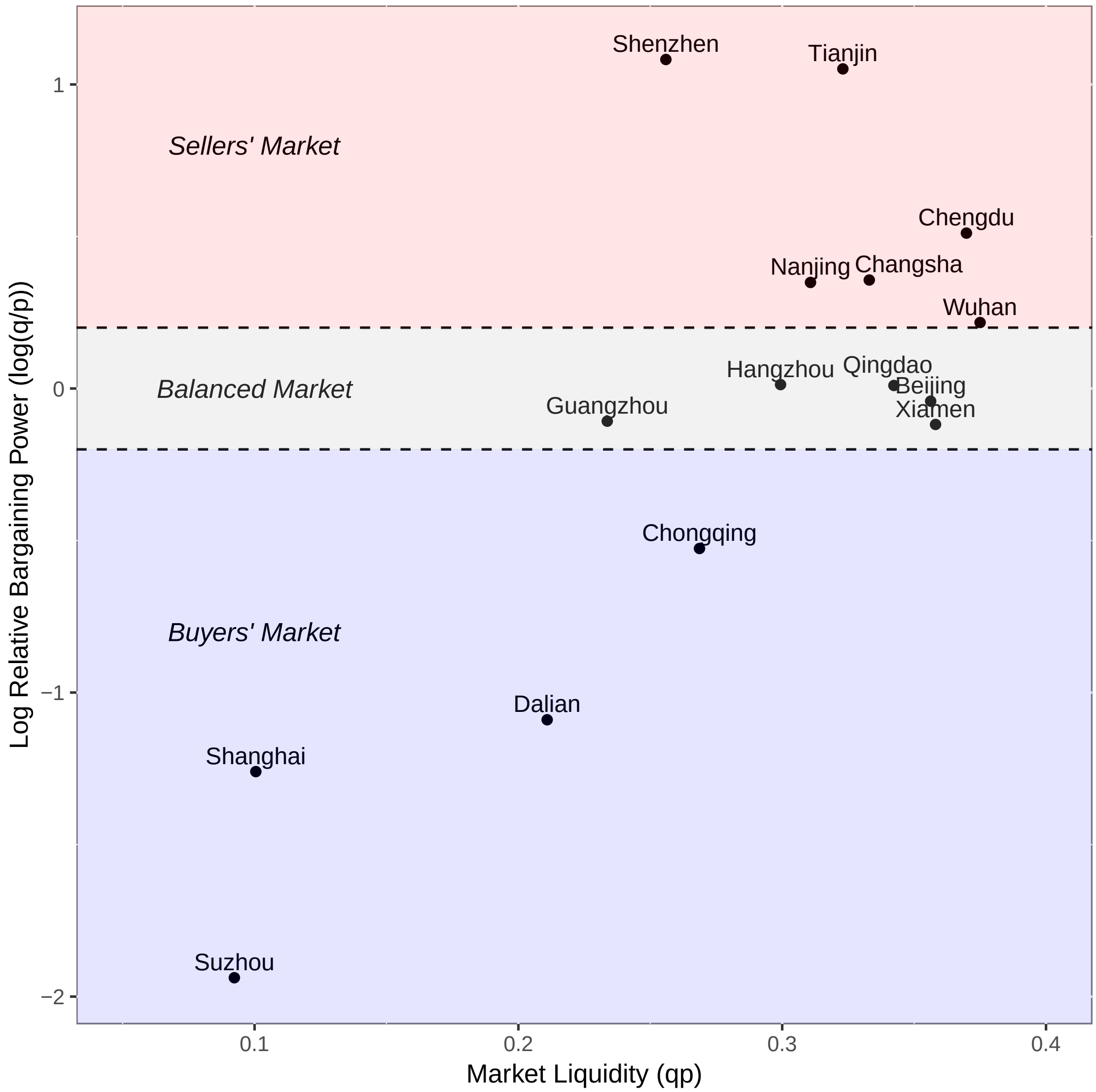


Figure 3: Market Liquidity and Relative Bargaining Power for The Whole Sample Period

Note: This figure plots the median of market liquidity and the relative market power of buyers and sellers for 15 major cities in China. The market liquidity is determined by the product of $\widehat{p}^s_{jmt}$ and $\widehat{q}_{jmt}$; the relative market power of sellers to buyers determined by the ratio of the probability of receiving a bid $\widehat{q}_{jmt}$ to seller's probability of selling for a bid $\widehat{p}^s_{jmt}$, presented in its logarithm. Both market liquidity and relative market power are calculated using the median of $\widehat{p}^s_{jmt}$ and $\widehat{q}_{jmt}$ estimated from Table 6. The log of the demand to supply ratio at -0.2 and 0.2 are the cutoffs that separate low, median, or high demand markets.

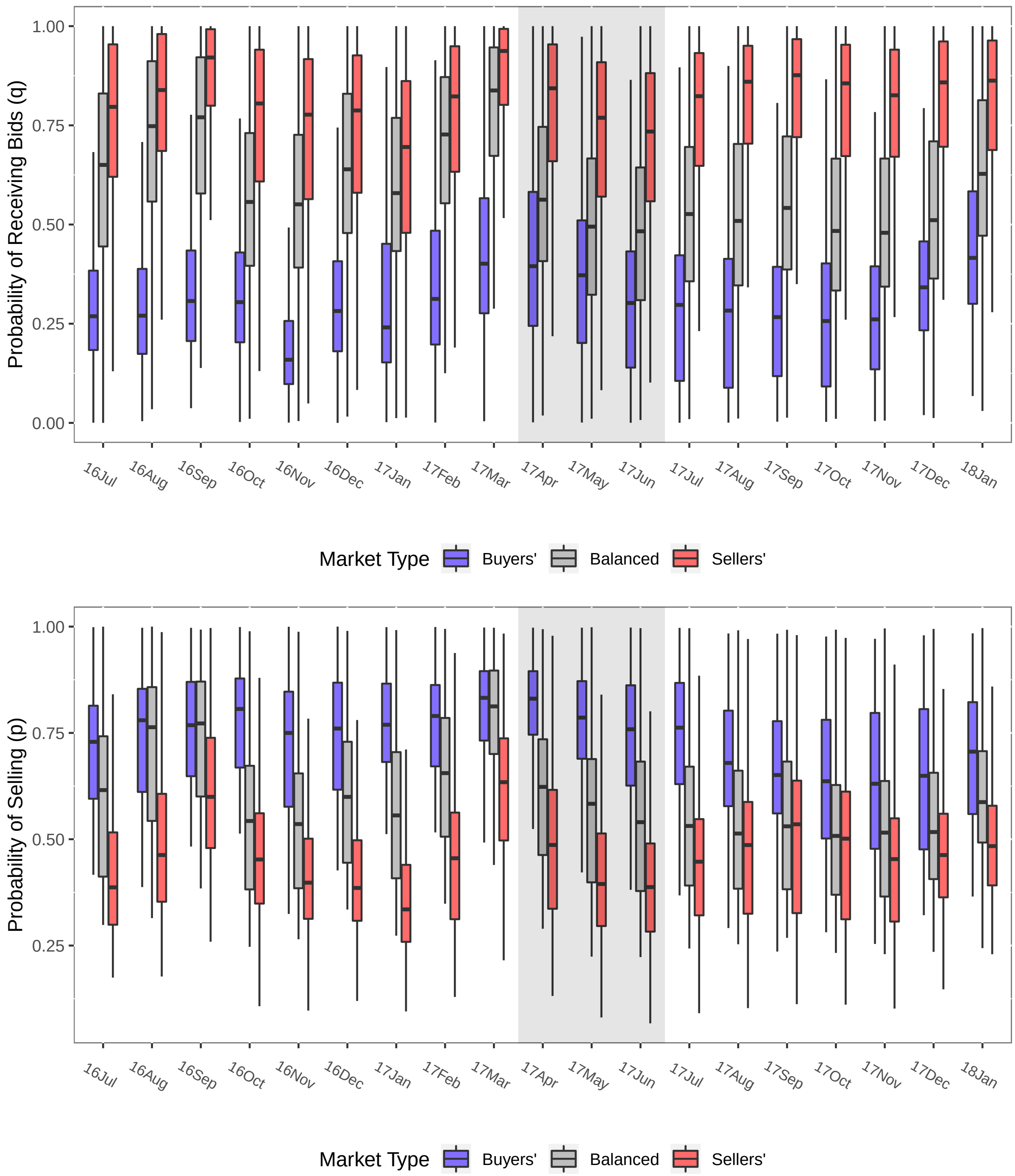


Figure 4: The Probability of Receiving Bids and the Probability of Selling over Time

Note: This figure plots the probability of receiving bids and the probability of selling over time for buyers' markets and sellers' markets respectively. The market liquidity is determined by the product of $\widehat{p}^s_{jmt}$ and $\widehat{q}_{jmt}$; the relative market power of sellers to buyers, defined as the ratio of the probability of receiving a bid $\widehat{q}_{jmt}$ to seller's probability of selling for a bid $\widehat{p}^s_{jmt}$, is presented in its logarithm. The cities where sellers have higher bargaining power than buyers over the whole sample period are classified as sellers' markets, including Tianjin, Shenzhen, Chengdu, Changsha, and Wuhan. Markets where seller's bargaining power is low are classified as buyers' markets, including Suzhou, Shanghai, Dalian, and Chongqing. The rest are classified as balanced markets. The 25th quantile, median, 75th quantile, and 95 percent confidence interval of buyers' markets (sellers' markets) are presented by the blue (red) boxplots.

separating housing supply and demand, it is clear that Shenzhen is a sellers' market while Chongqing is a buyers' market as shown in Figure 3; these insights cannot be obtained from the measure of time on the market and transaction prices in Figure 1.

Figure 4 illustrates how housing demand and supply evolve overtime. The 15 major cities are classified into three types, buyers' market (blue), balanced market (grey), or sellers' market (red).[24] During April and June 2017, mortgage interest rates increased significantly in all cities. As a result, the probability of having bids dropped in all types of markets due to an increase in financing cost for home buyers, consistent with the motivating evidence that housing demand decreases after tightening mortgage credit. At the same time, housing supply dropped, but at a relatively smaller rate than demand, consistent with the reduced-form finding that housing supply increased relative to demand. An important reason for the drop in supply is the decreased house prices, which reduces sellers' incentive to sell. And the effect is especially strong for markets where sellers have high bargaining power and optimistic about future house prices, as confirmed in the figure: The probability of selling a property had a small impact in buyers' markets while had larger impact in sellers' markets. In other words, the forward-looking expectations contribute to markets' heterogeneity. While this exercise focuses on the trend of equilibrium outcomes after a real world policy change, in Section 7, I simulate counterfactual policy changes, where the channel of house prices and expectations can be turned off.

6.2 Estimates for Per Period Utility

To determine how different property characteristics and market conditions affect the utility of owning a property, I regress the model estimated per period utility $\widehat{\delta}(\Omega_{jmt})$ obtained from equation (18) on property attributes, mortgage market conditions, and different market and time fixed effects. Table 7 summarizes the estimates for per period utility of owning a property. Column (1) shows the simplest setting with the equilibrium price for the property type (in 1 million CNY), attributes (size, age, and location), and time fixed effects as explanatory variables. The price has a negative and significant effect on the utility of holding a property, suggesting that higher prices correspond to higher opportunity costs of forgoing the selling option for sellers and higher cost of obtaining the utility of owning a property. Property size types are grouped by their decile and age types are grouped by their quintile.[25] Households derive higher utility from larger and younger properties. The baseline setting shown in Column (2) includes market-time fixed effects to account for any market-time unobservables. The results are similar to the simple model specification.

In Column (3), the interaction between property price, mortgage interest rate, and down payment requirements are included. Both mortgage interest rates and down payment requirements have a negative effect on the per period utility through house prices, meaning that the utility of owning a property decreases with the financing cost for mortgages and down payments. The triple interaction term has a positive coefficient,

[24] Since there is no clear threshold to determine a buyers' market or a sellers' market, I choose the log of the demand to supply ratio at -0.2 and 0.2 as the cutoffs separating markets with low, median, or high demand. Suzhou, Shanghai, Dalian, Chongqing are buyers' markets; Beijing, Guangzhou, Hangzhou, qingdao, and Xiamen are balanced markets; Changsha, Chengdu, Nanjing, Tianjin, Shenzhen, and Wuhan are sellers' markets.

[25] There are two reasons to use size and age quantiles instead of fixed effects. First, it is easier to be interpret households preference for the two property characteristics. Second, the two variables indeed affect utility linearly.

Table 7: Per Period Utility

	Per Period Utility		
	(1)	(2)	(3)
Price	-0.072^{***}	-0.086^{***}	0.212^{**}
	(0.003)	(0.002)	(0.089)
Price $\times$ Interest Rate			-0.052^{***}
			(0.019)
Price $\times$ Down Payment			-0.915^{***}
			(0.271)
Price $\times$ Interest Rate $\times$ Down Payment			0.162^{***}
			(0.057)
Size Decile	0.031^{***}	0.035^{***}	0.033^{***}
	(0.001)	(0.001)	(0.001)
Age Quintile	-0.029^{***}	-0.031^{***}	-0.030^{***}
	(0.002)	(0.001)	(0.001)
Constant	-0.682^{***}	-1.492^{***}	-1.486^{***}
	(0.026)	(0.026)	(0.026)
District Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	No	No
Market-Time Fixed Effects	No	Yes	Yes
Observations	152,800	152,800	152,800
R^2	0.262	0.678	0.678

Note: This table presents OLS regression results of per period utility on property prices, attributes, and market time fixed effects. The unit of observation is a property type in each market and month. The dependent variable is the estimated per period utility for each type of property in each market and time. Price is the total price of properties (in 1 Million CNY). Mortgage Interest Rate is the average annualized mortgage interest rate for first mortgage in percentage points. Down Payment requirements is the average of one minus Loan-to-Value ratio (normalized by 0.1). Size is the living space of a property categorized by decile. Age is the age of a property categorized by quintile. *p<0.1; **p<0.05; ***p<0.01

which indicates that the effect of mortgage interest rates and down payment requirements counteract each other. For example, consider a property buyer who needs mortgage credit to finance the purchase. Higher mortgage interest rates (down payment requirements) means higher financing cost for the mortgage (the down payment), making him worse off. But when down payment requirement is high, the total loan amount is low, and thus high mortgage interest rate has less impact on the total mortgage financing cost. Similarly, with a high mortgage interest rate, an increase in down payment requirements corresponds to a larger reduction in the cost of mortgage financing, which can mitigate the impact on price sensitivity and on willingness to pay.

A better way to interpret these results is to compare household's willingness to pay for property attributes, defined as the ratio of attributes' coefficient α_X to price coefficient α_P. In the baseline case, the willingness to pay for property attributes is $-\alpha_X/\alpha_P$. On average, households are willing to pay 407,000 CNY (approx. 57,400 USD) more for bigger properties in the adjacent size decile, and willing to pay 360,500 CNY (50,800 USD) more for younger properties in the adjacent age quintile. Table 8 reports the willingness to pay for an increase in attribute type given different mortgage interest rates and down payment requirements. In Panel A considers the willingness to pay for a larger size type. If the down payment requirement is 20% (i.e., the Loan-to-Value is 80%) and the mortgage interest rate is 3 percentage points, the willingness to pay for a property in the larger size decile is 1,103,700 CNY (approx. 156,000 USD), and a 1 percentage point increase in mortgage interest rate reduces the willingness to pay to 665,200 CNY (approx. 94,000 USD), equivalent to a 40% decrease. A 10 percentage points increase in down payment requirements decreases the willingness to pay to 454,100 CNY (approx. 77,100 USD), equivalent to a 59% decrease.

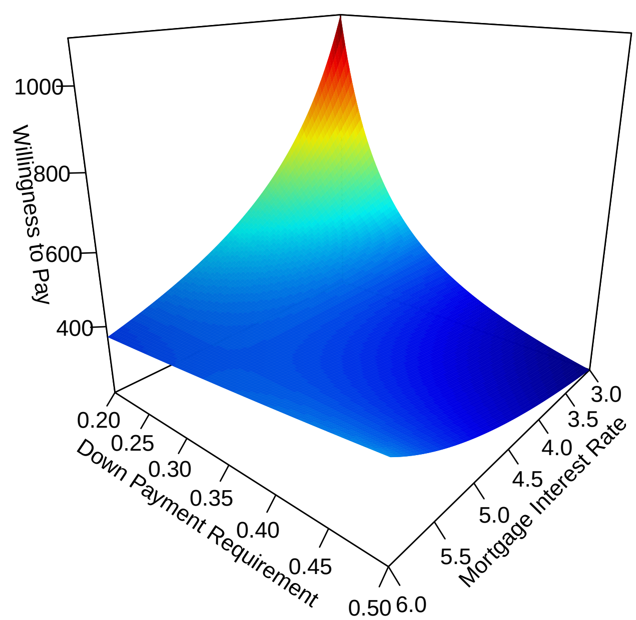


Figure 5: Willingness to Pay for A Larger Size Type

Note: This figure visualize the willingness to pay (in 1,000 CNY) for properties in a larger size type with different mortgage interest rates and down payment requirements as presented in Table 8 Panel A.

The marginal effect of an increase in mortgage interest rates (down payment requirements) is decreasing

Table 8: Willingness to Pay for An Increase in Attribute Quantile

	Down Payment Requirement			
Mortgage Interest Rate	**20%**	**30%**	**40%**	**50%**
Panel A: Size Decile				
3 pp.	1103.7	454.1	285.8	208.5
4 pp.	665.2	432.3	320.2	254.2
5 pp.	476.0	412.5	363.9	325.6
6 pp.	370.6	394.5	421.6	452.6
Panel B: Age Quintile				
3 pp.	-996.4	-409.9	-258.0	-188.3
4 pp.	-600.5	-390.3	-289.1	-229.5
5 pp.	-429.7	-372.4	-328.6	-293.9
6 pp.	-334.6	-356.1	-380.6	-408.6

Note: This table shows households' willingness to pay (in 1,000 CNY) for properties in a larger size type or an elder age type. Property size type are grouped by its decile and age type are grouped by its quintile. In the baseline case, the willingness to pay is defined as $-\alpha_X/\alpha_P$. Panel A presents the willingness to pay for an adjacent higher size type and Panel B for a larger age type.

with the level of down payment requirements (mortgage interest rates). For example, when the mortgage interest rate is 5 percentage points, increasing the down payment requirement from 20% to 30% reduces the willingness to pay for larger properties from 476,000 CNY (67,300 USD) to 412,500 CNY (58,300 USD), a 13% drop. When the down payment requirement is 30%, increasing the mortgage interest rate from 3 to 4 percentage points reduces the willingness to pay for larger property size from 454,100 CNY (64,200 USD) to 432,3 CNY (61,100 USD), a 5% drop. Moreover, mortgage interest rate (down payment requirement) may become ineffective when down payment requirement (mortgage interest rate) is too high, where an increase in mortgage interest rate (down payment requirement) may even increase the willingness to pay, an implication of the liquidity constraints argument. That is, when down payment requirements are so high that many home buyers are liquidity constrained, increasing mortgage interest rates leads to lower house prices and hence relaxes the binding constraint, making the down payment more affordable the purchase of a house possible. The willingness to pay for a higher age type is summarized in Table 8 Panel B, which is similar to that for size but with a negative sign indicating households' preference for younger properties.

Figure 5 visualizes the willingness to pay for a larger property type. The willingness to pay is very high when the mortgage interest rate and the down payment requirement are low (the north corner), and it decreases with mortgage interest rates (from the north to the west corner) and down payment requirements (from the north to the east corner). When the down payment is high, increasing mortgage interest rate increases households' willingness to pay (from the east to the south corner), while when the mortgage interest rate is high, increasing the down payment requirement has little impact on the willingness to pay (from the west to the south corner).

6.3 Model Fit

In this section, I provide the model performance results by comparing the model predicted hazard rate and its implied survival probability using the estimated $\widehat{q}_{jmt}$ and $\widehat{p}^{s}_{jmt}$.[26] Figure 6 compares observed and estimated hazard rates and survival probabilities for the three representative cities. The horizontal axis is the number of months that have passed since the listing. The figures in the left column plot 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 blue solid line is for observed hazard rates, while the red dashed line is for model predicted hazard rates. The figures in the right column plot the average survival probability, i.e., the probability that a property has not been sold after several months. The blue solid line is for observed survival probability while the red dashed 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. For hazard rate, model predictions are less volatile than actual data, but with similar magnitudes. The discrepancy towards the end of the horizontal axis tends to be large due to the small sample size for properties with a long time on the market. For the survival probability, the model estimation is very close to the actual realization. In general, the model performs well for almost all cities in the sample. The estimated hazard rate and survival probability are presented in Table A.3 and A.4 in the Appendix.

7 Counterfactuals

This section presents two counterfactual policy experiments that quantify how mortgage market conditions affect households' valuation of homeownership and thus their behavior in housing markets. I first simulate a 1 percentage point increase in mortgage interest rates and then a 10 percentage points increase in down payment requirements. Two scenarios are considered in each counterfactual exercise, without and with the expectation channel, to analyse the role of expectation in equilibrium. The key point here is to examine the temporary effect of mortgage policy interventions, keeping all other variables fixed, including the house prices. In the short term, a change in mortgage conditions first affects the utility and the value of homeownership, and then the probability of receiving bids and the probability of selling. This will affect the best bids that sellers may receive, in turn house prices. Therefore, counterfactual analyses can provide a clear causal interpretation on the pass-through mechanism. The long term effect however is beyond the scope of this counterfactual exercise, as the impact of house price changes on value functions is not endogenized. But we can infer the long term effect by comparing with the real world policy change in Section 6.1, where house prices are equilibrium outcomes changing over time.

[26] The hazard rate of property i that belongs to type j in market m after s months since listing is obtained from $\widehat{h}_i(s) = \widehat{q}_{jmt_{i,0}+s} \times \widehat{p}^{s}_{jmt_{i,0}+s}$. The survival probability is $\widehat{S}_i(s) = \prod_{\tau=1}^{s}(1 - \widehat{q}_{jmt_{i,0}+\tau} \times \widehat{p}^{s}_{jmt_{i,0}+\tau})$.

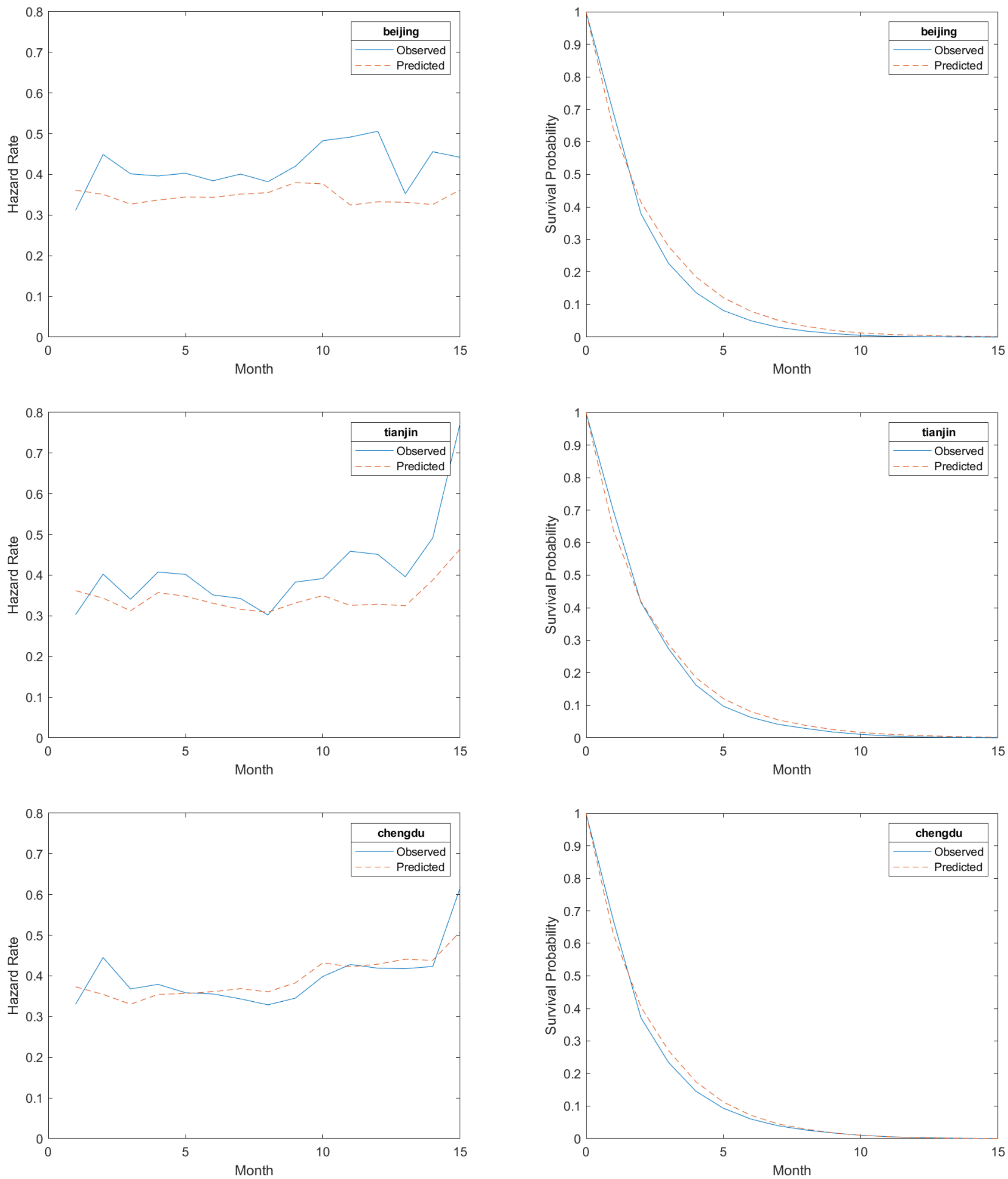


Figure 6: Hazard Rate and Survival Probability

Note: This figure plots the observed and estimated hazard rate and survival probability for the three representative cities: Beijing, Tianjin, and Chengdu. The horizontal axis is the number of months that has been past since listing. Blue lines stand for observed results. Red lines stand for model estimated results.

7.1 An Increase in Mortgage Interest Rates

First, I consider a 1 percentage point increase in mortgage interest rates for all markets, assuming all other state variables and parameter estimates are fixed.[27] Increasing mortgage interest rates affect both utility functions and value functions. The new value function is obtained by iteratively updating the old value function with the new value function in equation (8) until it converges. Mortgage interest rates affect the value of owning properties in two ways. On the one hand, it affects the utility of having a property as in the equation (20). On the other hand, the current mortgage interest rate has an impact on the expectation of the future value of property ownership as in the equation (19). If we only consider the impact on the utility part with the expectation part unchanged, we actually turn off the expectation channel. If we consider both the impact on the utility and the expectation, we activate the expectation channel. By turning on and off the expectation channel, we can compare new market outcomes with and without the expectation channel to quantify the importance of households' expectations.

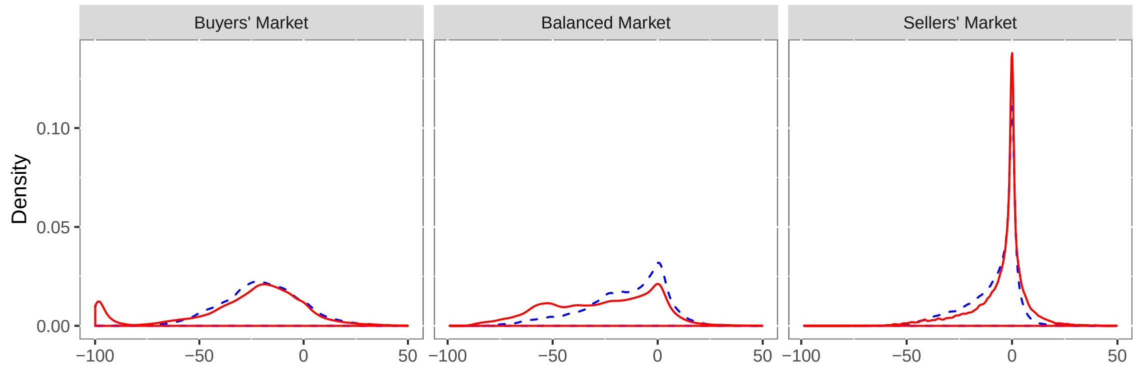
Table 9: Counterfactual Results: 1 Percentage Point Increase In Mortgage Interest Rates

	All		**Buyers'**		**Balanced**		**Sellers'**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD.**
Panel A: No Expectation								
Δ Demand	-12.6	17.9	-19.1	22.3	-14.8	19.6	-8.1	12.4
Δ Supply	10.5	13.4	8.0	9.0	8.5	13.1	13.2	14.6
Δ Price	-13.1	18.8	-19.4	23.1	-15.2	20.6	-8.8	13.5
Δ Liquidity	-4.7	16.1	-13.9	18.1	-9.2	16.5	2.7	10.8
Δ Bargaining Power	-68.0	19.3	-55.5	19.6	-65.4	19.2	-75.3	15.6
Panel B: With Expectation								
Δ Demand	-16.7	24.8	-27.3	31.0	-25.7	25.5	-4.9	13.4
Δ Supply	19.5	34.7	13.9	29.5	35.0	39.3	9.2	27.3
Δ Price	-17.4	25.6	-27.5	31.4	-26.5	26.5	-5.5	14.7
Δ Liquidity	-5.3	27.9	-23.2	30.2	-3.8	33.0	1.2	17.0
Δ Bargaining Power	-68.7	19.9	-59.6	22.3	-65.0	20.2	-75.7	15.7

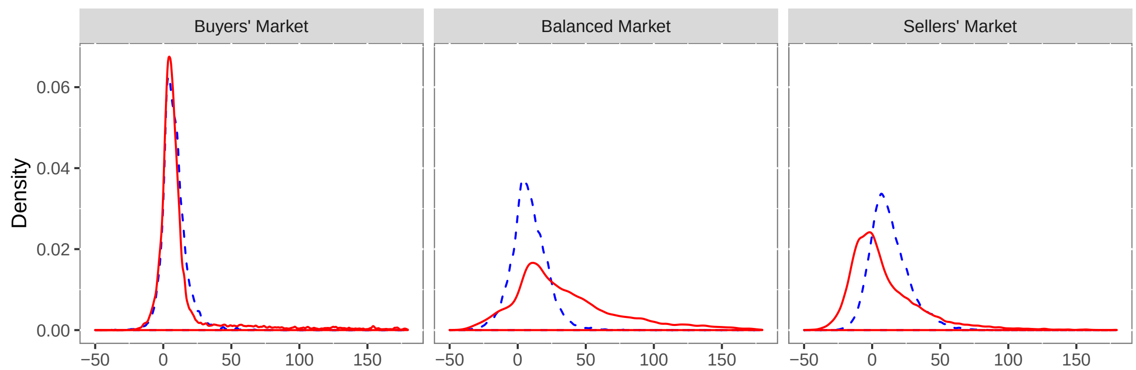
Note: This table summarizes the mean and standard deviation of percentage changes in housing demand (the probability of receiving bids), supply (the probability of selling), price (the highest bidding price), liquidity, and seller's bargaining power after a 1 percentage point increase in mortgage interest rates. Panel A only considers the interest rate change in the utility function. Panel B considers both the utility function and the expectation. The first two columns are statistics for all markets. The rest are three subsamples of buyer's, balanced, and sellers' markets.

Although house prices are not modelled as general equilibrium outcomes, inferring the highest bidding price received by buyers is feasible, as housing demand directly affects the number of coming bids. Thus, the fewer are the bids, the lower is the best possible price. Using the empirical distribution of the idiosyncratic term of transaction prices in equation (17), I simulate the possible bids and calculate the expected highest

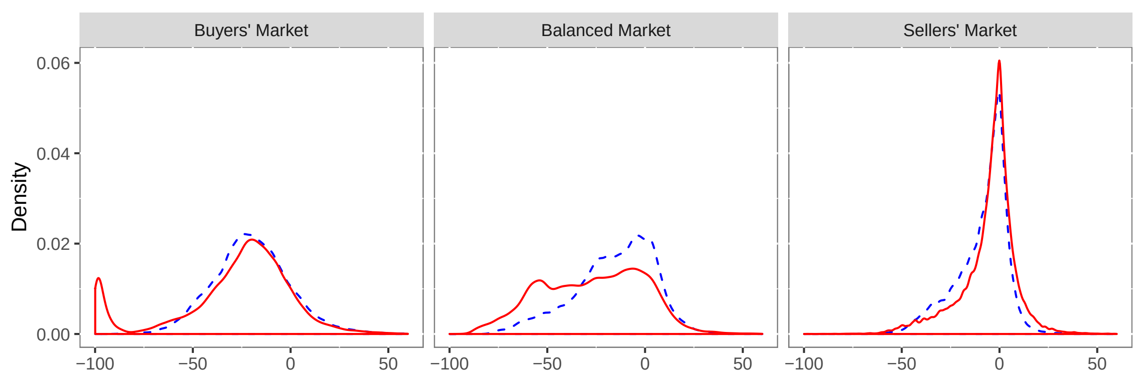
[27] Notice that the counterfactual increase in mortgage variables is assumed to be unexpected and temporary. It only affects the mortgage condition in the current period and the current expectation of the future, but not the mortgage condition in the future.



(a) Percentage Change in Probability of Receiving Bids



(b) Percentage Change in Probability of Selling



(c) Percentage Change in the Highest Bidding Price

Figure 7: Counterfactual Results: 1 Percentage Point Increase in Mortgage Interest Rates

Note: This figure illustrates the distribution of percentage changes in the probability of receiving bids, the probability of selling, and the highest bid after a 1 percentage point increase in mortgage interest rates. The blue dashed lines plot the results without the expectation channel, while the red solid lines plot the results with the expectation channel. Three subsamples are classified by seller's bargaining power as in Section 6.1.

bidding price for each seller, which reflect the policy impact on house prices. Note that the counterfactual analyses do not update those post-policy house prices in value functions to affect households' behavior. Conceptually, house prices are equilibrium results of housing demand and supply. Changes in mortgage credit conditions should first affect housing demand and supply, and then house prices. Practically, searching for the convergent value functions after policy changes while updating house prices is difficult. Therefore, the counterfactual analyses focus on the short-term effect of mortgage credit conditions.

Table 9 summarizes the percentage change in demand (probability of receiving bids), supply (probability of selling), price (highest bidding price), liquidity, and seller's bargaining power for each property. Panel A considers only the utility channel while Panel B considers both the utility and the expectation channel. Without the expectation channel, a 1 percentage point increase in mortgage interest rate leads to a 12.6% drop in the probability of receiving bids, a 10.5% increase in the probability of selling, a 13.1% drop in the highest bidding price, a 4.7% decrease in market liquidity, and a 68% decrease in seller's bargaining power, which correspond to lower housing demand, higher supply, lower house prices, lower market liquidity, and lower seller's bargaining power. When market players' expectation plays a role, both the drop in housing demand (16.7%) and the increase in housing supply (19.5%) become larger. The highest bidding price experiences a larger decrease (17.4%) due to faster shrinking demand. Similarly, market liquidity and seller's bargaining power experience a larger drop when the expectation plays a role. On average, forward-looking expectations amplify the effectiveness of mortgage interest rates.

However, the situation varies among different markets. As show in Column 3 to 8 of Table 9, the results are presented based on the three market types. When expectations are excluded, the increase in interest rates decreases demand by 19.1%, 14.8%, and 8.1% for buyer's, balanced, and sellers' markets respectively, whereas with the expectation channel, the demand dropped by 27.3%, 25.7%, and 4.9% respectively. The expectation channel amplifies mortgage interest rates' impact for buyer's and balanced markets while attenuates the effect for sellers' markets.

Figure 7 illustrates the distribution of percentage changes in housing demand, supply, and price for the three type of markets. The blue dashed line stands for results without the expectation channel, while the red solid line stands for results including expectations. Comparing across markets, sellers' markets have smaller changes in demand and supply than that in the other two market types, illustrated by the red solid lines' concentration at zero. The expectation channel and the utility channel work in the opposite direction in sellers' markets. Namely, in each figure the expectation channel (the red solid line) mitigates the effectiveness of mortgage interest rate, shifting the location of the blue dashed line towards zero. While in the other two markets the expectation channel (the red solid line) further increases changes in demand and supply, shifting the location of the blue dashed line away from zero, as households regard higher mortgage interest rates as a worse signal for future property value. Thus, the forward-looking expectations reinforce the disutility of high financing cost, amplifying the effect of increasing mortgage interest rates. The expectation channel is especially strong for balanced markets, explaining 42% of the changes in demand and 76% of the changes in supply. These results suggest that the expectation channel can make mortgage policies less effective in sellers' markets, while make buyer's and balanced markets become volatile.

Comparing the counterfacutal policy change in mortgage interest rates with the real world policy change, the results are consistent and complementary. First, the counterfactual results confirm previous reduced-form and structural empirical findings that higher mortgage interest rates result in lower housing demand, higher housing supply relative to demand, and hence lower prices and market liquidity. Second, in the short term, housing demand decreased and supply increased due to higher mortgage interest rates, while in the long run, decreased house prices discourage selling, giving rise to lower probabilities of selling as in Figure 4. Thus, we can expect the long term effect is smaller than the short term effect. Moreover, the role of expectation rationalize why sellers are more reluctant to sell after the adverse shock in sellers' markets: Given sellers' high bargaining power, a sudden increase in financing cost has little impact on their valuation for the future, but its adverse impact on house prices makes sellers unwilling to sell; while with low bargaining power in buyers' markets, sellers are impatient to sell when bad news hits.

7.2 An Increase in Down Payment Requirements

Table 10 and Figure 8 demonstrate how down payment requirements affect housing demand, supply, price, market liquidity and seller's bargaining power. Similar to the mortgage interest rate change, a 10 percentage points increase in down payment requirements leads to a drop in the probability of receiving bids (housing demand), an increase in the probability of selling (supply), a decrease in the highest bidding price received by sellers (price), a decrease in market liquidity, and a decrease in the seller bargaining power. The expectation channel attenuates (amplifies) the utility channel in sellers' (balanced) markets. In buyers' markets, the role of the expectation channel is mixed. The expectation channel amplifies the impact of higher down payment requirements on housing demand (-22.6% vs -19.1%) and prices (22.8% vs 19.4%), but weakens the impact on housing supply (-3.0% vs 8.4%), resulting lower market liquidity (-28.9% vs -13.6%).

7.3 Performance of Mortgage Credit Instruments

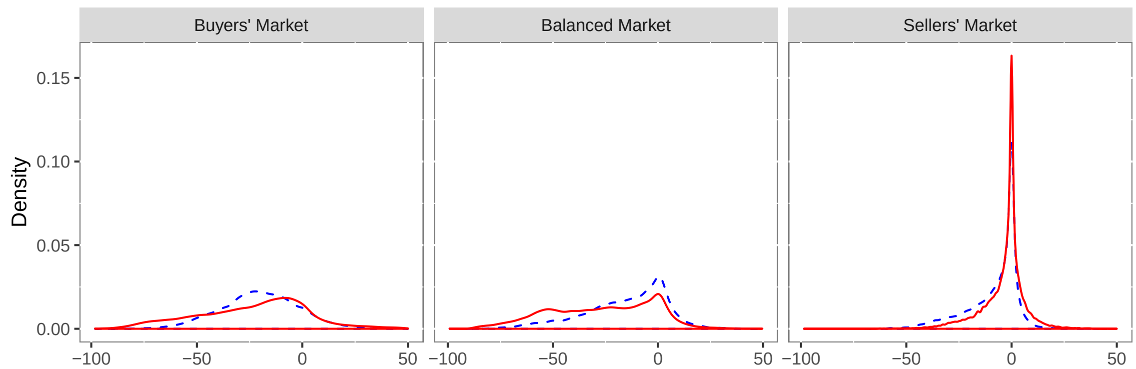
This section provides additional evidence on the performance of the two policy instruments. Instead of comparing different housing markets, the variation of counterfactual results within each city and month demonstrates how different characteristics affect the effectiveness of mortgage credit instruments. I estimate a simple linear model regressing changes in the probability of receiving bids (demand) and changes in the probability of selling (supply) from the two counterfactual experiments on property price, age, size, liquidation, seller's bargaining power, and market-time fixed effects.

Table 11 presents the regression results. In the higher mortgage interest rate case, that is the first two columns in Table 11, housing demand dropped and housing supply increased, and the effect is stronger for more expensive properties. Similarly, older and smaller properties experience larger drop in demand and higher increase in supply, suggesting households' preference for young and large properties. For property with high liquidity, that is the product of the two probabilities, the increase in mortgage interest rates is less effective in suppressing demand and promoting supply. For more popular properties whose sellers have higher bargaining power, the increase in mortgage interest rates is less effective in reducing buyer's demand but more effective in increasing seller's supply, mitigating the demand-supply imbalance. In the higher down payment requirement case, that is the last two columns of Table 11, the results are similar: Mortgage policies can more effectively reduce demand and increase supply for properties that are expensive, old, small,

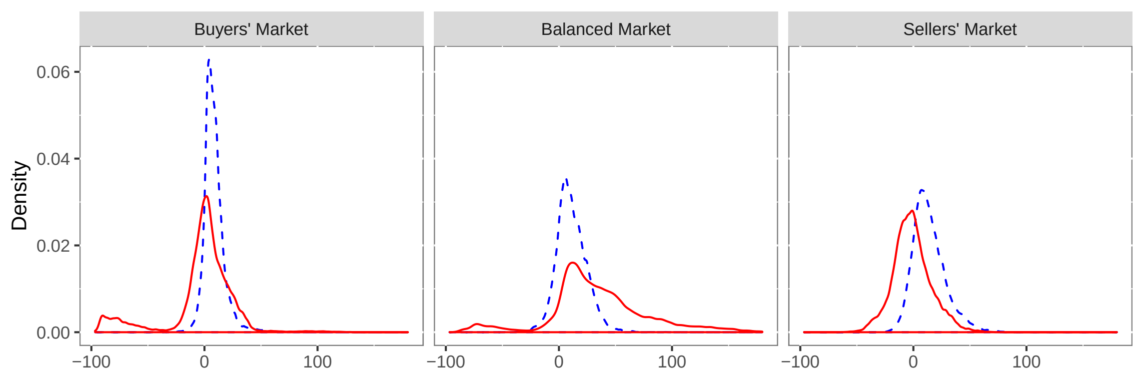
Table 10: Counterfactual Results: 10 Percentage Points Increase in Down Payment Requirements

	All		**Buyers'**		**Balanced**		**Sellers'**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD.**
Panel A: No Expectation								
Δ Demand	-12.6	18.0	-19.1	22.2	-14.9	19.8	-8.0	12.4
Δ Supply	12.0	13.5	8.4	9.1	11.2	13.4	14.2	14.7
Δ Price	-13.2	18.9	-19.4	23.0	-15.3	20.8	-8.8	13.4
Δ Liquidity	-3.4	16.6	-13.6	18.2	-7.1	17.3	3.8	11.1
Δ Bargaining Power	-67.7	19.3	-55.5	19.5	-64.8	19.4	-75.1	15.6
Panel B: With Expectation								
Δ Demand	-15.3	23.3	-22.6	27.0	-26.1	25.3	-3.3	10.8
Δ Supply	11.4	36.1	-3.0	30.5	34.3	43.7	-1.1	17.0
Δ Price	-15.9	24.1	-22.8	27.7	-27.0	26.2	-3.8	12.0
Δ Liquidity	-9.9	28.0	-28.9	27.9	-5.3	36.0	-5.6	13.1
Δ Bargaining Power	-70.0	19.5	-62.4	21.1	-65.6	20.4	-76.8	15.5

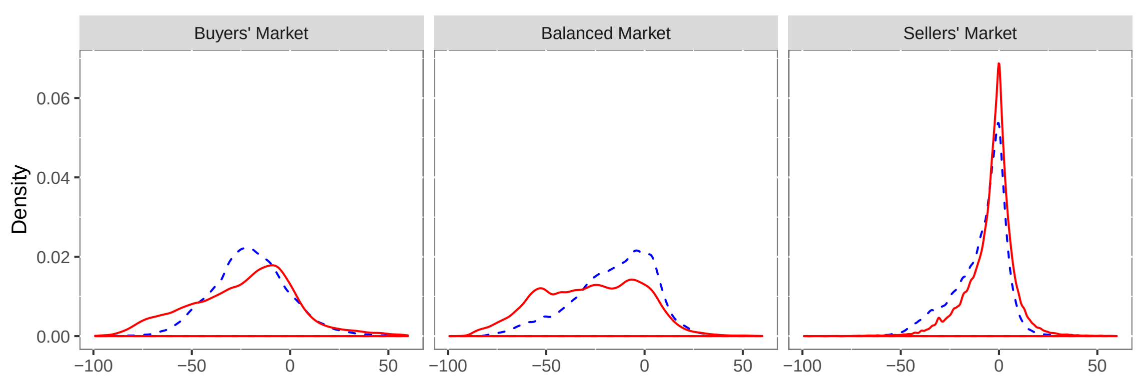
Note: This table summarizes the mean and standard deviation of percentage changes in housing demand (the probability of receiving bids), supply (the probability of selling), price (the highest bidding price), liquidity, and seller's bargaining power after a 1 percentage point increase in mortgage interest rates. Panel A only considers the interest rate change in the utility function. Panel B considers both the utility function and the expectation. The first two columns are statistics for all markets. The rest are three subsamples of buyer's, balanced, and sellers' markets.



(a) Percentage Change in Probability of Receiving Bids



(b) Percentage Change in Probability of Selling



(c) Percentage Change in the Highest Bidding Price

Figure 8: Counterfactual Results: 10 Percentage Points Increase in Down Payment Requirements

Note: This figure illustrates the distribution of percentage changes in the probability of receiving bids, the probability of selling, and the highest bid after a 10 percentage points increase in down payment requirements. The blue dashed lines plot the results without the expectation channel, while the red solid lines plot the results with the expectation channel. Three subsamples are classified by seller's bargaining power as in Section 6.1.

and illiquid, which are undesirable property characteristics. Moreover, they can decrease (increase) seller's bargaining power for popular (unpopular) properties, making supply and demand more balanced.

Table 11: The Performance of Mortgage Credit Instruments

	Mortgage Interest Rates		Down Payment Requirements	
	Δ Demand	Δ Supply	Δ Demand	Δ Supply
Total Transaction Price	-0.006^{***}	0.008^{***}	-0.010^{***}	0.014^{***}
	(0.0002)	(0.0003)	(0.0002)	(0.0002)
Age	-0.508^{***}	0.547^{***}	-0.465^{***}	0.397^{***}
	(0.005)	(0.006)	(0.005)	(0.005)
Size	0.052^{***}	-0.070^{***}	0.047^{***}	-0.063^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Liquidity	60.286^{***}	-80.944^{***}	54.900^{***}	-63.389^{***}
	(0.210)	(0.247)	(0.213)	(0.232)
Seller's Bargaining Power	7.201^{***}	9.647^{***}	7.843^{***}	5.019^{***}
	(0.046)	(0.054)	(0.047)	(0.051)
Constant	-59.838^{***}	72.598^{***}	-57.969^{***}	72.167^{***}
	(11.272)	(13.237)	(11.437)	(12.461)
Market-Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	328,169	328,169	328,169	328,169
R^2	0.586	0.709	0.517	0.762

Note: This table compares the performance of mortgage credit policies on different types of properties, regressing percentage changes in demand (probability of receiving bids) and supply (probability of selling to bidders) on property characteristics. The first two columns show the counterfactual with 1 percent point higher mortgage interest rates, while the last two columns show the counterfactual with 10 percentage points higher down payment requirements. Price is the total transaction price in 10,000 CNY, Age is the number of years since construction. Size is the living space in square meters. Liquidity is the estimated probability of having bids times the estimated probability of selling. Seller's Bargaining Power is the ratio of the probability of having bids to the probability of selling. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

8 Conclusion

In this paper, I investigate how mortgage credit conditions affect housing markets. The paper uses novel residential property transaction data, which has never been examined before, in China from December 2015 to January 2018 to show that higher mortgage interest rates and down payment requirements affect the value of homeownership, housing demand, supply, and house prices, market liquidity, and agents' bargaining power.

With reduced-form analyses, I document that after the large nationwide increase in mortgage interest rates in May 2017, monthly house price growth rate dropped by 3.8% on average. This effect is stronger for cities that were more affected by the policy change and for properties that were younger than 20 years, which are eligible for mortgage loans. Moreover, housing demand and market liquidity dropped, while housing supply increased relative to demand. Similarly, an over 15% increase in down payment requirements reduced the house price growth rate by 3% on average. However, these results say little of the underlying mechanism.

To examine the mechanism, I use a micro-founded structural model to disentangle the housing demand and supply channels in a dynamic setting, allowing the expectation of future states to affect forward-looking households' behavior. I show that house prices have a negative impact on the utility of holding a property, which corresponds to higher opportunity cost of not selling at higher price for the property owner, and higher cost of purchasing for potential buyers. Households enjoy higher utility from larger and newer properties. Moreover, higher mortgage interest rates and down payment requirements increase households' price sensitivity and hence decrease households' willingness to pay for favourable property attributes. On average, households are willing to pay 407,000 CNY (approx. 57,400 USD) more for larger properties in the adjacent size decile, and willing to pay 360,500 CNY (50,800 USD) more for younger properties in the adjacent age quintile. The willingness to pay for a larger size (lower age) type drops if the mortgage interest rate or the down payment requirement increase. The marginal effect of increasing the mortgage interest rate (down payment requirement) is reduced with a higher down payment requirement (mortgage interest rate), reflecting a substitution effect between the two policy instruments.

I conduct two counterfactual analyses to quantify how mortgage market conditions affect house prices through demand, supply, and the role of expectation in the price formation process. Simulating a 1 percentage point increase in mortgage interest rates, I find that sellers' probability of receiving bids drops by 16.7%, the probability of selling to bidders increases by 19.5%, the highest bidding price decreases by 17.4%, the market liquidity decreases by 5.3%, and seller's relative bargaining power decreases by 68.7%. The scenarios with and without the expectation channel suggest that expectations play an important role in housing markets. It may amplify the effect of mortgage credit policies on average, but attenuate the effect in sellers' markets. Similar results hold for the second counterfactual experiment where I simulate a 10 percentage points increase in down payment requirements. I show that policy intervention in mortgage credit can reduce the demand-supply imbalance, but it can have an unequally larger impact on unfavourable properties, such as expensive, old, small, and illiquid ones.

Overall, these results indicate that mortgage credit conditions have a large impact on housing markets. Interventions in mortgage interest rates and down payment requirements can change housing demand, supply, prices, and market liquidity, by affecting households' utility and valuation of owning homes. The results of policy interventions, however, can be quite unexpected in some circumstances. First, the counteractive effect between mortgage interest rates and down payment requirements can make mortgage credit policies ineffective. Second, forward-looking expectations may reduce the effectiveness of mortgage credit policies in sellers' markets while stimulate housing cycles in buyers' or balanced markets. Third, changing mortgage credit conditions has a larger impact on more unfavourable properties, rising distributional concerns.

Therefore, the benefits and costs of these policy interventions need further debate. This paper is an initial attempt at structurally analyzing the transmission mechanism of mortgage credit policy into housing markets. The general framework, which provides measures of housing demand, supply, price, market liquidity, and relative bargaining power, can be applied in other housing markets to evaluate different policy interventions. The model can be extended to account for households' heterogeneity and transaction costs, which constitute promising directions for future research.

References

Adelino, M., Schoar, A. and Severino, F. (2012), Credit supply and house prices: evidence from mortgage market segmentation, Technical report, National Bureau of Economic Research.

Adelino, M., Schoar, A. and Severino, F. (2015), 'House prices, collateral, and self-employment', *Journal of Financial Economics* **117**(2), 288–306.

Anglin, P. M. (1997), 'Determinants of buyer search in a housing market', *Real estate economics* **25**(4), 567–589.

Anglin, P. M., Rutherford, R. and Springer, T. M. (2003), 'The trade-off between the selling price of residential properties and time-on-the-market: The impact of price setting', *The Journal of Real Estate Finance and Economics* **26**(1), 95–111.

Armona, L., Fuster, A. and Zafar, B. (2018), 'Home price expectations and behaviour: Evidence from a randomized information experiment', *The Review of Economic Studies* **86**(4), 1371–1410.

Barberis, N., Greenwood, R., Jin, L. and Shleifer, A. (2018), 'Extrapolation and bubbles', *Journal of Financial Economics* **129**(2), 203–227.

Baryla, E. and Ztanpano, L. (1995), 'Buyer search duration in the residential real estate market: The role of the real estate agent', *Journal of Real Estate Research* **10**(1), 1–13.

Baryla, E., Zumpano, L. and Elder, H. (2000), 'An investigation of buyer search in the residential real estate market under different market conditions', *Journal of Real Estate Research* **20**(1-2), 75–91.

Bayer, P., McMillan, R., Murphy, A. and Timmins, C. (2016), 'A dynamic model of demand for houses and neighborhoods', *Econometrica* **84**(3), 893–942.

Bemanke, B. and Gertler, M. (1989), 'Agency costs, net worth, and business fluctuations', *American Economic Review* **79**(1), 14–31.

Case, K. E., Shiller, R. J. and Thompson, A. K. (2012), 'What have they been thinking? homebuyer behavior in hot and cold markets.', *Brookings Papers on Economic Activity* (2).

Chen, K. and Wen, Y. (2017), 'The great housing boom of china', *American Economic Journal: Macroeconomics* **9**(2), 73–114.

Di Maggio, M. and Kermani, A. (2017), 'Credit-induced boom and bust', *The Review of Financial Studies* **30**(11), 3711–3758.

Dong, Y., Meng, C., Firth, M. and Hou, W. (2014), 'Ownership structure and risk-taking: Comparative evidence from private and state-controlled banks in china', *International Review of Financial Analysis* **36**, 120–130.

Elder, H. W., Zumpano, L. V. and Baryla, E. A. (1999), 'Buyer search intensity and the role of the residential real estate broker', *The Journal of Real Estate Finance and Economics* **18**(3), 351–368.

Fang, H., Gu, Q., Xiong, W. and Zhou, L.-A. (2016), 'Demystifying the chinese housing boom', *NBER macroeconomics annual* **30**(1), 105–166.

Favara, G. and Imbs, J. (2015), 'Credit supply and the price of housing', *American Economic Review* **105**(3), 958–92.

Favilukis, J., Ludvigson, S. C. and Van Nieuwerburgh, S. (2017), 'The macroeconomic effects of housing wealth, housing finance, and limited risk sharing in general equilibrium', *Journal of Political Economy* **125**(1), 140–223.

Genesove, D. and Han, L. (2012), 'Search and matching in the housing market', *Journal of Urban Economics* **72**(1), 31–45.

Genesove, D. and Mayer, C. (2001), 'Loss aversion and seller behavior: Evidence from the housing market', *The quarterly journal of economics* **116**(4), 1233–1260.

Genesove, D. and Mayer, C. J. (1994), Equity and time to sale in the real estate market, Technical report, National Bureau of Economic Research.

Glaeser, E., Huang, W., Ma, Y. and Shleifer, A. (2017), 'A real estate boom with chinese characteristics', *Journal of Economic Perspectives* **31**(1), 93–116.

Glaeser, E. L., Gottlieb, J. D. and Gyourko, J. (2012), Can cheap credit explain the housing boom?, *in* 'Housing and the financial crisis', University of Chicago Press, pp. 301–359.

Glaeser, E. L. and Nathanson, C. G. (2017), 'An extrapolative model of house price dynamics', *Journal of Financial Economics* **126**(1), 147–170.

Glower, M., Haurin, D. R. and Hendershott, P. H. (1998), 'Selling time and selling price: The influence of seller motivation', *Real Estate Economics* **26**(4), 719–740.

Gowrisankaran, G. and Rysman, M. (2012), 'Dynamics of consumer demand for new durable goods', *Journal of Political Economy* **120**(6), 1173–1219.

Greenwald, D. (2018), 'The mortgage credit channel of macroeconomic transmission'.

Greenwood, R. and Shleifer, A. (2014), 'Expectations of returns and expected returns', *The Review of Financial Studies* **27**(3), 714–746.

Haruvy, E., Lahav, Y. and Noussair, C. N. (2007), 'Traders' expectations in asset markets: experimental evidence', *American Economic Review* **97**(5), 1901–1920.

Haurin, D. (1988), 'The duration of marketing time of residential housing', *Real Estate Economics* **16**(4), 396–410.

Head, A. and Lloyd-Ellis, H. (2012), 'Housing liquidity, mobility, and the labour market', *Review of Economic Studies* **79**(4), 1559–1589.

Hendel, I. and Nevo, A. (2006), 'Measuring the implications of sales and consumer inventory behavior', *Econometrica* **74**(6), 1637–1673.

Hendel, I., Nevo, A. and Ortalo-Magné, F. (2009), 'The relative performance of real estate marketing platforms: Mls versus fsbomadison. com', *American Economic Review* **99**(5), 1878–98.

Himmelberg, C., Mayer, C. and Sinai, T. (2005), 'Assessing high house prices: Bubbles, fundamentals and misperceptions', *Journal of Economic Perspectives* **19**(4), 67–92.

Hotz, V. J. and Miller, R. A. (1993), 'Conditional choice probabilities and the estimation of dynamic models', *The Review of Economic Studies* **60**(3), 497–529.

Hubbard, R. G. and Mayer, C. J. (2009), 'The mortgage market meltdown and house prices', *The BE Journal of Economic Analysis & Policy* **9**(3).

Hung, C.-H. D., Jiang, Y., Liu, F. H., Tu, H. and Wang, S. (2017), 'Bank political connections and performance in china', *Journal of Financial Stability* **32**, 57–69.

Karlstrom, A., Palme, M. and Svensson, I. (2004), 'A dynamic programming approach to model the retirement behaviour of blue-collar workers in sweden', *Journal of Applied Econometrics* **19**(6), 795–807.

Kennet, D. M. (1993), 'Did deregulation affect aircraft engine maintenance? an empirical policy analysis', *The Rand Journal of Economics* pp. 542–558.

Kennet, D. M. (1994), 'A structural model of aircraft engine maintenance', *Journal of Applied Econometrics* **9**(4), 351–368.

Khandani, A. E., Lo, A. W. and Merton, R. C. (2013), 'Systemic risk and the refinancing ratchet effect', *Journal of Financial Economics* **108**(1), 29–45.

Kiyotaki, N. and Moore, J. (1997), 'Credit cycles', *Journal of political economy* **105**(2), 211–248.

Kluger, B. D. and Miller, N. G. (1990), 'Measuring residential real estate liquidity', *Real Estate Economics* **18**(2), 145–159.

Krainer, J. (2001), 'A theory of liquidity in residential real estate markets', *Journal of urban Economics* **49**(1), 32–53.

Landvoigt, T., Piazzesi, M. and Schneider, M. (2015), 'The housing market (s) of san diego', *American Economic Review* **105**(4), 1371–1407.

Levitt, S. D. and Syverson, C. (2008), 'Market distortions when agents are better informed: The value of information in real estate transactions', *The Review of Economics and Statistics* **90**(4), 599–611.

Lin, X. and Zhang, Y. (2009), 'Bank ownership reform and bank performance in china', *Journal of Banking & Finance* **33**(1), 20–29.

Lippman, S. A. and McCall, J. J. (1986), 'An operational measure of liquidity', *The American Economic Review* **76**(1), 43–55.

Melnikov, O. (2013), ‘Demand for differentiated durable products: The case of the us computer printer market’, *Economic Inquiry* **51**(2), 1277–1298.

Mian, A. and Sufi, A. (2009), ‘The consequences of mortgage credit expansion: Evidence from the us mortgage default crisis’, *The Quarterly Journal of Economics* **124**(4), 1449–1496.

Mian, A. and Sufi, A. (2014), House price gains and us household spending from 2002 to 2006, Technical report, National Bureau of Economic Research.

Murphy, A. (2017), ‘A dynamic model of housing supply’.

Ortalo-Magne, F. and Rady, S. (2006), ‘Housing market dynamics: On the contribution of income shocks and credit constraints’, *The Review of Economic Studies* **73**(2), 459–485.

Pakes, A. (1986), ‘Patents as options: Some estimates of the value of holding european patent stocks’, *Econometrica* pp. 755–784.

Piazzesi, M. and Schneider, M. (2009), ‘Momentum traders in the housing market: survey evidence and a search model’, *American Economic Review* **99**(2), 406–11.

Rust, J. (1987), ‘Optimal replacement of gmc bus engines: An empirical model of harold zurcher’, *Econometrica* pp. 999–1033.

Rust, J. and Phelan, C. (1997), ‘How social security and medicare affect retirement behavior in a world of incomplete markets’, *Econometrica* pp. 781–831.

Sirmans, S., Macpherson, D. and Zietz, E. (2005), ‘The composition of hedonic pricing models’, *Journal of real estate literature* **13**(1), 1–44.

Smith, V. L., Suchanek, G. L. and Williams, A. W. (1988), ‘Bubbles, crashes, and endogenous expectations in experimental spot asset markets’, *Econometrica* pp. 1119–1151.

Stein, J. C. (1995), ‘Prices and trading volume in the housing market: A model with down-payment effects’, *The Quarterly Journal of Economics* **110**(2), 379–406.

Wang, S.-Y. (2011), ‘State misallocation and housing prices: theory and evidence from china’, *American Economic Review* **101**(5), 2081–2107.

Wu, J., Deng, Y. and Liu, H. (2014), ‘House price index construction in the nascent housing market: the case of china’, *The Journal of Real Estate Finance and Economics* **48**(3), 522–545.

Wu, J., Gyourko, J. and Deng, Y. (2016), ‘Evaluating the risk of chinese housing markets: What we know and what we need to know’, *China Economic Review* **39**, 91–114.

A Appendix

A.1 Real Estate Markets of the Other Chinese Cities

As supplements to the three representative cities, this section provides the same type of figures for the other 12 major cities. Figure A.1 illustrates housing price and transaction volume on the platform for the other 12 major cities. Figure A.2 illustrates the key mortgage credit variables for the other 12 major cities. Figure A.3 plots the model estimated and observed hazard rates for the other 12 major cities, while Figure A.4 compares the model estimated and observed survival probability for the other 12 major 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 $\varepsilon_{ijmt,d}$ (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 $\varepsilon_{ijmt,d}$ lead to

$$F(\Omega_{jmt+1}, S_{ijmt+1}, \varepsilon_{ijmt+1}|\Omega_{jmt}, S_{ijmt}, \varepsilon_{ijmt}, d^s_{ijmt}) = F_\varepsilon(\varepsilon_{ijmt+1})F(\Omega_{jmt+1}, S_{ijmt+1}|\Omega_{jmt}, S_{ijmt}, d^s_{ijmt}).$$

Since S_{ijmt} is also an unobservable state variable, I make another conditional independence assumption that whether there exists a bid in the next period S_{ijmt+1} do not depend on that of the current period S_{ijmt} conditional on the current state Ω_{jmt}, that is,

$$F(\Omega_{jmt+1}, S_{ijmt+1}|\Omega_{jmt}, S_{ijmt}, d^s_{ijmt}) = F_S(S_{ijmt+1}|\Omega_{jmt+1})F_\Omega(\Omega_{jmt+1}|\Omega_{jmt}, d^s_{ijmt}).$$

This assumption implies that the incidence of a coming bid is only determined by property attributes and current market conditions. Finally, assuming that individual households' action cannot affect macroeconomic conditions, $F_\Omega(\Omega_{jmt+1}|\Omega_{jmt}, d^s_{ijmt}) = F_\Omega(\Omega_{jmt+1}|\Omega_{jmt})$. As a result, the conditional probability of the state variables can be divided into three parts:

$$F(\Omega_{jmt+1}, S_{ijmt+1}, \varepsilon_{ijmt+1}|\Omega_{jmt}, S_{ijmt}, \varepsilon_{ijmt}, d^s_{ijmt}) = F_\varepsilon(\varepsilon_{ijmt+1})F_S(S_{ijmt+1}|\Omega_{jmt+1})F_\Omega(\Omega_{jmt+1}|\Omega_{jmt}).$$

A.2.2 Expected value functions in waiting and decision states

Denote $\overline{V}(\Omega_{jmt}, S_{ijmt})$ as the expected value function with respect to $\varepsilon_{ijmt,d}$. As sellers make decision to maximize the lifetime utility, which means

$$\begin{aligned}
\overline{V}(\Omega_{jmt}, S_{ijmt}) &= \int_\varepsilon \max_{d^s}\{V(\Omega_{jmt}, S_{ijmt}, \varepsilon_{ijmt,d}, d^s_{ijmt})\}\mathrm{d}F_\varepsilon(\varepsilon_{ijmt}) \\
&= \ln\left(\sum_{d^s} \exp\left(\overline{V}(\Omega_{jmt}, S_{ijmt}; d^s_{ijmt})\right)\right),
\end{aligned}$$

where the second equation comes from the properties of type I extreme value distribution.

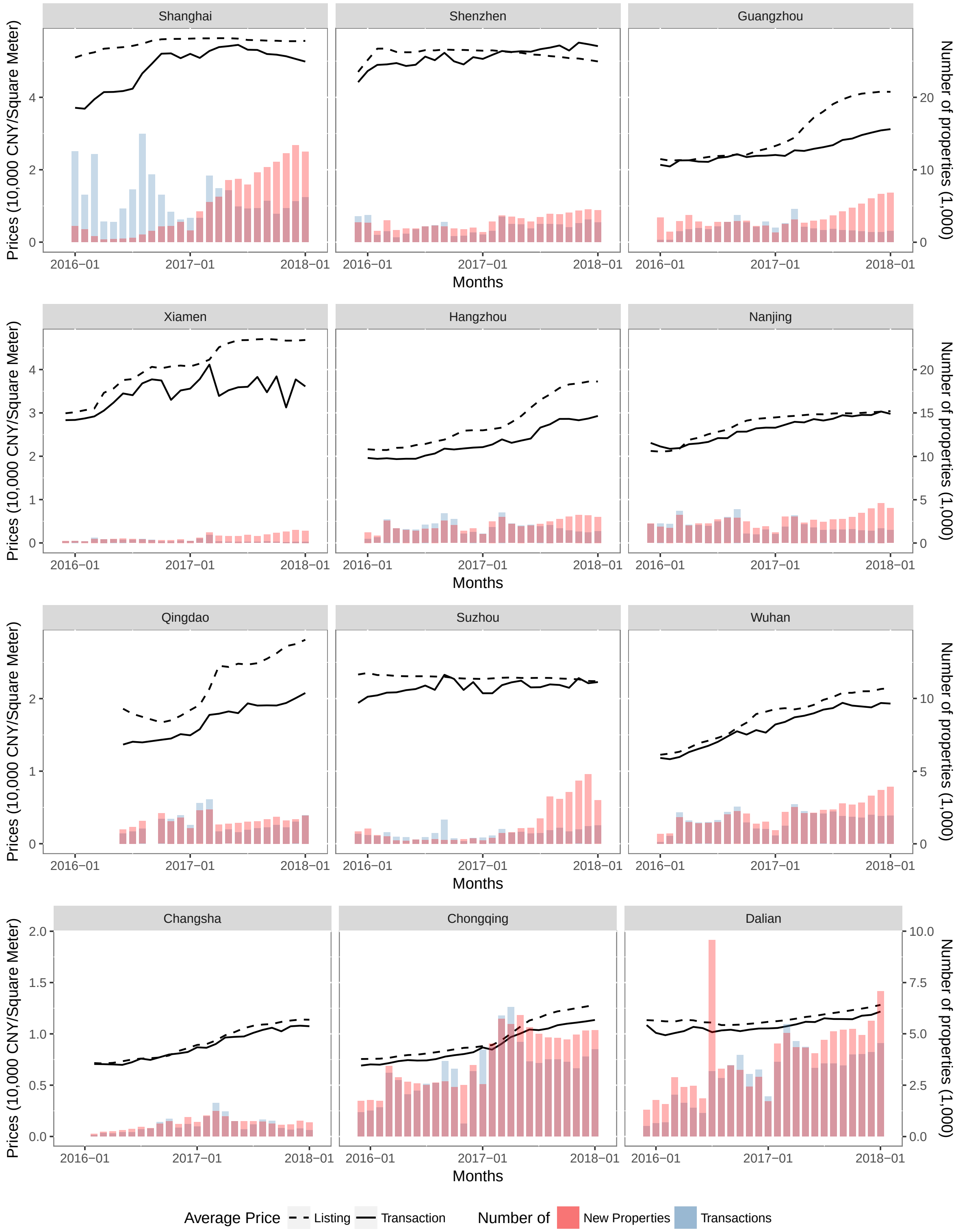


Figure A.1: Prices and Volumes

Note: This figure plots house prices and transaction volumes for the other major cities. The solid line is city level average transaction prices in 10,000 CNY per square meter. The dashed line is the city level average listing price of all properties listed in the market at the beginning of the month. Red bar shows the number of new properties (in 1,000) listed in the market in that month, while blue bar shows the number of transactions (in 10,000) occurred in that month. The data is available for Qingdao since June 2016, for Changsha since February 2016.

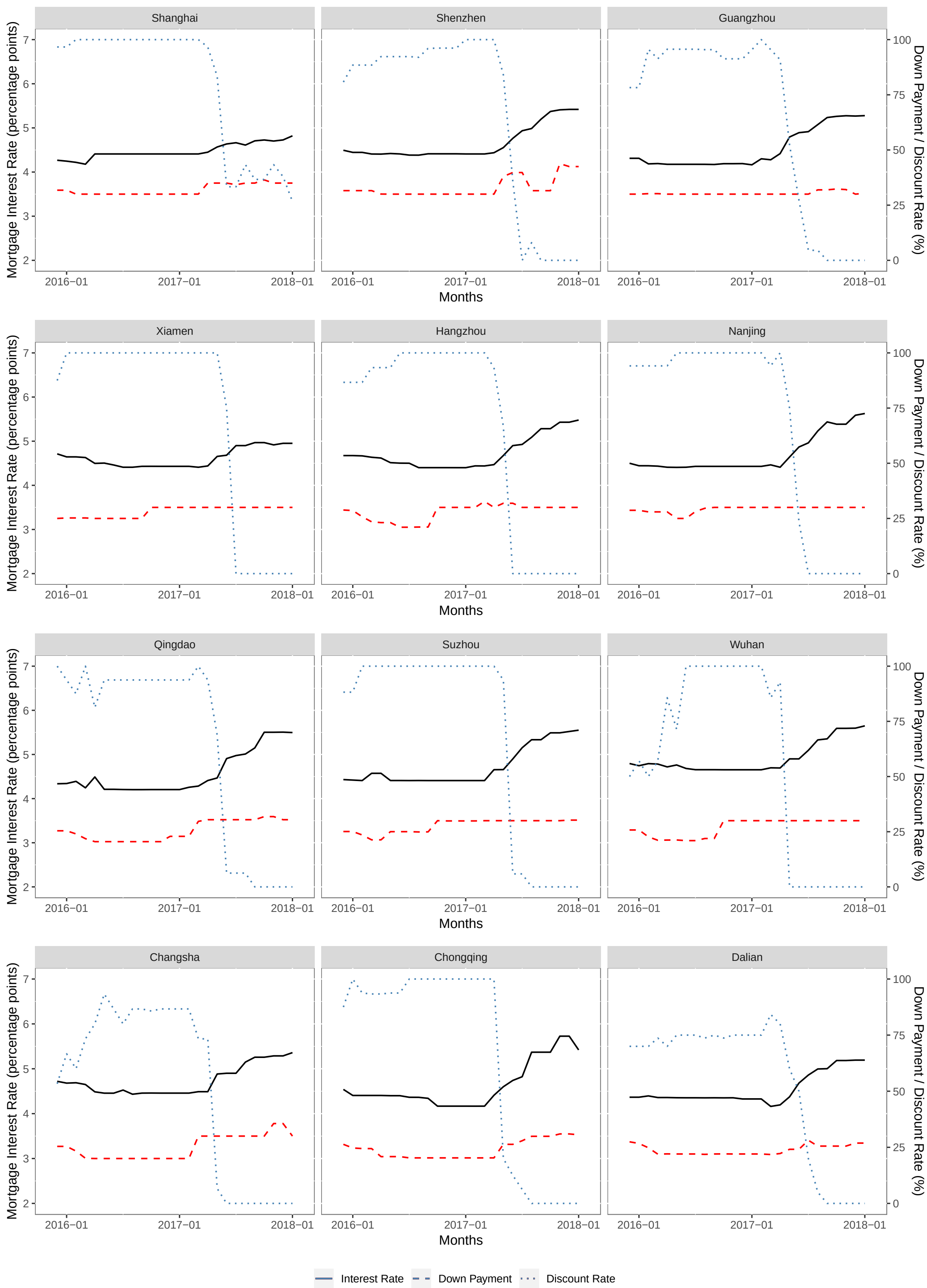


Figure A.2: Mortgage Market Condition

Note: This figure illustrates the variation in mortgage market conditions. The black solid line shows the average mortgage interest rate for the first mortgage in each city. The red dashed line represents the down payment requirement for the first mortgage in each city. The dashed blue line plots the fraction of banks that are giving discount on mortgage interest rate in each city.

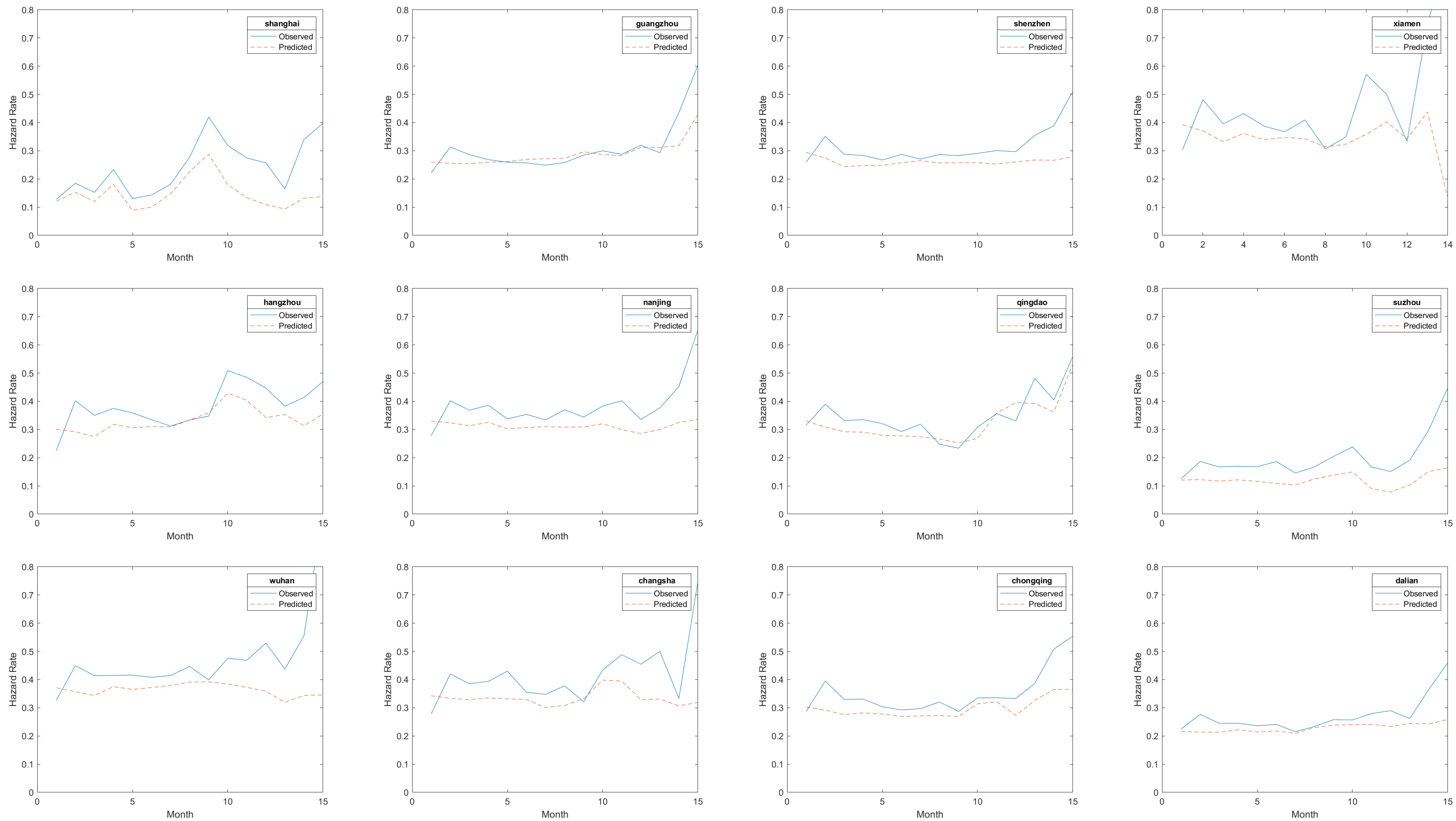


Figure A.3: Hazard Rate

Note: This figure plots the observed and estimated hazard rate for the other 12 major cities. The horizontal axis is the number of months that has been past since listing. Blue lines stand for observed results. Red lines stand for model estimated results.

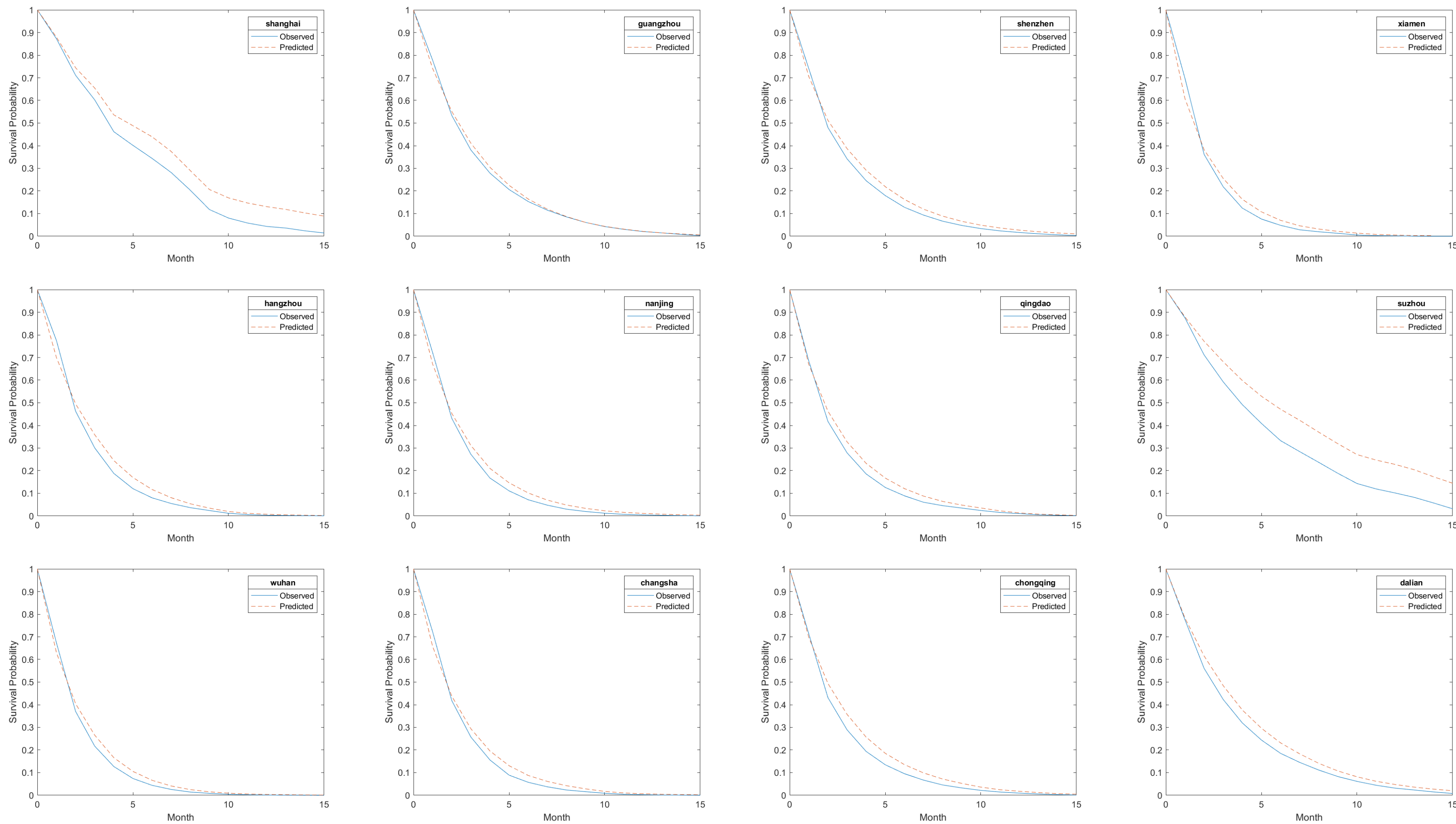


Figure A.4: Survival Probability

Note: This figure plots the observed and estimated survival probability for the other 12 major cities. The horizontal axis is the number of months that has been past since listing. Blue lines stand for observed results. Red lines stand for model estimated results.

In the waiting state, sellers can only hold the property, i.e., $d^s_{ijmt} = 0$. Hence, the expected value function in the waiting state is the expectation of value functions in equation (7) over the idiosyncratic term.

$$\begin{aligned}
\overline{V}(\Omega_{jmt}, 0) &= \delta(\Omega_{jmt}) + \beta \int_{\Omega} \int_{S} \overline{V}(\Omega_{jmt+1}, S_{ijmt+1}) \mathrm{d}F_S(S_{ijmt+1}|\Omega_{jmt+1}) \mathrm{d}F_{\Omega}(\Omega_{jmt+1}|\Omega_{jmt}) \\
&= \delta(\Omega_{jmt}) + \beta \int_{\Omega} \left[q_{jmt+1}\overline{V}(\Omega_{jmt+1}, 1) + (1 - q_{jmt+1})\overline{V}(\Omega_{jmt+1}, 0) \right] \mathrm{d}F_{\Omega}(\Omega_{jmt+1}|\Omega_{jmt}) \\
&= \delta(\Omega_{jmt}) + \beta \mathbb{E} \left[q_{jmt+1}\overline{V}(\Omega_{jmt+1}, 1) + (1 - q_{jmt+1})\overline{V}(\Omega_{jmt+1}, 0) | \Omega_{jmt} \right];
\end{aligned}$$

In the decision state, sellers can choose between the selling $d^s_{ijmt} = 1$ and holding $d^s_{ijmt} = 0$, and hence there are two components: If sellers choose to sell, the value function equals zero; if choose to hold, the value function equals that in the waiting state.

$$\begin{aligned}
\overline{V}(\Omega_{jmt}, 1) &= \ln \left(\sum_{d^s} \exp \left(\overline{V}(\Omega_{jmt}, 1, d^s_{ijmt}) \right) \right) \\
&= \ln \left(1 + \exp \left(\overline{V}(\Omega_{jmt}, 0) \right) \right).
\end{aligned}$$

The above equation suggests that the exponential of value function in the decision state equals the exponential value of selling plus the exponential value of holding as in the waiting state.

A.3 Estimating the Normalized Value Function

Instead of using the empirical probability $\widehat{p}^b_{jmt}$ 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

$$\widehat{\widehat{p}}^b_{jmt} = \frac{\sum_{i=1}^{N_{mt}} 1_{[d^b_{imt}=j]} \cdot W^j_i}{\sum_{i=1}^{N_{mt}} W^j_i},$$

where N_{mt} is the number of all transactions in market m at time t, and W^j_i 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

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

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.