Essays on China's Housing Market

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Abstract

Motivated by the emergence of various bubble detection models in recent decades and the practice of governments implementing loan-to-value (LTV) ratio policies to stabilize the real estate market, this thesis attempts to answer the following questions: (i) how panel data on house prices can be used to identify possible price bubbles and whether different assumptions and models generate different predictions even when the data are the same, (ii) whether LTV ratio limits are effective in regulating house price growth, and (iii) whether LTV rules influence households' decision to buy homes and the type of homes they buy.

Based on the data for major cities in China, the results of four commonly used bubble detection methods are compared. It is found that although the data are the same, different assumptions and models may lead to different conclusions. China's first- and second-tier cities are all identified by one or more of these models as having real estate bubbles. By applying a standard fixed effects model with variable treatment intensity, the study shows that the LTV policy is effective in dealing with increasing house prices. That is, tightening policies tend to exert a greater impact on house prices. On the other hand, the quantities of homes purchased respond symmetrically to changes in regulatory LTV ratios. There is no statistically significant difference between the extent to which loosened LTVs stimulate home buying and the extent to which tightened LTVs inhibit home buying. One possible explanation is that housing supply is rigid downwards. When the government tightens LTV constraints, housing demand declines but housing supply is fixed, so house price inflation slows down more sharply.

These findings have important implications for the implementation of LTV ratio policies.

Firstly, governments should develop a variety of indicators for bubble prediction to closely monitor the real estate market dynamics. Secondly, government intervention in the housing market through credit controls has been effective. During both the housing boom and bust, LTV rules significantly affect households' demand for homes. The responsiveness of house prices also depends on the elasticity of housing supply. LTV regulation in areas with low housing supply elasticity can achieve better results in stabilizing house prices.

JEL Classification: D14; D31; D91; G21; G28; R10; R21; R31; R38

Keywords: House prices; Bubble prediction; Macroprudential regulation; Household leverage; Loan-to-value ratio

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Introduction

Global house prices have risen rapidly since the 2000s. According to the International Monetary Fund's Global Real House Price Index, the average real house price in 57 countries at the end of 2007 was 59.38% higher than at the beginning of 2000. However, in 2008, house prices began to collapse, unleashing a global financial crisis that wreaked havoc on the real economy. Unemployment rose sharply. For example, the United States (US)'s unemployment rate jumped to 9.3% in 2009, a 26-year high, while the United Kingdom (UK)'s unemployment rate rose to 7.6% in the same year, the largest increase since 1982.

The housing crash of 2008 was inextricably linked to the dramatic growth of the US subprime mortgage market. According to the Financial Crisis Inquiry Report, mortgage debt in the US nearly doubled between 2001 and 2007, rising from US$91,500 to US$149,500 per household, while wages generally stagnated. Studies have shown that credit expansion caused by loose lending restrictions was the main reason for the sharp rise in house prices (Aliber et al., 2015; Gelain et al., 2018; and Justiniano et al., 2019). Owing to the excessive growth in credit, governments have taken a series of measures aimed at restraining the credit boom.

Monetary policy can curb the supply of housing loans by raising interest rates or reducing the money supply, but this can widen output gaps and cause widespread unemployment with heavy costs in terms of increasing systemic fragility and distorting macroeconomic indicators. Fiscal measures, such as raising property taxes or curbing mortgage interest tax deductions, could also theoretically reduce demand for housing, but their effect depends crucially on the behaviour of home buyers (Crowe et al., 2013). Specifically, when house prices soar, households may not respond much to tax changes because the capital gains from rising prices far outweigh the tax costs of buying a home. Compared with monetary and fiscal policies, macroprudential policies, such as limits on loan-to-value (LTV) ratios, have certain advantages in regulating real estate credit and allocating housing resources to more qualified buyers. The LTV limits directly target household mortgage debt levels and restrict the maximum amount that can be borrowed for a home loan. By building theoretical models, Rubio (2016) and, Alpanda and Zubairy (2017) have demonstrated that implementing LTV rules for mortgages is a more effective and lower-cost way to reduce household debt, promote financial stability and improve social welfare.

In addition to these findings, researchers have sought to determine whether the LTV ratio policy stabilises house prices and how it affects households' buying behaviour, but so far there is no definitive conclusion on these issues. Ahuja and Nabar (2011), Igan and Kang (2011) and Hwang et al. (2013) argue that LTV caps reduce the rate of house price appreciation, whereas Neagu et al. (2015), Vandenbussche et al. (2015) and Cerutti et al. (2017) find that LTVs have a poor effect on restraining growth in house prices. One possible reason is that most previous studies have used dummy variables to represent policy interventions, which cannot reflect the intensity of policy actions. Other studies have used cross-country data sets to study the impact of LTV limits, but the specific requirements and current levels of LTV limits may vary from country to country, affecting the accuracy of policy effect estimates.

Econometric evidence about the effect of LTV policy at the extensive margin is also limited, and studies have drawn mixed conclusions. By establishing a calibrated general equilibrium model, Bajari et al. (2013) argue that tightening the LTV limit causes households to delay buying homes and relaxing the limit stimulates immediate purchases. Halket and Vasudev (2014) also find, through theoretical modelling, that the change in LTV requirement causes households to adjust their home buying behaviour, but the relaxation of this measure mainly makes people more inclined to purchase larger homes rather than incentivise them to purchase earlier. The study by Tzur-Ilan (2020) provides empirical evidence that the implementation of LTV restrictions did not reduce property transactions. Instead, borrowers with limited access to credit have bought cheaper, smaller homes, moved away from central business districts and chosen poorer socioeconomic areas. With the deepening of the debate on the role of LTV restrictions for mortgages, this study further investigates the impact of the LTV ratio policy on the intensive and extensive margins of home purchases and provides practical suggestions for the implementation of the policy.

Many governments began to impose limits on LTV ratios after the 2008–2009 global recession. Although these measures vary in the specific conditions under which they are implemented, their actual impact is often difficult to estimate. The major challenge arises from the inability to know how the target variables would have changed in the absence of the intervention. The current study addresses this issue in the context of China’s real estate market, which has long been criticized for a property bubble, with central and local governments regularly issuing LTV policies. The local variations in LTV caps resulting from the release of national policies form a unique advantage in estimating the impact of LTV policies.

This thesis begins with an introduction of the situation of China’s real estate market and evaluates whether there is a housing price bubble. This is followed by a background of the establishment of China’s LTV ratio policy and measurement of the effectiveness of the policy in regulating house prices. Thereafter, it explores the impact of the LTV policy on housing purchase decisions of home buyers in which it is found that restrictions on LTV ratios have a statistically significant effect on whether people buy homes, but not on the size or location of the home they buy.

Specifically, the first chapter of the thesis describes four widely used bubble detection models namely: (i) the log periodic power law singularity model; (ii) the dynamic Gordon growth model; (iii) the user cost model and; (iv) the Case-Shiller model. Some of the models use purely statistical methods, while others use rents, incomes and other fundamental factors to calculate the underlying value of home prices. This chapter makes good use of data from China to explore how panel data on house prices can be used to identify possible price bubbles and whether the different assumptions and models generate different predictions even when the data are the same.

The second chapter studies the impact of LTV policy on house prices. The LTV rule for mortgages aims to regulate house prices by restricting the supply of credit, but empirical literature does not provide a consistent conclusion on the role of this policy in shaping housing price dynamics. To test the effectiveness of the policy, difference-in-differences estimation is employed. When a national policy is introduced to reduce the maximum allowable LTV ratio for mortgage loans, the cities whose LTV cap remains unchanged due to the implementation of more stringent local LTV policies are taken as the control group, which represents the counterfactual situation of the cities whose LTV cap is reduced under the requirements of the national LTV policy. Departing from the common method of using dummy variables to represent policy release in the literature, the level of LTV cap is used as the independent variable to measure the degree of exposure to the policy with regard to the direction and magnitude of changes in the LTV caps. The results show that the LTV ratio policy is effective in dealing with increasing house prices. That is, tightening policies tend to exert a greater impact on house prices. The findings of study support the hypothesis that the elasticity of urban housing supply affects the effectiveness of LTV policy.

The third chapter examines the effect of LTV policy on household purchasing decisions. For the first time, this empirical study takes into account both the loosening and tightening LTV actions and allows LTV limits to vary over time, so as to comprehensively examine the policy effects at the household level. A logistic model is used to explore the impact of LTV ratio policy on the probability of household purchase where the policy applied, and to measure the distributional effects of this policy for heterogeneous households. The results show that a drop in LTV caps leads to a lower homeownership rate, whereas an increase in the maximum LTV ratio encourages households to buy homes. The findings also suggest that the LTV policy is more restrictive for older households and households with less education. In addition, the subjective attitude of households towards financial risk also affects the policy effectiveness. This study demonstrates that the LTV policy has less impact on households with a higher risk preference.

Chapter 1

Measurement and Estimation of Real-Estate Bubble in China

1.1 Introduction

Real estate bubble can lead to economic and social structural imbalance, financial crisis and other serious consequences. When an economy is experiencing a housing bubble, the bulk of its capital is concentrated in the real estate sector and speculation is rampant. Given the close relationship between the real estate and the banking sectors, once a real estate bubble bursts, the banks involved are also at a risk of collapse. Such a phenomenon often sets off a chain reaction which leaves other banks exposed to runs. According to the IMF estimates published in 2003, the bursting of a property bubble is twice as costly and lasts twice as long as the bursting of an equity bubble. Compelled by the above findings of the IMF, a variety of models for detecting real estate bubbles have emerged, to identify bubbles as early as possible and develop countermeasures.

This paper complements existing studies by exploring how panel data on house prices can be used to identify possible price bubbles and whether different assumptions and models generate different predictions even when the data are the same. The analysis is conducted using data for the Chinese economy, given that China's real estate market has long been viewed as experiencing a property price bubble due to the rapid price growth, especially in upper-tier cities. According to the National Bureau of Statistics, residential prices in Shenzhen increased at an annual rate of 63.4% in April 2016 while the annual price increase in Beijing stood at 30.4% in September 2016. Over the past decade, property prices in Beijing have risen faster than in other major international cities such as London, New York and Sydney. Rising prices in China's core cities also have significant spillover effects, affecting price movements in the rest of the country (Yang et al., 2018).

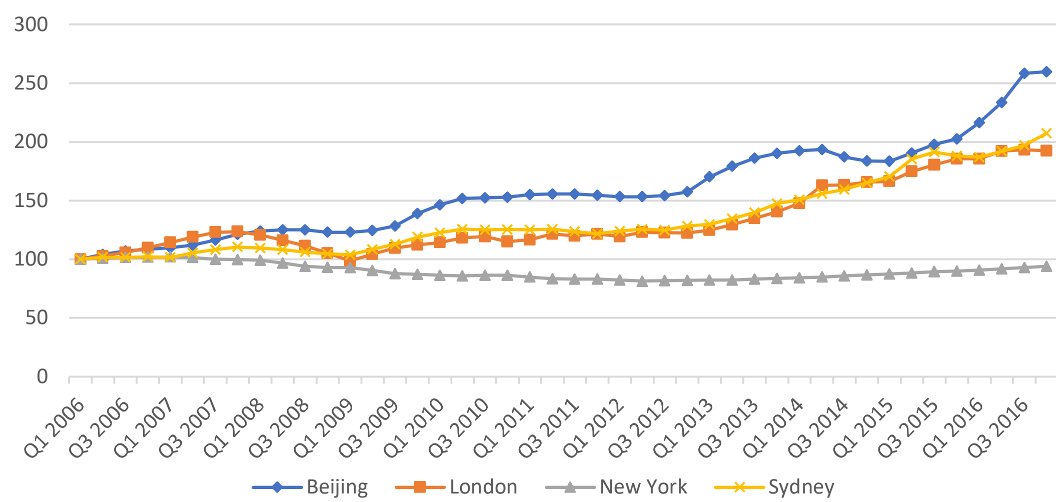

Figure 1.1. House price indices of major international cities (Q1 2006 = 100)

Data Source: National Bureau of Statistics of China, UK Nationwide Building Society, Federal Housing Finance Agency, Australian Bureau of Statistics

Nevertheless, the rapid rise in house prices alone is not conclusive evidence of a bubble in the market. Various definitions of asset bubbles emphasise the fact that an initial price increase creates expectations of further price increases which, in turn, attracts new buyers. At this point, the price has decoupled from the value of the asset and its profitability. In this study, a housing bubble is defined as an increase in house prices that is not based on changes in their fundamental values but is primarily caused by the behaviour of market participants, and household income levels are unlikely to support these prices indefinitely. The detection of housing bubble in literature can be roughly divided into two categories: (1) analysing the characteristics of present value of houses by pure statistical method and; (2) estimating the implied fundamental value of houses based on income, rental price and other real estate market indicators.

One of the widely used models is the log periodic power law singularity (LPPLS) model. The LPPLS is a rational expectation model proposed by Johansen et al. (2000) to study bubbles and crashes. It was first used to diagnose stock market bubbles, then expanded to examine time series related to house price indices, credit risk, rupture, earthquakes, and world population. The establishment of LPPLS model is based on the existence of positive feedbacks in the housing market and the economy. The model assumes that when actual returns or other economic indicators are above average, traders tend to hold a more optimistic attitude, which is contagious and locally self-reinforcing. This process leads to a temporary deviation of equilibrium prices from fundamental values, forming a speculative bubble. If the tendency of traders to imitate the behaviour of those near them rises to a critical point, many traders may place sell orders at the same time, causing a market crash. Since a crash is indeterminate, it is described as the probability per unit of time that the crash will occur in the next instant, if it has not already occurred. Given that there is a finite probability that a bubble will not cause a crash and that traders can be compensated by a rapid rise in prices, it is rational for them to remain invested in spite of a bubble (Sornette 2003).

The LPPLS structure provides a flexible framework for bubble detection and regime shift prediction in housing price series. Zhou and Sornette (2006) used this model to study whether there was a real estate bubble in the US after the "new economy" bubble burst in 2000, when the Federal Reserve sharply reduced the short-term interest rate yields. The authors found that 21 states and the District of Columbia showed the characteristics of a super-exponential bubble, and that the turning point was likely around mid-2006.

Another model is the Gordon growth model, which aims at identifying the bubble-induced excess of the price-to-rent ratio over market fundamentals, rather than analysing house price growth on a purely statistical basis. Brunnermeier and Julliard (2008) pointed out that under the condition of dynamic optimization, the equilibrium real price of a property should be equal to the present discounted value of future real rents and the discounted resale value of the property. Therefore, they set up a dynamic Gordon growth model with rational bubbles to differentiate the fundamental components from the implied mispricing component, and then uses a vector autoregression (VAR) system to estimate each component of the price-to-rent ratio.

The dynamic Gordon growth model helps to distinguish between movements in house prices caused by fundamental factors and those caused by bubbles. Liu et al. (2017) further used this model and combined the method of variance decomposition to evaluate the real estate bubbles in Beijing, Shanghai, Guangzhou and Shenzhen in China. Since rent and expected return are considered as the two most important fundamental factors leading to price fluctuations, the authors decomposed the logarithmic price-to-rent ratio into rational bubbles, discounted expected future rent growth rates and discounted expected future returns on housing, to see whether house price movements are dependent on the latter two factors, which represent the fundamentals of real estate. The current research adopts this approach and expands their analysis to 34 Chinese cities.

Another way to determine the fundamental value of a house based on current rent is by using the user cost model. The model holds that the annual cost of owning a house should be equal to the annual rent in an equilibrium real estate market. This is the case because if it is more expensive to own a home, people will choose to rent, and vice versa. The only reason buyers are willing to pay more than rent is to get excess capital gains, and then a bubble exists.

Himmelberg et al. (2005) applied the user cost model to investigate the housing price bubbles in metropolitan statistical areas of the US. The authors constructed a measure of the cost of home ownership, from which they determined how high a market was valued relative to its historical valuation. Building on their work, Mayer and Sinai (2007) extended the user cost method and examined whether fundamental factors represented in terms of user cost could justify movements in house prices. They regressed the price-to-rent ratio on a user cost term and other behavioural factors. The results indicated that the surge in US house prices in the 1980s looked more like a behavioural bubble than in the 2000s. In the first decade of the 21st century, fundamentals dominated, but expectations of rising house prices continued to play a significant role.

Based on the user cost framework, Ren et al. (2013) analysed the impact of economic fundamentals and house price expectations on the rent-price ratio in Beijing from 2005 to 2010. They argued that Beijing's rising house prices were mainly caused by people's irrational expectations about future house prices and stressed the dangers of this situation. Deng et al. (2017) added that the price-to-rent ratio in Beijing had exceeded 50, in which case a small adverse change in interest rates or expectations of future price increases could lead to a sharp drop in house prices.

Other studies have focused more on the role of income growth in explaining the pattern of rising house prices. Case and Shiller (2003) argued that a fundamental consideration in determining whether a bubble exists is the stable relationship between income and other fundamental factors and house prices over time and space. When house prices deviate from people's incomes and other fundamentals in the economy, buyers will feel that if they do not buy now, they will not be able to afford a house in the future. If housing supply cannot be increased in the short term, then house prices will rise further and become unaffordable, thereby prompting more people to buy houses. The increase in demand will push up house prices and create a cycle of rising prices.

Case and Shiller started with a regression analysis of house prices and incomes, and then added other fundamental variables, such as population, non-farm payrolls, unemployment, housing starts and mortgage rates. In addition, they used the estimated coefficients to forecast US house prices from 2000 to 2002 to examine the strength of the real estate industry in the context of the stock market crash and economic recession. The results showed that eight states had housing bubbles, given that incomes in those states did not explain house price movements well; that the ratio of house prices to income fluctuated; and that actual house prices between 2000 and 2002 were consistently higher than predicted prices based on the previous housing market performance.

The above four bubble detection models cover the commonly cited measures used to assess housing valuations. This paper uses these models to assess potential housing price bubbles in 34 first- and second-tier cities in China from 2008 to 2015. The innovation of this paper lies not in the method, but in comparing different models for house price bubbles to see if different conclusions can be drawn under the same data. These findings document another important example of test methodology.

The rest of the paper is structured as follows. Section 1.2 provides institutional background about housing market in China. Section 1.3 describes the key data sources and summary statistics. Section 1.4 briefly discusses the derivation process of the four widely used models. Section 1.5 presents the empirical results. Section 1.6 concludes.

1.2 Institutional Background

In China, real estate cannot be owned on a freehold basis, but only on a leasehold basis. The subject of land ownership is the state or the collectives, and any other unit or individual can only obtain the right to use land. The maximum number of years for assigning the right to the use of the land shall be determined according to the purpose of the land. Land for residential purposes shall be used for 70 years; land for industrial purposes shall be used for 50 years; land for purposes of educational, scientific and technological, cultural, health care or sports shall be used for 50 years; land for commercial, tourism or recreational purposes shall be used for 40 years; and land for combined usage or other purposes shall be used for 50 years. After the expiration of the term of use, the land shall revert to the government, and the above-ground buildings shall still belong to the owners. If the owners apply for the right to use the land again, they should pay the land transfer fee according to the current land price. Thus, the purchase of commercial housing rights must only be established on the basis of 70 years of land use rights. After the housing developer obtains the land lease right from the land administration department, the land use right enters the market circulation.

Since the enactment of the Law of the People's Republic of China on Land Administration in 1986, land-use rights in China can be transferred and traded. Based on the typical 70-year lease term of residential land, the land use rights expire in 2056 at the earliest. The Property Law stipulates that land use rights for residential construction will be automatically renewed when the term expires, but it does not provide detailed provisions on how the lease renewal process should be carried out or how much fees might be charged, and there is no relevant legal interpretation.

1.3 Data and Summary Statistics

1.3.1 House Prices and Rents

The data for second-hand home prices and rents in 34 first- and second-tier cities was obtained from the China Real Estate Price Platform. Table 1.1 and Table 1.2 show the descriptive statistics of the annual growth rate of house prices and annual growth rate of rents from January 2008 to December 2015 (sample starting time varies by city), respectively.

Among these cities, the average growth rate of house prices was generally high over the sample period, with Beijing experiencing the fastest growth of 18.6% per year while Chengdu experienced the slowest growth of 4% per year. In terms of volatility, Haikou, Beijing, Ningbo and Shenzhen saw the biggest fluctuations in housing price growth, with the maximum annual growth rate reaching 94.1%, 76.9%, 69.5% and 64.4%, respectively. From December 2009 to April 2010, prices in Haikou accelerated dramatically, rising at an annual rate of 94.1% from 14%. After a steep climb, the growth rate of house prices plummeted, turning negative in September 2011. The housing price in Shenzhen soared from April 2015 to the end of the sample period, reaching a maximum annual growth rate of 64.4% in December 2015.

Table 1.1. Descriptive statistics of house prices

City	Starting time	2015M12	Maximum	Minimum	Mean	Standard deviation	Observation
Beijing	2009M04	0.074	0.769	-0.101	0.186	0.197	81
Tianjin	2008M01	0.015	0.403	-0.098	0.105	0.129	96
Shijiazhuang	2009M01	0.022	0.273	-0.036	0.102	0.084	84
Taiyuan	2009M01	0.043	0.207	-0.011	0.083	0.052	84
Hohhot	2010M11	0.018	0.514	-0.063	0.112	0.180	62
Shenyang	2008M04	-0.024	0.313	-0.075	0.074	0.111	93
Dalian	2008M06	-0.014	0.459	-0.094	0.061	0.140	91
Changchun	2009M01	-0.040	0.423	-0.049	0.111	0.146	84
Harbin	2009M01	0.045	0.301	-0.079	0.049	0.104	84
Shanghai	2008M04	0.114	0.444	-0.291	0.100	0.138	93
Nanjing	2008M06	0.044	0.522	-0.175	0.105	0.148	91
Hangzhou	2009M03	-0.005	0.528	-0.167	0.070	0.176	82
Ningbo	2008M06	-0.032	0.695	-0.133	0.061	0.185	91
Hefei	2009M01	0.102	0.243	-0.009	0.087	0.071	84
Fuzhou	2009M01	0.111	0.393	-0.124	0.100	0.129	84
Xiamen	2009M01	0.091	0.429	-0.296	0.143	0.145	84
Nanchang	2008M03	-0.004	0.333	-0.096	0.080	0.099	94
Jinan	2009M01	0.007	0.351	-0.059	0.096	0.115	84
Qingdao	2008M01	-0.028	0.345	-0.162	0.069	0.121	96
Zhengzhou	2009M01	0.034	0.404	-0.047	0.121	0.122	84
Wuhan	2008M07	0.102	0.318	-0.156	0.098	0.114	90
Changsha	2008M06	-0.008	0.322	-0.083	0.073	0.114	91
Guangzhou	2008M03	0.029	0.481	-0.159	0.150	0.139	94
Shenzhen	2008M10	0.644	0.644	-0.214	0.173	0.145	87
Nanning	2009M01	0.025	0.465	-0.036	0.080	0.131	84
Haikou	2009M08	0.000	0.941	-0.145	0.133	0.303	77
Chongqing	2008M08	-0.033	0.411	-0.107	0.079	0.141	89
Chengdu	2008M08	-0.042	0.275	-0.083	0.040	0.098	89
Guiyang	2009M01	0.040	0.269	-0.068	0.066	0.083	84
Kunming	2009M01	0.008	0.460	-0.087	0.091	0.166	84
Xi’an	2008M01	-0.059	0.405	-0.059	0.105	0.132	96
Lanzhou	2009M01	0.018	0.484	-0.028	0.133	0.155	84
Yinchuan	2009M12	-0.062	0.349	-0.097	0.061	0.111	73
Urumqi	2009M01	-0.083	0.424	-0.088	0.119	0.139	84

Data source: China Real Estate Price Platform

Comparing Table 1.1 and Table 1.2, it can be seen that during the sample period, the average annual growth rate of housing price was higher than the average annual growth rate of rent in most cities, except Hohhot, Harbin, Nanchang, Zhengzhou, Guiyang, Kunming, Lanzhou, Yinchuan and Urumqi. At the end of the sample period, although the growth rate of housing prices slowed down, the cities registered higher growth rate of housing prices than that of rents except for Beijing, Shenyang, Shanghai, Hangzhou, Nanchang, Changsha, Guangzhou, Xi'an and Urumqi. Moreover, the rate of house price growth was generally more volatile than the rate of rent growth. Only in Tianjin, Taiyuan, Dalian, Hefei, Qingdao, Guiyang, Kunming, Yinchuan, and Urumqi did the maximum rate of rent growth exceed the maximum rate of house price growth.

Table 1.2. Descriptive statistics of rents

City	Starting time	2015M12	Maximum	Minimum	Mean	Standard deviation	Observation
Beijing	2009M04	0.103	0.291	-0.047	0.087	0.074	81
Tianjin	2008M01	-0.002	0.789	-0.265	0.044	0.164	96
Shijiazhuang	2009M01	-0.045	0.248	-0.048	0.080	0.082	84
Taiyuan	2009M01	-0.053	0.287	-0.082	0.080	0.093	84
Hohhot	2010M11	-0.077	0.318	-0.077	0.117	0.118	62
Shenyang	2008M04	-0.019	0.295	-0.182	0.029	0.102	93
Dalian	2008M06	-0.052	0.758	-0.194	0.060	0.174	91
Changchun	2009M01	-0.062	0.264	-0.068	0.069	0.090	84
Harbin	2009M01	0.009	0.213	-0.054	0.060	0.058	84
Shanghai	2008M04	0.141	0.415	-0.418	0.016	0.120	93
Nanjing	2008M06	-0.001	0.418	-0.347	0.056	0.130	91
Hangzhou	2009M03	0.010	0.347	-0.087	0.064	0.086	82
Ningbo	2008M06	-0.035	0.295	-0.138	0.028	0.080	91
Hefei	2009M01	0.032	0.282	-0.342	0.068	0.147	84
Fuzhou	2009M01	0.002	0.232	-0.201	0.068	0.084	84
Xiamen	2009M01	0.023	0.297	-0.056	0.091	0.079	84
Nanchang	2008M03	0.015	0.290	-0.037	0.092	0.078	94
Jinan	2009M01	-0.017	0.270	-0.043	0.083	0.070	84
Qingdao	2008M01	-0.037	0.417	-0.186	0.023	0.113	96
Zhengzhou	2009M01	0.018	0.288	-0.021	0.121	0.064	84
Wuhan	2008M07	0.052	0.285	-0.054	0.086	0.064	90
Changsha	2008M06	0.035	0.272	-0.056	0.057	0.060	91
Guangzhou	2008M03	0.054	0.181	-0.150	0.058	0.070	94
Shenzhen	2008M10	0.180	0.228	-0.065	0.079	0.066	87
Nanning	2009M01	-0.011	0.229	-0.097	0.035	0.058	84
Haikou	2009M08	-0.032	0.549	-0.052	0.077	0.118	77
Chongqing	2008M08	-0.041	0.254	-0.051	0.070	0.066	89
Chengdu	2008M08	-0.045	0.200	-0.110	0.038	0.075	89
Guiyang	2009M01	-0.050	0.319	-0.050	0.075	0.084	84
Kunming	2009M01	-0.014	0.467	-0.074	0.107	0.130	84
Xi'an	2008M01	-0.032	0.145	-0.040	0.048	0.050	96
Lanzhou	2009M01	0.005	0.307	0.005	0.147	0.082	84
Yinchuan	2009M12	-0.066	0.564	-0.098	0.110	0.172	73
Urumqi	2009M01	-0.015	0.440	-0.066	0.124	0.114	84

Data source: China Real Estate Price Platform

1.3.2 Incomes

The level of income affects the demand for housing and is one of the main factors supporting the growth of the housing market. The data on per capita disposable income of urban residents by city were obtained from the Wind Economic Database, Qianzhan Database, Municipal Statistical Bulletin on Economic and Social Development and Municipal Statistical

Table 1.3. Descriptive statistics of incomes

City	Starting time	2015M12	Maximum	Minimum	Mean	Standard deviation	Observation
Beijing	2009M04	0.089	0.132	0.089	0.103	0.012	81
Tianjin	2008M01	0.082	0.177	0.082	0.111	0.025	96
Shijiazhuang	2009M01	0.080	0.137	0.080	0.105	0.015	84
Taiyuan	2009M01	0.076	0.168	0.025	0.099	0.035	84
Hohhot	2010M11	0.076	0.147	0.076	0.111	0.025	62
Shenyang	2008M04	0.070	0.283	0.064	0.118	0.042	93
Dalian	2008M06	0.068	0.158	0.068	0.114	0.024	91
Changchun	2009M01	0.066	0.163	0.066	0.114	0.023	84
Harbin	2009M01	0.075	0.141	0.075	0.111	0.018	84
Shanghai	2008M04	0.084	0.138	0.081	0.105	0.018	93
Nanjing	2008M06	0.083	0.142	0.083	0.112	0.018	91
Hangzhou	2009M03	0.083	0.134	0.083	0.108	0.014	82
Ningbo	2008M06	0.084	0.134	0.082	0.106	0.015	91
Hefei	2009M01	0.090	0.179	0.090	0.120	0.025	84
Fuzhou	2009M01	0.078	0.195	0.067	0.109	0.026	84
Xiamen	2009M01	0.075	0.147	0.075	0.108	0.020	84
Nanchang	2008M03	0.098	0.161	0.090	0.120	0.020	94
Jinan	2009M01	0.080	0.150	0.080	0.110	0.020	84
Qingdao	2008M01	0.081	0.163	0.081	0.116	0.023	96
Zhengzhou	2009M01	0.087	0.144	0.087	0.109	0.017	84
Wuhan	2008M07	0.095	0.164	0.095	0.123	0.021	90
Changsha	2008M06	0.085	0.181	0.085	0.123	0.026	91
Guangzhou	2008M03	0.088	0.131	0.088	0.107	0.013	94
Shenzhen	2008M10	0.090	0.127	0.090	0.103	0.012	87
Nanning	2009M01	0.075	0.209	0.075	0.115	0.030	84
Haikou	2009M08	0.076	0.180	0.076	0.111	0.029	77
Chongqing	2008M08	0.083	0.155	0.083	0.112	0.021	89
Chengdu	2008M08	0.080	0.149	0.080	0.116	0.021	89
Guiyang	2009M01	0.091	0.170	0.082	0.109	0.024	84
Kunming	2009M01	0.085	0.194	0.085	0.135	0.028	84
Xi’an	2008M01	0.081	0.247	0.081	0.157	0.049	96
Lanzhou	2009M01	0.105	0.156	0.093	0.120	0.018	84
Yinchuan	2009M12	0.082	0.141	0.082	0.104	0.018	73
Urumqi	2009M01	0.147	0.147	0.061	0.112	0.025	84

Data source: Wind Economic Database, Qianzhan Database, Municipal Statistical Bulletin on Economic and Social Development and Municipal Statistical Yearbook

Yearbook. Table 1.3 shows descriptive statistics of the annual growth rate of per capita disposable income.

The growth rate of per capita disposable income in many cities declined during the sample period. In Beijing, Xiamen, Zhengzhou, Guangzhou, Shenzhen, Haikou and Lanzhou, the average annual growth rate of house prices was more than one percentage point higher than the average annual growth rate of income. In all cities, house price growth was more volatile than income growth. The maximum rate of growth in house prices far outstripped the maximum rate of growth in incomes.

1.3.3 Other Fundamentals

Data on mortgage interest rates and 10-year deposit rates come from the People's Bank of China. Data on consumer price index, resident population, number of employed persons and urban registered unemployment rate are obtained from the Wind Economic Database. The

Table 1.4. Descriptive statistics of other fundamental variables (2008–2015)

Variable	Obs	Mean	Std. Dev	Min	Max
Mortgage rate	96	0.065	0.007	0.049	0.078
10-year deposit rate	96	0.037	0.004	0.028	0.046
Consumer price index	96	0.028	0.023	-0.018	0.087
Unemployment rate	2932	0.030	0.003	0.014	0.042
Resident population	2932	0.013	0.006	-0.002	0.041
Employed persons	2932	0.036	0.027	0.007	0.097
Loan-to-value cap	2932	0.722	0.034	0.707	0.727
Housing starts	2932	99.549	65.916	20.224	362.01

Notes: 1. 'Mean' reports the average of the city mean for each indicator. 'Std. Dev' reports the average of the city standard deviation for each indicator. For the unemployment rate, resident population, employed persons, loan-to-value cap and housing starts, 'Min' and 'Max' report the minimum and maximum city mean, respectively.

2. Mortgage rate, 10-year deposit rate and consumer price index are uniform across the country. The consumer price index translates into the rate of inflation. The statistics of resident population and employed persons are the annual growth rates of these two indicators. Loan-to-value cap is the average loan-to-value ratio cap for first-time homebuyers over the prior year. The unit of housing starts is 10 thousand square metre.

newly started floor space of commercial residential buildings by city is available monthly from the China Real Estate Index System. The loan-to-value caps are taken from policy documents posted on local government websites. Table 1.4 reports descriptive statistics for these fundamental variables.

The People's Bank of China adjusted benchmark mortgage interest rates 19 times between 2008 and 2015. Mortgage rates were cut during the financial crisis to stimulate the housing market and stayed low through 2009 and 2010. After a brief rise, rates fell again, with the benchmark mortgage rate falling to an all-time low of 4.9% at the end of 2015. The 10-year deposit rate also dropped precipitously in 2008, then rose gradually until 2014, when there was a significant downward trend. In terms of inflation, from 2008 to the first half of 2009, the CPI continued to decline, with the price growth rate falling from 8.7% to -1.8%.

The average unemployment rate in various cities ranged from 1.4% to 4.2%, with Beijing having the lowest average and Shanghai the highest. Although Shanghai's registered urban unemployment rate was high, its total employment growth rate was also high, averaging 5.6% a year. This suggests that there may be plenty of job and skill mismatches in the labour market. In general, the population growth of first-tier cities is greater than that of second-tier cities, with Tianjin having the largest population growth rate, followed by Guangzhou, Beijing, Shenzhen, Urumqi and Shanghai.

The central government and some local governments impose loan-to-value limits for first-time homebuyers. The LTV cap was raised at the end of 2008, then lowered uniformly to 70% in 2010 and stayed there until it was gradually increased again in 2015. Finally, in terms of housing starts, Chongqing has the largest the amount of housing starts among the sample cities, averaging 3.62 million square meters per month. The level of housing starts in Shanghai is similar to that in Beijing, with particularly sharp fluctuations in 2011 and before. In Shenzhen, by contrast, the level of housing starts is much lower and has become increasingly volatile since 2012.

1.4 Model Description

1.4.1 The Log Periodic Power Law Singularity Model

The LPPLS model is used to explain the rise and fall of asset price trends. Although such trends are often triggered by fundamentals, they have their own dynamic mechanism independent of fundamental factors. Investors' overconfidence, imitative behaviour and herd behaviour raise the expectations of future capital gains, creating a positive feedback loop that allows price trends to become self-reinforcing. Thus, the LPPLS method detects real estate bubbles and predicts crashes or regime changes by capturing positive feedbacks on house prices in the market. A bubble is defined as an increase in house prices at a faster-than-exponential rate. Under the framework of the LPPLS model, it considers rational agents who are risk-neutral and have rational expectations, so the stochastic process of house price $p(t)$ follows a martingale process, that is, the expectation of rational agents for the house price at a certain point in the future is equal to the current price of the house.

$$E_t[p(t')] = p(t), \forall t' > t \tag{1.1}$$

where $E_t[\cdot]$ represents the conditional expectation based on all available information up to time t. No matter how a rational agent uses his experience acquired before time t, all he can expect is that the house price at time t' in the future can only be $p(t)$, which is a necessary condition for no arbitrage.

As mentioned above, the probability of the real estate market crash is not zero, so a jump process j is defined to be zero before the crash and one after the crash. Since the critical time at which a crash may occur is unknown, it is characterized by a stochastic variable. The probability density function of this stochastic variable is expressed as $q(t)$, the cumulative distribution function as $Q(t)$. Therefore, given the fact that the crash has not yet occurred, the probability per unit of time that it will occur in the next instant, namely the crash hazard rate, is defined by equation (1.2), where the numerator is the probability of the crash happening and the denominator is the probability that the crash hasn't happened yet.

$$h(t) = \frac{q(t)}{1-Q(t)} \tag{1.2}$$

The hazard rate is the key variable in modelling the behaviour of house prices before a crash. Although it is not possible to trace the house price set by the interaction between agents from a micro perspective because the house price movement generated by each transaction has a direction and size, it can be better traced down if all the house price movements in the market can be represented together from a macro perspective. This is called the mean field representation. Based on the mean field theory, the hazard rate can be described by equation (1.3) to model the self-fulfilling process, that is, a loss of confidence will result in a large number of agents taking the same sell position, which can produce a severe market slump.

$$\frac{dh}{dt} = Dp^{\mu}, \ \ \mu > 0 \tag{1.3}$$

where D is a constant greater than zero. Consider an ideal market with no rental yield, ignoring interest rates, risk aversion and market liquidity constraints, so that the fundamental value of a house is zero, and any positive value represents a bubble. In this case, $p(t)$ can be thought of as the price that exceeds the fundamental value. The basic idea expressed in equation (1.3) is that when the market price of housing deviates from its fundamental value, confidence loss quantified in terms of hazard rate will increase. House prices must therefore rise to compensate for the increased risk.

The LPPLS model assumes that the dynamics of house prices satisfies a stochastic differential equation with drift and jump. If the house price $p(t)$ drops by a fixed percentage $\kappa \in (0,1)$ during a crash, the differential equation for the house price is given as below:

$$dp = \mu(t)p(t)dt - \kappa p(t)dj \tag{1.4}$$

where $\mu(t)$ is the drift and j is the discontinuous jump as defined previously.

Taking the expectation on both sides of the above equation gives the following expression:

$$\begin{aligned} E[dp] &= \mu(t)p(t)dt - \kappa p(t)[P(dj=0)\times(dj=0) + P(dj=1)\times(dj=1)] \\ &= \mu(t)p(t)dt - \kappa p(t)[0 + h(t)dt] \\ &= \mu(t)p(t)dt - \kappa p(t)h(t)dt \end{aligned} \tag{1.5}$$

where $P(\cdot)$ represents the probability of an event happening. The condition of no arbitrage and the assumption of rational expectations mean that the conditional expectation of house price should be equal to zero, so $\mu(t)p(t)dt - \kappa p(t)h(t)dt = 0$, and by transformation, $\mu(t) = \kappa h(t)$. Substitute this equality into equation (1.4), and the differential equation describing the house price dynamics before the crash is given by:

$$\begin{gathered} dp = \kappa h(t)p(t)dt - 0 \\ \frac{1}{p(t)}\frac{dp}{dt} = \kappa h(t) \\ d(\ln p(t)) = \kappa h(t) \end{gathered} \tag{1.6}$$

Integrate both sides of equation (1.6) from t_0 to t as follows, and the solution is:

$$\int_{t_0}^{t} \mathrm{d}(\ln p(t)) = \int_{t_0}^{t} \kappa h(t')dt'$$

$$\ln p(t) - \ln p(t_0) = \kappa \int_{t_0}^{t} h(t')dt'$$

$$\ln \left[\frac{p(t)}{p(t_0)}\right] = \kappa \int_{t_0}^{t} h(t')dt' \quad (1.7)$$

Equation (1.7) indicates that the more likely the real estate market is to crash, the faster the house price should rise, in order to compensate agents for the losses caused by the increased risk of a market crash. Thus, Johansen et al. (2000) adopt the result that a system of variables close to the critical point can be characterized in the form of a power law, and the susceptibility of the system diverges as shown in equation (1.8). The susceptibility, which measures the sensitivity of agents' average state to small global effects, is thought to best describe the probability that a large group of agents suddenly agree on a view of market conditions and act in concert.

$$\chi \approx A(K_c - K)^{-\gamma} \quad (1.8)$$

where K is the coupling strength. The LPPLS method assumes that irrational agents imitate the behaviour of others around them through a complex network of interpersonal interactions, which may lead to the development of endogenous instability. Once the real estate market enters an unstable stage, any small disturbance will cause the market to move dramatically. The parameter K governs the agent's tendency towards imitation and K_c is the critical point that determines the properties of the system. A is a positive constant and γ greater than zero is called the critical exponent of susceptibility. When K is much smaller than K_c, the sensitivity of the average state to small global effects is small, the group of agents who act in agreement remains small in size, and imitation spreads only among close neighbours. In this case, the susceptibility of the system is limited. However, when K increases and approaches K_c, the system becomes extremely sensitive to a small global disturbance, the agents acting in unison form large clusters, and imitation spreads over long distances. This triggers a strong tendency for positive feedbacks in the system, causing prices to shoot up or collapse. In this case, the susceptibility of the system goes to infinity.

This simple version of the model assumes that agents are placed on a two-dimensional grid in the Euclidean plane and that each agent has its nearest neighbour in the four directions of east, south, west and north respectively. However, under this setting, investors are related to each other in a uniform way, and it is impossible to describe the affinity between investors and the size difference of investment groups. Therefore, Johansen et al. (2000) extend the above model by using a recursive construction of the hierarchical diamond lattice. Instead of using the two-dimensional grid, the hierarchical diamond lattice creates four new links between the two agents to replace the previous straight line and thus forms the shape of a diamond. The two original agents are now in opposite vertices of the diamond, and the other two vertices are occupied by two new agents. Then, iterate the operation. The basic properties of this model are similar to those of the previous model with the two-dimensional network, except that the critical exponent can be a complex number. The general solution for the susceptibility of the system becomes:

$$\begin{aligned}\chi &\approx RE[A_0(K_c-K)^{-\gamma}+A_1(K_c-K)^{-\gamma+i\omega}+\cdots]\\ &\approx {A_0}'(K_c-K)^{-\gamma}+{A_1}'(K_c-K)^{-\gamma}\cos[\omega\ln(K_c-K)+\psi]+\cdots \qquad (1.9)\end{aligned}$$

where A_0, A_1, ω, ψ are real numbers, and $RE[\cdot]$ represents the real part of a complex number. Compared with equation (1.8), the power law in equation (1.9) is modified by oscillations. These oscillations are called "log-periodic" because they are periodic in the logarithm of $(K_c - K)$. Since $\ln(K_c - K)$ tends to minus infinity as K approaches K_c, these oscillations are accelerating, and their frequency explodes when the critical time is reached.

Let t_c be the first time that $K(t_c)$ is equal to K_c. Before the critical time t_c, there is the following approximation:

$$K_c - K(t) \approx constant \times (t_c - t) \tag{1.10}$$

Suppose that the hazard rate of crash behaves in the same manner as the susceptibility near the critical point. Thus, the following equation can be obtained:

$$h(t) \approx B_0(t_c - t)^{-\alpha} + B_1(t_c - t)^{-\alpha}\cos[\omega\ln(t_c - t) + \psi'] \tag{1.11}$$

where B_0, B_1 are positive constants. For an economic reason, the exponent α must be between zero and one, otherwise, as time approaches t_c, the house price tends to infinity (if the bubble has not burst). It is important to note that the critical time t_c is not the time of the crash, because the crash could occur at any time before t_c, although this is not very likely. t_c is the pattern of the distribution of the time of the crash, that is, the time when the crash is most likely to occur. It can be seen from equation (1.11) that the risk of a crash increases enormously when approaching the critical time.

Substitute the expression of the hazard rate given in equation (1.11) into equation (1.7) to derive the evolution of house price before the crash:

$$\ln\left[\frac{p(t)}{p(t_c)}\right] \approx \kappa\int_{t_c}^{t}\{B_0(t_c - t')^{-\alpha} + B_1(t_c - t')^{-\alpha}\cos[\omega\ln(t_c - t') + \psi']\}dt' \tag{1.12}$$

where $p(t_c)$ is the house price at the critical time t_c (provided no crash has been triggered). Let $\Upsilon(t') = \omega\ln(t_c - t') + \psi'$, then equation (1.12) can be rewritten as:

$$\ln p(t) - \ln p(t_c) \approx \kappa \int_{t_c}^{t} [B_0 (t_c - t')^{-\alpha} + B_1 (t_c - t')^{-\alpha} \cos \Upsilon(t')] dt' \qquad (1.13)$$

According to the integration algorithm, the following expression is obtained:

$$\begin{aligned} \int_{t_c}^{t} (t_c - t')^{-\alpha} dt' &= -\frac{1}{1-\alpha} (t_c - t')^{1-\alpha} |_{t_c}^{t} \\ &= -\frac{1}{\beta} (t_c - t)^{\beta} \end{aligned} \qquad (1.14)$$

where $\beta = 1 - \alpha \in (0,1)$. A positive value of β guarantees that house prices will be limited at the critical time of the bubble and quantifies the power law acceleration of prices.

$$\begin{aligned} \int_{t_c}^{t} (t_c - t')^{-\alpha} \cos \Upsilon(t')\, dt' &= -\frac{(t_c - t')^{1-\alpha}}{\omega^2 + (1-\alpha)^2} [\omega \sin \Upsilon(t') + (1-\alpha) \cos \Upsilon(t')] |_{t_c}^{t} \\ &= -\frac{(t_c - t)^{\beta}}{\omega^2 - \beta^2} [\omega \sin \Upsilon(t) + \beta \cos \Upsilon(t)] \\ &= -\frac{(t_c - t)^{\beta}}{\sqrt{\omega^2 + \beta^2}} [\frac{\omega}{\sqrt{\omega^2 + \beta^2}} \sin \Upsilon(t) + \frac{\beta}{\sqrt{\omega^2 + \beta^2}} \cos \Upsilon(t)] \\ &= -\frac{(t_c - t)^{\beta}}{\sqrt{\omega^2 + \beta^2}} \cos[\Upsilon(t) - \theta] \end{aligned} \qquad (1.15)$$

where $\theta \in (0,2\pi)$ is a phase parameter. $\sin \theta = \frac{\omega}{\sqrt{\omega^2 + \beta^2}}$ and $\cos \theta = \frac{\beta}{\sqrt{\omega^2 + \beta^2}}$.

Substitute equation (1.14) and equation (1.15) into equation (1.13) and get:

$$\ln p(t) - \ln p(t_c) \approx -\frac{\kappa B_0}{\beta} (t_c - t)^{\beta} - \frac{\kappa B_1}{\sqrt{\omega^2 + \beta^2}} (t_c - t)^{\beta} \cos[\Upsilon(t) - \theta]$$

$$\ln p(t) \approx \ln p(t_c) - \frac{\kappa B_0}{\beta} (t_c - t)^{\beta} - \frac{\kappa B_1}{\sqrt{\omega^2 + \beta^2}} (t_c - t)^{\beta} \cos[\omega \ln(t_c - t) + \psi' - \theta] \quad (1.16)$$

Taking the expectation of equation (1.16), and the form of a log-periodic power law singularity (LPPLS) for the logarithm of the house price is given by:

$$E[\ln p(t)] = A + B(t_c - t)^m + C(t_c - t)^m \cos[\omega \ln(t_c - t) - \phi] \qquad (1.17)$$

where $p(t)$ represents the house price index and $E[\ln p(t)]$ is the expected logarithmic price at the date of the termination of the bubble; t_c denotes the critical time, that is, the estimate date of termination of the bubble and transition in a new regime, so that $t < t_c$; $A = E[\ln p(t_c)]$ is the expected logarithmic price that reaches its peak when the bubble comes to an end at the critical time, $B = -\frac{\kappa B_0}{\beta}$ is the amplitude of the power law acceleration, and $C = -\frac{\kappa B_1}{\sqrt{\omega^2+\beta^2}}$ is the amplitude of the log-periodic oscillations; m denotes the degree of the super exponential growth, ω denotes the scaling ratio of the temporal hierarchy of oscillations, and $\phi = \theta - \psi'$ denotes the time scale of the oscillations.

The LPPLS filter rule is $0 < m < 1$. Under this condition, a singularity exists at critical time t_c and the house price is still finite. A singularity is the point at which a system undergoes a phase transition, when positive feedbacks become unsustainable and the market enters a critical state. The probability of an imminent phase transition increases as the singularity approaches, accompanied by higher and higher frequency oscillations in the process.

1.4.2 The Dynamic Gordon Growth Model

The dynamic Gordon growth model is based on the theory that asset prices should equal the sum of discounted cash flows. The derivation of the model begins with the definition of the total return on housing prices in the $t+1$ period, which is the appreciation of the housing price plus the rental income:

$$R_{t+1} = \frac{P_{t+1}+V_{t+1}}{P_t} \tag{1.18}$$

where P denotes the real house price and V denotes the real rent.

After rearranging equation (1.18) and taking the logarithm and applying Taylor approximation, the following equation can be obtained:

$$p_t - v_t = k - r_{t+1} + \Delta v_{t+1} + \rho(p_{t+1} - v_{t+1}) \tag{1.19}$$

where $p_t \equiv \ln(P_t)$, $v_t \equiv \ln(V_t)$, $r_{t+1} \equiv \ln(R_{t+1})$, $\Delta v_{t+1} \equiv v_{t+1} - v_t$, $\rho \equiv 1/(1+\exp(\overline{v-p}))$ and $\overline{v-p}$ represents the sample mean of the log rent-price ratio, k is a constant. Next, carry out a forward iteration on equation (1.19), ignore the constant term, and then take the expectation on both sides to get:

$$p_t - v_t = E_t\left[\sum_{j=1}^{\infty} \rho^{j-1} \Delta v_{t+j}\right] - E_t\left[\sum_{j=1}^{\infty} \rho^{j-1} r_{t+j}\right] + E_t[\lim_{j\to\infty} \rho^j (p_{t+j} - v_{t+j})] \quad (1.20)$$

Since $E_t[\lim_{j\to\infty} \rho^j (p_{t+j} - v_{t+j})]$ would be zero with the transversality condition, the fundamental house price can be written as:

$$p_t{}^* = E_t\left[\sum_{j=1}^{\infty} \rho^{j-1} \Delta v_{t+j}\right] - E_t\left[\sum_{j=1}^{\infty} \rho^{j-1} r_{t+j}\right] + v_t \quad (1.21)$$

Then, a bubble can be defined as the actual house price exceeds its fundamental value as shown in equation (1.22):

$$b_t = p_t - p_t{}^* \quad (1.22)$$

Substitute equation (1.21) into equation (1.22) and set $\eta_{v,t} = E_t\left[\sum_{j=1}^{\infty} \rho^{j-1} \Delta v_{t+j}\right]$ and $\eta_{r,t} = E_t\left[\sum_{j=1}^{\infty} \rho^{j-1} r_{t+j}\right]$, so equation (1.22) becomes:

$$b_t = p_t - v_t + \eta_{r,t} - \eta_{v,t} \quad (1.23)$$

Note that $\eta_{v,t}$ is the expected sum of discounted future rental growth rates and $\eta_{r,t}$ is the expected sum of discounted future returns. These two terms represent the fundamentals of the real estate market, denoted by f_t as $f_t = \eta_{v,t} - \eta_{r,t}$. Thus, the relationship between the price-to-rent ratio, the bubble and market fundamentals can be expressed as:

$$p_t - v_t = \eta_{v,t} - \eta_{r,t} + b_t \quad (1.24)$$

Since the discounted expected future returns and the discounted expected future rent growth rate cannot be directly observed, a first-order VAR system with three state variables is used to estimate $\eta_{r,t}$ and $\eta_{v,t}$. Define $Z_t \equiv (r_t, \Delta v_t, p_t - v_t)'$, where r_t is the log of the real annual return, Δv_t is the log real annual rental growth rate, and $p_t - v_t$ is the logarithm of price-to-rent ratio. Let A be the coefficient matrix. Then, the two fundamental terms can be estimated by equations (1.25) and (1.26) respectively:

$$\eta_{r,t} = e1' A(I - \rho A)^{-1} Z_t \tag{1.25}$$

$$\eta_{v,t} = e2' A(I - \rho A)^{-1} Z_t \tag{1.26}$$

where I is the identity matrix, $e1' \equiv (1 \quad 0 \quad 0)$ and $e2' \equiv (0 \quad 1 \quad 0)$. On this basis, the size of the rational bubble can be indirectly measured according to the expression of the real estate bubble described in equation (1.23).

After that, in order to analyse the driving factors of the price-to-rent ratio, variance decomposition is applied to estimate the magnitude of the various components of the variance of the price-to-rent ratio, as shown in the following equation:

$$\begin{aligned}\mathrm{Var}(p_t - v_t) = {} & Var(\eta_{r,t}) + Var(\eta_{v,t}) + Var(b_t) - 2Cov(\eta_{r,t}, \eta_{v,t}) \\ & -2Cov(\eta_{r,t}, b) + 2Cov(\eta_{v,t}, b)\end{aligned} \tag{1.27}$$

The variance of the bubble, the expected rent growth rate, the expected return, and the covariance between them are then divided by the variance of the price-to-rent ratio to look at the relative influence of the fundamental and the bubble factors in the real estate market.

1.4.3 The User Cost Model

The user cost method compares the cost of owning a home with the cost of renting to determine whether the housing market is out of equilibrium. Compared with constructing a supply-demand equilibrium model of housing market to judge the rationality of housing price, the advantage of this method is that housing price does not need to be expressed as an equation of a series of macroeconomic factors related to supply and demand. Therefore, there is no risk of missing a certain economic fundamental factor. In addition, the rent-to-price ratio involved in the user cost model measures the return on investment of housing. This ratio can effectively distinguish the investment attribute of housing from the consumption attribute of housing, which is the key to understand the rationality of housing market price and housing bubble (Ren et al., 2013).

The model assumes that the fundamentals are reflected in user costs. Specifically, the annual cost of owning a house is defined by equation (1.28):

$$\text{Annual Cost of Ownership} = P_{\mathrm{t}}{r^{\mathrm{f}}}_{\mathrm{t}} + P_{\mathrm{t}}\omega_{\mathrm{t}} - P_{\mathrm{t}}\tau_{\mathrm{t}}({r^{\mathrm{m}}}_{\mathrm{t}} + \omega_{\mathrm{t}}) + P_{\mathrm{t}}\delta_{\mathrm{t}} - P_{\mathrm{t}}g_{\mathrm{t+1}} + P_{\mathrm{t}}\gamma_{\mathrm{t}} \quad (1.28)$$

where P_{t} is the local house price, ${r^{\mathrm{f}}}_{\mathrm{t}}$ is the risk-free interest rate which represents the opportunity cost of buying a house, ω_{t} is the property tax rate, τ_{t} is the effective income tax rate, ${r^{\mathrm{m}}}_{\mathrm{t}}$ is the mortgage loan rate, δ_{t} is the housing maintenance cost factor, $P_{\mathrm{t}}g_{\mathrm{t+1}}$ represents the expected appreciation of house prices, and $P_{\mathrm{t}}\gamma_{\mathrm{t}}$ represents the additional risk premium of owning a home over renting it. Since China has not levied a residential property tax and there are no income tax preferential policies on mortgage interest rate, equation (1.28) can be simplified as:

$$\text{Annual Cost of Ownership} = P_{\mathrm{t}}{r^{\mathrm{f}}}_{\mathrm{t}} + P_{\mathrm{t}}\delta_{\mathrm{t}} - P_{\mathrm{t}}g_{\mathrm{t+1}} + P_{\mathrm{t}}\gamma_{\mathrm{t}} \quad (1.29)$$

Himmelberg et al. (2005) point out that it is more appropriate to use real long-term interest rates to measure the opportunity cost of capital. In this regard, the current study uses the yield on the 10-year Treasury and converts it to the real rate by subtracting the expected rate of inflation. Based on the literature that uses constant-gain learning to explain inflation dynamics (Cieslak and Povala 2015), the expected inflation rate is calculated by constructing a discounted moving average of past CPI inflation, $\tau_t^{CPI} = \tau_{t-1}^{CPI} + (1-\upsilon)(\pi_t - \tau_{t-1}^{CPI})$, where π_t is the observed value of the inflation rate and τ_t^{CPI} is the expectation of future inflation rate. In the absence of data on the expected rate of inflation in China, the value of υ is set at

0.95 as in Qiang et al. (2018). Consistent with World Bank (1992), the annual depreciation rate of urban housing in China is set at 2%, which is equivalent to the straight-line depreciation rate for 50 years. Following Himmelberg et al. (2005) and Mayer and Sinai (2007), it is assumed that households have static long-run expectations of house price growth and the average real growth rate of house prices from 2006 to 2015 is used to measure the expected rate of appreciation. In addition, previous studies typically set the risk premium on home purchases at a constant 2%. However, due to the rapid rise of China's house prices, the use of a 2% risk premium in some cities will result in a negative cost of owning a home, and the constant risk premium does not reflect the difference in housing risk across cities. Some studies suggest that housing is riskier in high-priced cities because prices in those cities are more volatile (Case and Shiller, 2003; Hwang and Quigley, 2006). Owing to this, the study uses the standard deviation of real growth rate of house prices from 2006 to 2015 as the risk premium of each city.

Theoretically, housing market equilibrium means that the expected annual cost of ownership should be equal to the rent that buyers are willing to pay, as shown in the following equation:

$$R_{\mathrm{t}} = P_{\mathrm{t}}[{r^{\mathrm{f}}}_{\mathrm{t}} + \delta_{\mathrm{t}} - g_{\mathrm{t+1}} + \gamma_{\mathrm{t}}] \tag{1.30}$$

where R_{t} is the annual rent. Denote u_{t} as the user cost of housing, so $u_{\mathrm{t}} = {r^{\mathrm{f}}}_{\mathrm{t}} + \delta_{\mathrm{t}} - g_{\mathrm{t+1}} + \gamma_{\mathrm{t}}$. By rearranging, equation (1.30) can be written as:

$$\frac{P_t}{R_t} = \frac{1}{u_t} \tag{1.31}$$

The empirical method to test bubbles is to regress the log of the price-to-rent ratio on the log of the inverse user cost, capital availability, backwards-looking expectations of house price growth and an indicator of inflation:

$$\ln\left(\frac{P_t}{R_t}\right) = \alpha + \beta \ln\left(\frac{1}{u_t}\right) + \gamma LTV_t + \delta B_t + \varphi CPI_t + \varepsilon_t \tag{1.32}$$

where LTV_t is the average loan-to-value cap for first-time homebuyers over the prior year, which reflects the easy availability of capital; B_t denotes the average house price growth rate over the prior year, which is a proxy for behavioural conjectures of homebuyers; CPI_t denotes the consumer price index in China, which measures inflation.

1.4.4 The Case-Shiller Model

Case and Shiller (2003) made clear the important role of personal income growth in explaining the housing price rise. They used fundamental factors, such as the price-to-income ratio, mortgage rates, housing starts and employment numbers, to look at past housing bubbles and to predict future housing price trends.

According to their research method, house price indexes are applied to the median housing prices in December 2018 to construct the housing price series based on equation (1.33). The baseline figures for city-level median housing prices were provided by the Joint Laboratory for Housing Big Data and the Housing Big Data Project Team of the National Academy of Economic Strategy, Chinese Academy of Social Sciences.

$$P_t = P_{2018:12} I_t \tag{1.33}$$

where P_t represents the median house price per square metre at time t and $P_{2018:12}$ represents the median unit price of housing released in December 2018 for each city. I_t denotes the sales price index of newly constructed commercialized buildings, $2018{:}\,12 = 1.0$. The time series of median home prices is then used to calculate the price-to-income ratio.

Thereafter, the research uses the constructed housing price series, per capita income and other fundamental variables to conduct a regression analysis, to investigate whether these macroeconomic variables have a stable relationship with housing prices across time and space. The basic regression equation is shown as follows:

$$HP_t = \alpha + \beta INC_t + \varepsilon_t \tag{1.34}$$

where HP_t is the housing price, represented by the level of housing price or the quarterly change of housing price. INC_t denotes the level of per capita disposable income of urban households.

On this basis, several other fundamental variables are added into equation (1.34) as additional explanatory variables to obtain equation (1.35):

$$HP_t = \alpha + \beta INC_t + \gamma POP_t + \delta EMPL_t + \theta MR_t + \rho UR_t + \sigma HS_t + \varepsilon_t \tag{1.35}$$

where POP_t denotes the quarterly change of resident population, $EMPL_t$ denotes the quarterly change of the number of employed persons, MR_t is the mortgage interest rate, UR_t is the urban registered unemployment rate, HS_t is the newly started floor space of commercial residential buildings.

Using data from the sample up to the fourth quarter of 2013, the study estimates the coefficients in the price level equation for each city, and then uses these estimates to predict the level of house prices from the first quarter of 2014 to the fourth quarter of 2015. When house price forecasts are consistently lower than actual prices, it indicates that house price growth is out of line with economic fundamentals and there may be a bubble.

1.4.5 Criteria for Determining Bubbles

The above sections describe in detail how to test real estate price bubbles using the LPPLS model, the dynamic Gordon growth model, the user cost model, and the Case-Shiller model. This section summarizes the criteria for identifying bubbles in the four models, as shown in the table below.

Table 1.5. Criteria for identifying bubbles in different models

Bubble detection models	There is a bubble in house prices, if	Interpretation
The LPPLS model	The degree of the super exponential growth m ranges between 0 and 1.	The price growth becomes unsustainable, and at the critical time t_c the rate of growth becomes infinite.
The dynamic Gordon growth model	In the variance decomposition of the ratio of house price to rent, the contribution of the components related to rational bubble is greater than that of the components related to expected return and expected rent growth rate.	The biggest cause of the volatility of the price-to-rent ratio is the rational bubble
The user cost model	The estimated coefficient on user cost is well below 1, and when other behavioural variables are added, the estimated coefficient on user cost becomes much smaller and no longer significant.	The run-up in house prices is not supported by economic fundamentals. Instead, the house price boom is more of a behavioural bubble.
The Case-Shiller model	The ratio of house price to income is volatile and house price forecasts are consistently lower than actual prices.	The rise in house prices is not well explained by changes in fundamentals.

1.5 Empirical Analysis

1.5.1 The Log Periodic Power Law Singularity Model

The bounded rationality of markets is the primary reason for the formation of asset price bubbles, and the credit expansion acts as the booster of bubble growth (Aliber et al, 2015). By describing the positive feedback of increasing return expectations caused by the imitative behaviour among investors and the herding effect, the LPPLS model provides a flexible framework for the detection of real estate market bubbles. The upward trend in the market makes it more likely that prices will continue to rise until they reach a critical point at which they explode into infinity. Based on this theory, bubbles correspond to super-exponential growth in the price series. Table 1.6 reports the LPPLS output of 34 first- and second-tier cities in China. The linear-logarithmic plot of the LPPLS fit is shown in Figure A1.1 in the appendix.

Table 1.6. Parameter estimation of LPPLS model

City	A	B	C	m	t_c	ω	The time of the crash or regime change
Beijing	7.085	-0.305	0.009	0.379	177.44	6.454	2024:02
Tianjin	5.045	-0.011	0.010	0.615	95.000	12.593	2016:01
Shijiazhuang	5.057	-228.39	228.40	0.446	86.646	6.283	2016:04
Taiyuan	3.447	1453.8	1453.3	0.224	99.521	12.567	2017:05
Hohhot	4.220	0.267	0.267	2.293	116.63	6.283	2020:08
Shenyang	3.830	915.58	915.48	0.454	114.67	6.283	2017:11
Dalian	4.053	606.66	606.56	0.404	109.68	6.283	2017:08
Changchun	4.850	42.859	42.871	0.809	100.29	6.283	2017:06
Harbin	4.402	114.50	114.72	0.202	92.430	6.283	2016:10
Shanghai	5.099	-0.025	0.000	0.631	92.000	10.873	2016:01
Nanjing	4.999	-0.003	0.000	1.008	90.126	9.737	2016:01
Hangzhou	4.896	0.006	0.015	0.342	81.000	6.112	2016:01
Ningbo	4.980	0.000	0.003	0.758	90.000	12.437	2016:01
Hefei	4.922	-52.628	52.667	0.458	83.676	12.566	2016:01
Fuzhou	2.379	1145.0	1144.0	0.193	105.75	6.283	2017:11
Xiamen	4.886	1566.6	1566.7	0.149	88.339	12.566	2016:06
Nanchang	4.520	0.006	0.006	2.610	204.25	6.283	2025:04
Jinan	4.669	-200.21	200.45	0.206	90.089	6.283	2016:08
Qingdao	4.154	227.87	227.79	0.258	106.84	6.283	2016:12
Zhengzhou	4.903	266.49	266.66	0.281	90.703	12.567	2016:08
Wuhan	4.132	119.76	119.74	0.628	135.21	6.283	2019:11
Changsha	1.893	441.56	441.10	0.348	130.72	6.283	2019:05
Guangzhou	7.717	-1.337	0.025	0.160	149.51	6.118	2020:09
Shenzhen	5.358	-11.88	11.856	0.743	86.000	6.284	2016:01
Nanning	4.800	143.20	143.21	0.306	93.282	12.566	2016:11
Haikou	250.29	-0.070	0.017	1.262	746.63	6.276	2071:11
Chongqing	4.690	-16.447	17.451	0.357	96.412	6.283	2016:09
Chengdu	4.762	114.70	114.70	0.563	95.972	12.566	2016:08
Guiyang	4.817	17.964	18.062	0.582	102.82	12.566	2010:02
Kunming	3.575	172.60	172.76	0.484	132.18	6.283	2020:02
Xi’an	4.934	60.469	60.472	0.872	105.52	6.283	2016:11
Lanzhou	4.071	92.798	92.790	0.545	126.59	6.283	2019:08
Yinchuan	3.562	656.01	655.91	0.546	99.092	6.283	2018:04
Urumqi	2.678	641.98	641.80	0.484	129.88	6.283	2019:11

The mechanism by which positive feedback causes house prices to grow faster than the exponential is captured by the exponent m. In the theoretical framework of the LPPLS model, the value of m should be within the range of (0, 1), which indicates the existence of bubbles. This condition ensures that the crash hazard rate is accelerated with time and that the house price remains finite at all time including the critical time. However, the value of m greater than 1 or less than 0 is also possible to occur. A negative value of m is associated with unrealistic diverging prices, indicating that the logarithm of the house price is singular when approaching the critical time, that is, the house price would explode to infinity in a finite time. A value of m greater than 1 corresponds to a deceleration in prices, which means that there is no bubble in house prices. Brée and Joseph (2013) argued that imposing a restriction on m to make its value fall between 0 and 1 might not be conducive to finding the best fitting result of the Log Periodic Power Law approach. Therefore, this paper does not restrict the value of m. If the value of m is found to be greater than 1, the model is rejected.

In 30 of the 34 sample cities, the value of parameter m is greater than 0 and less than 1, indicating that the crash hazard rate accelerates with time and there is a bubble in the real estate market. The logarithm of the house price at the critical time would be finite, but the first derivative of the logarithm of the house price would have a singularity. The value of m in all the six first-tier cities in China, including Beijing, Shanghai, Guangzhou, Shenzhen, Tianjin and Chongqing, falls within the range of 0 to 1 and the value of parameter B is negative, which ensure that house prices have been rising. However, in Hohhot, Nanjing, Nanchang and Haikou, the value of m is greater than 1. In this case, the crash hazard rate is not accelerating, which means there is no bubble in these cities. Another study using the LPPLS model to detect real estate bubbles in these cities is Zhi et al. (2019), which also provides evidence of an unsustainable speculative component in house prices. Using time series data from January 2008 to May 2017, the authors find that ten cities, including Tianjin, Shijiazhuang, Taiyuan, Shanghai, Nanjing, Hefei, Xiamen, Wuhan, Shenzhen and Chengdu, display positive bubble signals respecting LPPLS filtering conditions. Compared with their results, the current study shows more cities showing signs of a real estate bubble before the end of 2015. The possible reason is that the extremely strict regulatory policies implemented by local governments on the property market since March 2016 have played a role in calming the real estate boom.

The house price index column is converted to evenly spaced numbers over a specified interval, starting at 0 and increasing by 1 every month thereafter, to estimate the unknown model parameters. Once the parameter estimates are obtained, the value of parameter t_c is converted to a calendar month to show the time when a crash or regime change is most likely to occur. The results suggest that for Tianjin, Shanghai, Nanjing, Hangzhou, Ningbo, Hefei and Shenzhen, the estimated critical time is January 2016, while for Haikou, the model gives the most distant critical time. Note that the value of the critical time is close to the last data points in some cases, and a similar situation also appears in the LPPLS output of Zhi et al. (2019). This is the result of characterization of power law behaviour, which indicates that power law fitting is not very reliable in estimating a critical time (Zhou and Sornette, 2006). As mentioned earlier, a market reaching a critical point does not necessarily lead to a crash. It also allows for a soft landing that reduces downside risk, giving investors a chance to profit from the expansion of the bubble. That is why it is still rational for investors to continue investing in the knowledge that a bubble is developing.

To summarize, the LPPLS model describes the dynamics of the bubble component independent of the fundamental house price. Except for the cities of Hohhot, Nanjing, Nanchang and Haikou, the values of exponent m in other cities are all within the range of 0 to 1, indicating that the house price growth during the sample period is not sustainable and there is a housing bubble in these cities.

1.5.2 The Dynamic Gordon Growth Model

The first-order VAR system with house return rate, rent growth rate and house price rent ratio as state variables is used to estimate the discount expected future rent growth rate and the discounted expected future returns. With these two variables, according to equation (1.23), the rational bubble component is obtained from the logarithm of the ratio of house price to annualized rent in each city. Table 1.7 reports the results of variance decomposition of the price-to-rent ratio by using equation (1.27). The contribution of the terms associated with rational bubbles to the volatility of the price-to-rent ratio is greater than the contribution of the terms associated with expected housing returns and the expected rental growth rates, except for the cities of Shijiazhuang, Dalian, Kunming and Yinchuan. Thus, the bubble is the leading factor of price-to-rent ratio fluctuation in most cities.

Among the six components of the variance of the price-to-rent ratio, the covariance between the expected returns and the rational bubble usually has the largest contribution. Several studies have suggested that low expected returns lead to higher asset prices (Case and Shiller, 2003; Weeken, 2004; Krainer and Wei, 2004; Campbell et al., 2009; Favilukis et al., 2017). When buyers have strong expectations of future house price changes and perceive little risk, that is, when the risk premium or expected return is low, they will be influenced by the investment motivation to buy real estate, thus pushing up house prices. However, the results of this paper show that the covariance between the rational bubble and the expected housing returns is positive in all cities except one, which is consistent with the findings of Liu et al. (2017) using data from four first-tier cities in China. The larger the rational bubble grows, the higher the expected returns become, which fits the definition of a bubble. Investors assume that house prices will continue to rise and that they will be able to sell their assets at a higher price in the future, making their investments less risky. The massive demand for housing causes current house prices to overshoot fundamentals, leading to a bubble (Brunnermeier and Oehmke, 2013). The positive correlation between the rational bubble and the expected returns indicates that investors' expectation of future housing price rise makes them have higher expected returns.

In Taiyuan, Hefei, Qingdao and Guiyang, the biggest cause of price-to-rent volatility comes from the covariance between rational bubbles and expected rental growth rates. The negative value of this covariance term for these four cities indicates that the larger the bubble is, the lower the expected rent growth will be. This suggests that investors are not paying enough attention to the rental market and are mainly looking for capital gains from rising house prices. In other words, bubble growth in these cities is not supported by rental fundamentals. Specifically, in cities with a negative covariance between the rational bubble and expected rent growth, the bubble-induced rise in house prices does not raise the expected growth rate of rents, while in cities with a positive covariance, the expected rate of rent growth rises as the rational bubble grows.

Table 1.7. Variance decomposition for price-to-rent ratio

Panel A City	Var(η_r)	Var(η_v)	Var(b)	-2Cov(η_r, η_v)	-2Cov(η_r,b)	2Cov(η_v,b)
Beijing	2.027	0.093	1.690	-0.430	-3.569	0.210
Tianjin	0.499	0.120	0.450	-0.197	-0.737	-0.097
Shijiazhuang	0.447	0.290	0.315	-0.461	-0.412	-0.173
Taiyuan	0.026	0.421	0.335	-0.157	0.110	-0.732
Hohhot	2.557	0.070	2.371	-0.555	-4.879	0.451
Shenyang	1.109	0.060	0.982	-0.179	-2.011	0.055
Dalian	0.672	0.607	0.377	-0.952	-0.391	-0.309
Changchun	5.204	0.039	4.457	-0.844	-9.625	0.774
Harbin	0.845	0.004	0.941	-0.043	-1.772	0.039
Shanghai	0.101	0.060	0.119	-0.066	-0.171	-0.015
Nanjing	0.273	0.009	0.266	-0.053	-0.509	0.032
Hangzhou	0.792	0.153	0.632	-0.403	-1.224	0.064
Ningbo	2.950	0.011	2.805	-0.335	-5.743	0.326
Hefei	0.510	1.496	1.465	-0.638	-0.410	-2.418
Fuzhou	0.977	0.078	0.863	-0.269	-1.764	0.120
Xiamen	0.141	0.041	0.219	-0.051	-0.256	-0.069
Nanchang	0.255	0.069	0.366	-0.018	-0.520	-0.145
Jinan	2.243	0.044	2.008	-0.370	-4.204	0.281
Qingdao	0.129	0.133	0.144	-0.146	-0.088	-0.151
Zhengzhou	1.953	0.099	2.269	0.030	-4.109	-0.232
Wuhan	0.573	0.003	0.573	-0.058	-1.143	0.054
Changsha	0.928	0.005	0.989	-0.001	-1.897	-0.014
Guangzhou	0.331	0.090	0.243	-0.173	-0.485	0.033
Shenzhen	0.765	0.107	0.570	-0.394	-1.272	0.252
Nanning	2.485	0.053	2.357	-0.122	-4.738	-0.021
Haikou	5.374	0.053	4.608	-1.053	-9.943	0.973
Chongqing	1.563	0.078	1.348	-0.394	-2.829	0.242
Chengdu	0.253	0.025	0.300	-0.032	-0.515	-0.024
Guiyang	0.084	0.103	0.179	-0.050	-0.124	-0.185
Kunming	1.661	0.701	0.532	-1.893	-1.501	0.505
Xi’an	2.026	0.036	1.767	-0.236	-3.755	0.172
Lanzhou	4.972	0.065	4.869	-0.568	-9.788	0.468
Yinchuan	0.201	0.172	0.037	-0.358	-0.108	0.065
Urumqi	5.038	0.036	4.484	-0.844	-9.501	0.794

Except for Zhengzhou, the covariance between the expected returns and the expected rental growth rates in other cities is positive. This is consistent with the findings of some previous studies (Vuolteenaho, 2002; Campbell et al., 2009; Liu et al., 2017). One possible explanation for this positive correlation between the expected housing returns and the expected rental growth rates is that the market does not respond in a timely or sufficient manner to the fundamental information provided by rental changes. When investors expect a higher rate of rental growth, house prices in the market fail to rise sufficiently, resulting in higher expected returns.

Table 1.7. Variance decomposition for price-to-rent ratio (cont.)

Panel B City	$\frac{Var(\eta_r)}{Var(p-v)}$	$\frac{Var(\eta_v)}{Var(p-v)}$	$\frac{Var(b)}{Var(p-v)}$	$\frac{-2Cov(\eta_r,\eta_v)}{Var(p-v)}$	$\frac{-2Cov(\eta_r,b)}{Var(p-v)}$	$\frac{2Cov(\eta_v,b)}{Var(p-v)}$
Beijing	100.24	4.603	83.564	-21.287	-176.50	10.383
Tianjin	13.067	3.128	11.776	-5.146	-19.277	-2.548
Shijiazhuang	74.650	48.317	52.475	-76.925	-68.705	-28.811
Taiyuan	8.064	131.15	104.28	-48.846	34.095	-227.75
Hohhot	169.11	4.660	156.77	-36.700	-322.67	29.839
Shenyang	71.582	3.884	63.363	-11.568	-129.78	3.519
Dalian	143.22	129.35	80.433	-202.89	-83.234	-65.876
Changchun	984.18	7.313	842.82	-159.55	-1820.1	146.38
Harbin	56.455	0.274	62.883	-2.902	-118.33	2.619
Shanghai	3.566	2.125	4.199	-2.328	-6.026	-0.537
Nanjing	14.964	0.479	14.569	-2.920	-27.851	1.759
Hangzhou	60.489	11.660	48.242	-30.789	-93.506	4.902
Ningbo	217.12	0.814	206.44	-24.692	-422.70	24.023
Hefei	91.035	266.84	261.38	-113.79	-73.078	-431.39
Fuzhou	173.75	13.904	153.44	-47.788	-313.59	21.279
Xiamen	5.730	1.653	8.911	-2.079	-10.405	-2.810
Nanchang	34.482	9.322	49.457	-2.480	-70.169	-19.613
Jinan	606.41	11.941	542.84	-99.897	-1136.3	75.983
Qingdao	6.749	6.957	7.531	-7.676	-4.634	-7.927
Zhengzhou	192.27	9.707	223.42	2.975	-404.52	-22.861
Wuhan	180.27	0.807	180.34	-18.209	-359.28	17.079
Changsha	87.614	0.451	93.382	-0.126	-179.05	-1.277
Guangzhou	8.343	2.276	6.121	-4.346	-12.218	0.825
Shenzhen	27.975	3.897	20.847	-14.398	-46.542	9.222
Nanning	173.04	3.674	164.18	-8.478	-329.99	-1.431
Haikou	481.77	4.712	413.04	-94.364	-891.36	87.203
Chongqing	213.57	10.644	184.23	-53.822	-386.69	33.074
Chengdu	36.630	3.556	43.577	-4.691	-74.624	-3.447
Guiyang	12.444	15.346	26.521	-7.412	-18.456	-27.444
Kunming	310.30	131.02	99.434	-353.67	-280.33	94.238
Xi'an	201.85	3.596	176.04	-23.527	-374.08	17.121
Lanzhou	272.78	3.552	267.16	-31.144	-537.03	25.684
Yinchuan	21.324	18.226	3.926	-37.909	-11.429	6.864
Urumqi	705.23	5.005	627.61	-118.15	-1329.9	111.17

In summary, the results of this study match those of Liu et al. (2017), which adopted the dynamic Gordon growth model to identify the main causes of house price growth in Beijing, Shanghai, Guangzhou and Shenzhen. The findings suggest that it is mostly the bubble that has pushed up house prices in these four cities. On the basis of their research, the current study expands the sample to 34 first-tier cities and second-tier cities in China. With the exception of Shijiazhuang, Dalian, Kunming and Yinchuan, the rational bubble is the major driving factor behind the fluctuation of the price-to-rent ratio in the other 30 cities, while the expected housing return and the expected rental growth rate have less impact. Moreover, the results show that high expected returns coexist with rational bubbles. This confirms the definition of a bubble, which is a temporary rise in prices caused by excessive expectations of capital gains from future house price increases. In all the sample cities, the volatility of the rational bubble and the expected return on housing exceeds the volatility of the price-to-rent ratio, indicating that these two components play a prominent role in the fluctuation of house prices.

1.5.3 The User Cost Model

Using equation (1.32), a regression analysis of the 34 sample cities is conducted to assess whether the rational component and the behavioural component can explain the changes in the price-to-rent ratio and their relative importance. After calculating the user cost of housing, the logarithm of the price-to-rent ratio is, first, regressed on the logarithm of the inverse of the user cost, before adding other behavioural factors. The results are shown in Tables 1.8 and 1.9. If the user cost model holds and the assumption of static expectations of house price growth is correct, the coefficient β is expected to be 1.

As it can be seen from Table 1.8, only Hohhot's estimated coefficient on the user cost term is close to 1, which is statistically significant at the level of 0.01. According to the estimate, a 10% drop in user cost relative to the sample average would raise Hohhot's house prices by 11%

if rents remained constant[1]. When other behavioural variables are added in Table 1.9, the user cost coefficient estimated by regression hardly decreases, and still maintains a high statistical significance. This shows that in Hohhot, the change of the price-to-rent ratio does not deviate from the economic fundamentals, and there is no price bubble in the real estate market. Dalian, Nanchang, Guiyang and Kunming also have a positive coefficient on user cost with high statistical significance, but the estimated values of the coefficient are far less than 1. Changes of the price-to-rent ratio in these cities can be explained by changes of fundamental factors proposed by the user cost model, but the price-to-rent ratio is not sensitive to fundamental changes, indicating signs of real estate bubble. For the remaining 29 cities, their estimated user cost coefficients are either insignificant or of the wrong sign, suggesting that economic fundamentals cannot explain the variation in the price-to-rent ratio and that there is a bubble in the real estate market. Other studies that applied user cost models, such as Mayer and Sinai (2007) and Chen et al. (2009), have also estimated negative and significant coefficients.

The estimated coefficient on the loan-to-value ratio cap is expected to be positive, as tighter government restrictions on home loans make it harder for households to finance home purchases and thus depress prices. However, in nearly half of the cities in the sample, the estimated loan-to-value coefficients are statistically significantly negative, especially in cities with high and volatile housing prices. The negative correlation between the price-to-rent ratio and the loan-to-value limit may be due to the fact that local governments tend to lower LTV caps during a housing boom to curb the rise of housing prices (Mayer and Sinai, 2007). In

[1] The average user cost in Hohhot during the sample period is 0.077. A 10% reduction would generate a user cost of 0.0693. Thus, the inverse of the user cost would increase from 12.987 to 14.43, an increase of 11.111%. Multiplying 11.111% by the estimated coefficient on the user cost term of 0.99 gives a 11% increase in house prices. The average user cost over the sample period for each city is shown in Table A1.1 in the appendix.

addition to the impact of loan-to-value restrictions, expectations of price increases based on past price growth rates between buyers and sellers in the property market may also translate into prices. Therefore, the average price increase of the previous year is used as a measure of backwards-looking expectations, but the regression results show that this variable has limited explanatory power for the ratio of house prices to rents. Mayer and Sinai (2007) also find that the explanatory power of one-year backwards looking expectations is low and the estimated coefficient often has the wrong sign, whereas medium-term backwards looking expectations play a prominent role in explaining changes in the price-to-rent ratio. Another important behavioural variable is inflation, which is used to test whether the inflation illusion exists. The results show that the coefficient on inflation is positive and statistically significant in most cities, indicating that high inflation rates are associated with high housing price-to-rent ratios.

Previous studies using the user cost model to investigate the real estate market in China have also revealed the existence of bubbles. Chen et al. (2009) studied the housing price fluctuations in Beijing, Shanghai, Guangzhou and Shenzhen from 1993 to 2008. Their results showed that the user cost coefficients were estimated to be around 0.1 or negative, but proxy variables that represent expectations of future house price growth and the illusion of money had a significant impact on rent-price ratios. The authors concluded that price fluctuations in these cities, particularly in Shenzhen, were largely driven by people’s expectations of future price increases, rather than fundamental factors represented by user costs. Another attempt to analyse the situation of China’s real estate market with the user cost model is Ren et al. (2013). Using data from eight urban districts in Beijing, they found that much of the change in housing prices between 2005 and 2010 was driven by expectations of house price growth

Table 1.8. Regressions of price-to-rent ratio on user cost

	Log of the price-to-rent ratio									
	Beijing	Tianjin	Shijiazhuang	Taiyuan	Hohhot	Shenyang	Dalian	Changchun	Harbin	Shanghai
Log of the inverse user cost	-0.349***	-0.481***	-0.249***	-0.063	0.990***	-0.180*	0.200***	-0.064	-0.001	-0.998***
	(0.096)	(0.116)	(0.057)	(0.057)	(0.131)	(0.107)	(0.053)	(0.065)	(0.113)	(0.148)
Observations	81	96	84	84	62	93	91	84	84	93
R^2	0.143	0.154	0.187	0.015	0.487	0.030	0.140	0.011	0.000	0.333
	Nanjing	Hangzhou	Ningbo	Hefei	Fuzhou	Xiamen	Nanchang	Jinan	Qingdao	Zhengzhou
Log of the inverse user cost	-0.482***	0.237	-0.235*	0.041	-0.208***	-0.591***	0.195***	-0.086	-0.291**	0.060
	(0.111)	(0.187)	(0.120)	(0.072)	(0.073)	(0.115)	(0.059)	(0.052)	(0.130)	(0.073)
Observations	91	82	91	84	84	84	94	84	96	84
R^2	0.174	0.020	0.041	0.004	0.090	0.242	0.107	0.032	0.051	0.008
	Wuhan	Changsha	Guangzhou	Shenzhen	Nanning	Haikou	Chongqing	Chengdu	Guiyang	Kunming
Log of the inverse user cost	-0.142***	-0.107	-0.830***	-0.887***	0.126	0.292	-0.120	0.019	0.194***	0.377***
	(0.037)	(0.073)	(0.197)	(0.191)	(0.117)	(0.262)	(0.073)	(0.071)	(0.057)	(0.070)
Observations	90	91	94	87	84	77	89	89	84	84
R^2	0.144	0.024	0.162	0.203	0.014	0.016	0.030	0.001	0.124	0.261
	Xi'an	Lanzhou	Yinchuan	Urumqi						
Log of the inverse user cost	-0.078	0.143	0.021	0.048						
	(0.072)	(0.100)	(0.111)	(0.071)						
Observations	96	84	73	84						
R^2	0.012	0.025	0.001	0.006						

Notes: 1. t-statistics are reported below the estimates in parentheses.
2. *** indicates significance at the 1% level; ** indicates significance at the 5% level; * indicates significance at the 10% level.

Table 1.9. Regressions of price-to-rent ratio on user cost and other behavioural variables

	Log of the price-to-rent ratio									
	Beijing	Tianjin	Shijiazhuang	Taiyuan	Hohhot	Shenyang	Dalian	Changchun	Harbin	Shanghai
Log of the inverse user cost	-0.792***	-0.656***	-0.380***	-0.128**	0.981***	-0.365***	0.177***	-0.166***	0.292***	-1.190***
	(0.065)	(0.112)	(0.041)	(0.059)	(0.081)	(0.108)	(0.046)	(0.029)	(0.045)	(0.141)
Lagged 1-year LTV cap	-9.414***	-2.673***	-1.600***	-0.199	3.007***	-1.428***	0.189	-0.803***	3.327***	-2.031***
	(0.759)	(0.625)	(0.162)	(0.177)	(0.495)	(0.381)	(0.171)	(0.104)	(0.153)	(0.386)
Lagged 1-year growth rate	-0.327**	-0.133	-0.089	-0.565***	0.101	0.078	0.256	-0.224**	0.037	-0.251
	(0.153)	(0.542)	(0.158)	(0.181)	(0.168)	(0.299)	(0.168)	(0.109)	(0.167)	(0.256)
Inflation rate	4.570***	-1.799*	-0.001	0.440	2.884***	0.773	1.594***	2.955***	2.855***	-0.212
	(0.522)	(0.966)	(0.358)	(0.320)	(0.599)	(0.635)	(0.334)	(0.200)	(0.306)	(0.640)
Observations	81	96	84	84	62	93	91	84	84	93
R^2	0.778	0.345	0.648	0.161	0.879	0.199	0.418	0.830	0.865	0.493
	Nanjing	Hangzhou	Ningbo	Hefei	Fuzhou	Xiamen	Nanchang	Jinan	Qingdao	Zhengzhou
Log of the inverse user cost	-0.582***	0.320***	0.049	0.240***	-0.254***	-0.894***	0.046	-0.062**	-0.501***	0.149***
	(0.116)	(0.084)	(0.090)	(0.053)	(0.047)	(0.073)	(0.043)	(0.030)	(0.110)	(0.032)
Lagged 1-year LTV cap	-1.152***	1.558***	2.547***	1.675***	-0.021	-3.561***	-1.216***	0.408***	-2.518***	1.303***
	(0.386)	(0.174)	(0.318)	(0.179)	(0.146)	(0.286)	(0.190)	(0.113)	(0.371)	(0.141)
Lagged 1-year growth rate	0.171	-0.010	-1.051***	0.515***	-0.240*	0.039	0.241	0.501***	-0.289	0.477***
	(0.284)	(0.103)	(0.165)	(0.163)	(0.123)	(0.225)	(0.177)	(0.112)	(0.293)	(0.157)
Inflation rate	0.864	5.402***	4.573***	0.241	3.242***	-1.488***	1.570***	2.290***	-0.573	4.383***
	(0.730)	(0.317)	(0.454)	(0.315)	(0.268)	(0.459)	(0.342)	(0.202)	(0.567)	(0.278)
Observations	91	82	91	84	84	84	94	84	96	84
R^2	0.302	0.846	0.601	0.553	0.695	0.796	0.601	0.724	0.406	0.847

Notes: 1. t-statistics are reported below the estimates in parentheses.

2. *** indicates significance at the 1% level; ** indicates significance at the 5% level; * indicates significance at the 10% level.

Table 1.9. Regressions of price-to-rent ratio on user cost and other behavioural variables (cont.)

	Log of the price-to-rent ratio									
	Wuhan	Changsha	Guangzhou	Shenzhen	Nanning	Haikou	Chongqing	Chengdu	Guiyang	Kunming
Log of the inverse user cost	-0.178***	-0.144**	-1.063***	-1.292***	-0.033	0.092	-0.134**	0.007	0.224***	0.421***
	(0.025)	(0.063)	(0.170)	(0.125)	(0.073)	(0.185)	(0.055)	(0.044)	(0.037)	(0.047)
Lagged 1-year LTV cap	-0.221*	-0.099	-3.822***	-3.529***	-1.001***	0.341	0.325	0.418**	0.715***	0.636***
	(0.111)	(0.270)	(0.434)	(0.297)	(0.238)	(0.257)	(0.205)	(0.163)	(0.176)	(0.139)
Lagged 1-year growth rate	-0.116	-0.255	0.348	0.195	-0.939***	0.214***	0.017	0.017	-0.046	0.329**
	(0.112)	(0.204)	(0.263)	(0.166)	(0.222)	(0.076)	(0.163)	(0.170)	(0.218)	(0.157)
Inflation rate	2.104***	3.668***	-1.834**	0.382	4.499***	3.481***	3.346***	3.696***	3.340***	2.042***
	(0.214)	(0.525)	(0.735)	(0.535)	(0.426)	(0.802)	(0.415)	(0.326)	(0.321)	(0.334)
Observations	90	91	94	87	84	77	89	89	84	84
R^2	0.656	0.441	0.571	0.789	0.674	0.693	0.556	0.667	0.685	0.714

	Xi'an	Lanzhou	Yinchuan	Urumqi
Log of the inverse user cost	-0.135*	0.251***	0.303***	0.024
	(0.074)	(0.043)	(0.081)	(0.045)
Lagged 1-year LTV cap	-0.823**	2.424***	1.980***	0.658***
	(0.323)	(0.180)	(0.256)	(0.157)
Lagged 1-year growth rate	-0.131	0.659***	0.473**	0.465***
	(0.259)	(0.188)	(0.217)	(0.137)
Inflation rate	0.469	5.000***	0.964	3.488***
	(0.525)	(0.331)	(0.621)	(0.287)
Observations	96	84	73	84
R^2	0.101	0.861	0.675	0.705

Notes: 1. t-statistics are reported below the estimates in parentheses.
2. *** indicates significance at the 1% level; ** indicates significance at the 5% level; * indicates significance at the 10% level.

rather than economic fundamentals.

To sum up, according to the user cost model, most of China's 34 first- and second-tier cities have seen a real estate price bubble after the 2007–08 financial crisis. In all cities except Hohhot, the rational component of house prices represented by the user cost does little to explain the change in the ratio of house prices to rents, while behavioural factors, especially the illusion of inflation, have a great influence, providing evidence that the surge in house prices in China is more of a behavioural bubble.

1.5.4 The Case-Shiller Model

This method evaluates house price bubbles by examining the volatility of the house price to income ratio and the extent to which economic fundamentals explain the changes in house price. The price-to-income ratio (PIR) is defined as the ratio of the relationship between the median size of a housing unit, the median house price and annual income per capita. The formula is $PIR = \frac{Median\ price\ per\ square\ metre * Median\ housing\ size}{Income\ per\ capita}$. The time series of the median housing price is constructed based on equation (1.33) using the house price index from the National Bureau of Statistics of China and the median unit price of housing in each city in December 2018 published by the Joint Laboratory for Housing Big Data and the Housing Big Data Project Team of the National Academy of Economic Strategy, Chinese Academy of Social Sciences. The median home size data comes from the sixth census in 2010. On the other hand, regression analysis is conducted according to equations (1.34) and (1.35) to see whether income itself can explain the changes in the house price and whether the goodness of fit can be improved after adding other fundamental factors. Descriptive statistics of house price to income ratios and determination coefficients of regression equations are shown in Table 1.10.

Table 1.10. Ratio of house price to income and results of regressions explaining house prices

City	Ratio				Quarter of peak	R^2 of regression of house price on	
	Trough	Peak	Standard Deviation	In 2015:4		Income per capita	Other fundamental variables
Beijing	46.061	61.456	4.655	47.704	2010:2	0.885	0.934
Tianjin	32.144	52.685	5.974	32.144	2008:1	0.838	0.941
Shijiazhuang	31.585	43.442	4.033	31.585	2010:4	0.859	0.957
Taiyuan	21.388	33.371	4.030	21.388	2009:4	0.781	0.870
Hohhot	15.904	22.865	1.943	15.904	2010:4	0.361	0.905
Shenyang	11.821	22.211	2.951	11.821	2008:2	0.664	0.922
Dalian	15.391	28.613	3.852	15.391	2008:2	0.720	0.923
Changchun	17.597	28.691	3.743	17.597	2009:4	0.733	0.870
Harbin	14.959	26.043	3.731	14.959	2009:1	0.696	0.952
Shanghai	30.703	46.855	4.648	33.695	2008:2	0.871	0.904
Nanjing	31.938	52.484	5.983	32.861	2008:2	0.859	0.907
Hangzhou	22.133	40.663	6.310	22.374	2009:4	0.001	0.352
Ningbo	21.809	38.973	6.184	21.809	2008:2	0.070	0.727
Hefei	23.993	38.401	5.068	23.993	2010:2	0.823	0.948
Fuzhou	43.820	63.707	6.898	43.980	2009:1	0.835	0.952
Xiamen	12.369	16.641	1.300	13.913	2009:4	0.850	0.949
Nanchang	23.428	44.235	5.810	23.428	2008:1	0.781	0.898
Jinan	23.970	37.835	4.907	24.015	2009:1	0.759	0.892
Qingdao	25.624	50.790	7.553	25.624	2008:1	0.499	0.786
Zhengzhou	24.281	34.888	3.617	24.281	2009:1	0.925	0.965
Wuhan	24.026	44.038	5.979	24.026	2008:3	0.859	0.916
Changsha	15.276	27.773	3.733	15.276	2008:2	0.771	0.914
Guangzhou	23.244	33.615	2.807	23.878	2008:1	0.898	0.978
Shenzhen	18.347	29.270	2.518	29.270	2015:4	0.578	0.911
Nanning	16.653	27.521	3.435	16.653	2009:1	0.735	0.860
Haikou	32.241	61.686	8.894	32.241	2010:1	0.106	0.912
Chongqing	28.293	49.736	6.783	28.293	2008:3	0.682	0.860
Chengdu	23.049	40.696	5.605	23.160	2008:3	0.782	0.906
Guiyang	15.532	24.795	3.043	15.532	2009:4	0.806	0.932
Kunming	16.319	30.800	4.747	16.319	2009:4	0.645	0.929
Xi’an	15.746	33.609	5.074	17.110	2008:1	0.909	0.945
Lanzhou	21.395	40.490	6.059	21.395	2009:2	0.646	0.949
Yinchuan	14.669	23.835	2.760	14.669	2010:1	0.633	0.912
Urumqi	14.167	27.987	4.197	14.167	2009:4	0.585	0.955

Source: Author’s calculations.

Notes: 1. Observations are for the 32 quarters from 2008 to 2015, though the sample period begins at different times for each city.

2. Regressions use the following fundamental variables as additional explanatory variables, namely resident population, employed persons, mortgage rates, unemployment rate, and housing starts.

House price-to-income ratios vary widely across the 34 cities. Take Xiamen and Haikou as examples. During the sample period, the price-to-income ratio of Xiamen is relatively low, which has been between 12.4 and 16.6. A simple regression of median house prices on per capita annual income in Xiamen yields an R-squared value of 0.85. In Haikou, by contrast, the price-to-income ratio fluctuates wildly, from 32.2 to 61.7. Income accounts for only 10.6% of the change in Haikou's house prices. The same is true of Hangzhou and Ningbo, where the explanatory power of income to housing price changes is also low and the price to income ratio is highly volatile.

According to the results calculated in Table 1.10, the house price to income ratios in China are extraordinarily high. An analysis by the Financial Times in 2017 also illustrates that some of China's first-tier cities are among the most expensive in the world in terms of house price to income ratios. While these figures provide an initial impression of housing affordability in China, the high price-to-income ratios need to be interpreted with caution, as China has been cited to have a large amount of 'grey' income (Wang and Woo, 2011; and Deng et al., 2015). These hidden incomes outside the scope of state regulation can skew the measured ratios. In addition, this study followed the method of Case and Shiller (2003) to calculate this ratio by dividing the median home price by per capita income. If household income was used as a measure of income, the ratio of house prices to income in each city would be lower than the figure shown in the table.

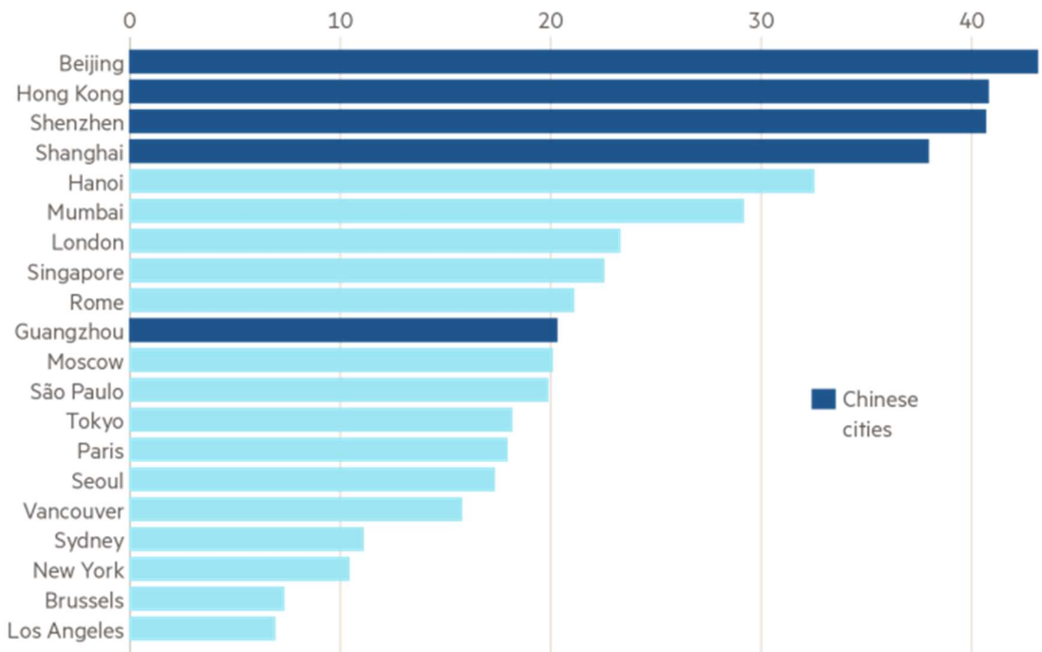

Figure 1.2 Ratio of house price to income in major Chinese cities compared to other countries

Source: The Finance Times

Cities with stable price-to-income ratios are expected to have higher R-squared values, meaning that the model would fit the data better in this case. The plots of the ratio of house price to income for four selected cities in Figure 1.3 show the pattern of variation of this ratio. In Haikou, Hangzhou and Ningbo, the rise in price-to-income ratios is followed by a long period of persistent decline. Haikou's price-to-income ratio, which started off at a relatively high level of 40.6 in the third quarter of 2009, rose by half to 61.7 in the first quarter of 2010, before falling all the way down to 32.2 at the end of 2015. The Hangzhou market looks much like Ningbo, with the price-to-income ratio falling by nearly half from around 40 to just over 20. Xiamen, by contrast, has a relatively stable price-to-income ratio. Thus, income explains much of the rise in house prices in Xiamen, but it is not a good predictor of house price movements in Haikou, Hangzhou and Ningbo.

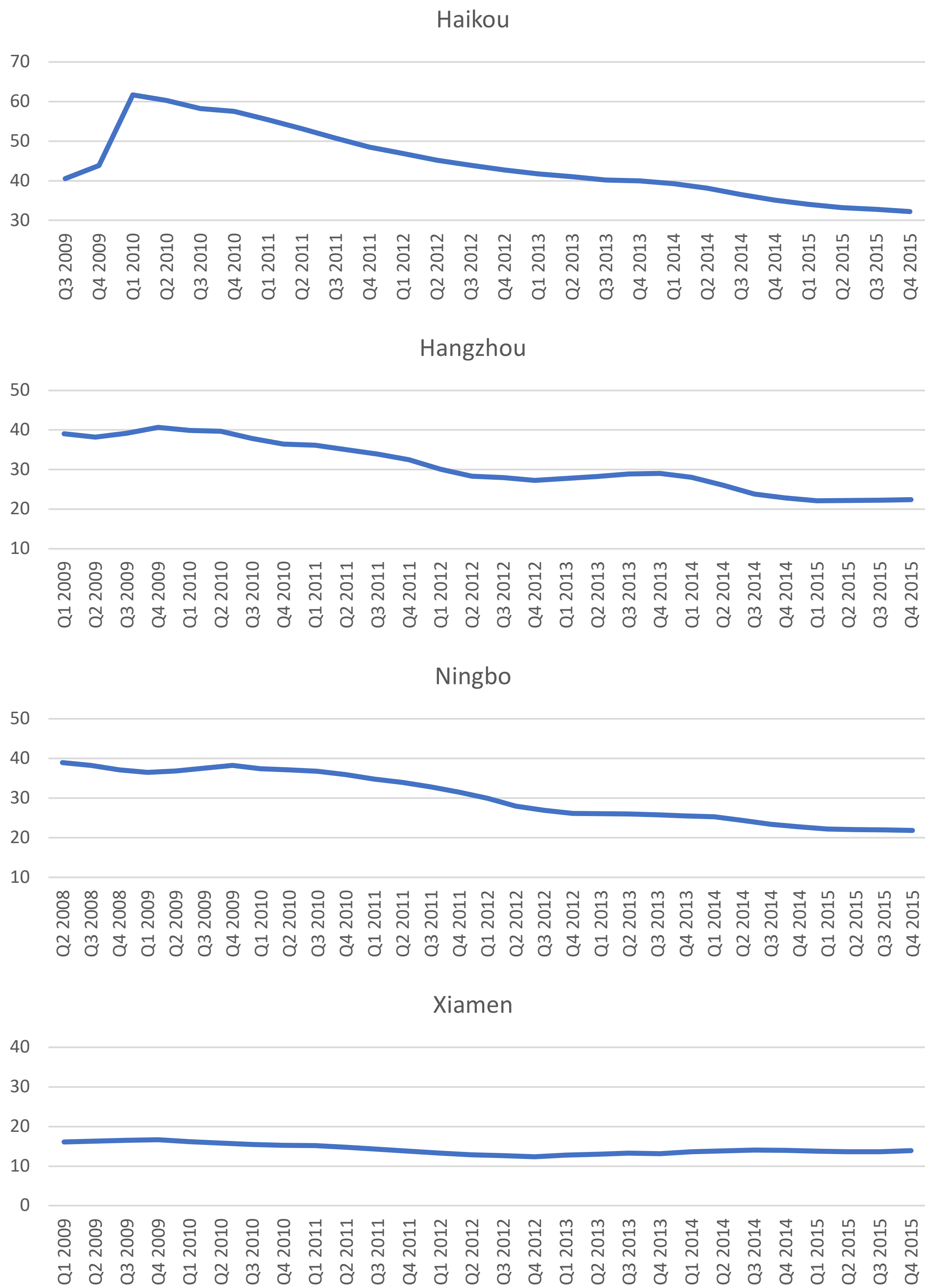

Figure 1.3. Ratio of house prices to personal income per capita in selected cities

Source: Author's calculations using data from the National Bureau of Statistics of China, the Joint Laboratory for Housing Big Data and the Housing Big Data Project Team of the National Academy of Economic Strategy, Chinese Academy of Social Sciences.

In order to investigate the relationship between the housing price and other fundamental variables, the level of the housing price and the quarterly changes of the housing price are taken as dependent variables for linear reduced-form regressions. The results are reported in Tables 1.10 and 1.11. Population change, employment change, mortgage rate, unemployment rate and housing starts significantly improve the coefficient of determination of the model, especially for cities such as Haikou, Ningbo, Hohhot, Urumqi and Shenzhen where income is a less powerful explanatory factor for housing price changes. But for Hangzhou, even taking these fundamental variables into account, the R^2 of its regression equation remains very low. Only 35.2% of the variance in house prices can be predictable from fundamentals. In this case, no statement can be made about bubbles from the Case-Shiller model, because the model doesn't fit the Hangzhou data.

Table 1.11 shows the pattern of significant coefficients for the regression of house prices on fundamental variables. Detailed regression results can be found in Table A1.2 in the appendix. Because the equations are in reduced form, there is inherent simultaneity problem in parameter estimation. The change in population may have a positive impact on house prices as a proxy for housing demand. On the other hand, the growth of housing price may have a negative impact on the population change because the high housing cost is an unfavourable factor that hinders people from settling down. Similarly, the change in employment could exert a positive impact on house prices because the good employment situation makes more people can afford to buy houses, which promotes the prosperity of the real estate market. On the other hand, rising housing prices may have a negative impact on employment growth because it means an increase in the cost of living, which makes workers discouraged from moving to areas with high housing prices. The change in employment has a significant positive effect in 17 of the 68 equations. The unemployment rate has a significant negative effect in 13 of the 68 equations.

The level of mortgage rates can also drive housing price dynamics. Rising interest rates will increase the cost of mortgages, and higher mortgage payments will discourage potential home buyers. The high cost of mortgage payments may also force some existing buyers to sell. More sellers and fewer buyers will lead to lower prices. But on the other hand, the mortgage interest rate may also be raised by the government in an effort to restrain the housing price rise, thus forming a positive correlation between the mortgage interest rate and the housing price. In the equations in which the change in house price is the dependent variable, the coefficient on mortgage rate is statistically significant and negative in five of the 34 cities. However, in the price level equations, the estimated coefficient on this variable is statistically significant but positive in 18 of the 34 cities.

Housing starts has a statistically significant and positive coefficient in five of the 68 equations, while the coefficient on housing starts is insignificant in all other equations. This result could also be caused by simultaneity. An increase in housing starts eases the upward pressure on house prices by increasing supply, but higher prices also give builders an incentive to start more housing.

It is worth noting that, with only about seven years of quarterly data, it is impossible to test the stationarity of the time series, as such a test would not have power in this case. While Case and Shiller (2003) had a longer period of data, their results were still not robust but volatile. However, the Case-Shiller model is designed to highlight bubble signals, rather than

Table 1.11. Regressions of house prices on fundamentals

Independent variable	Beijing	Tianjin	Shijiazhuang	Taiyuan	Hohhot	Shenyang	Dalian	Changchun	Harbin
	Dependent variable: quarterly change in house prices								
Change in population	–				+	–	–		
Change in employment			+		–	+		+	
Mortgage rate	–		–						
Unemployment rate	–		+		+				
Housing starts								+	
Income per capita	–		+				–	–	
Observations	27	32	28	28	21	31	31	28	28
R^2	0.545	0.388	0.531	0.194	0.758	0.625	0.403	0.432	0.417
	Dependent variable: quarterly level of house prices								
Change in population			+		–	+			
Change in employment		+		–	+	+	+		
Mortgage rate			+	+		+		+	+
Unemployment rate	–	+		+	+				+
Housing starts			+						+
Income per capita	+	+	+	+	+	+	+	+	
Observations	27	32	28	28	21	31	31	28	28
R^2	0.934	0.941	0.957	0.870	0.905	0.922	0.923	0.870	0.952

Note: A plus sign indicates that the coefficient on the variable is positive and statistically significant at the 5% level, and a minus sign indicates that the coefficient on the variable is negative and statistically significant at the 5% level.

Table 1.11. Regressions of house prices on fundamentals (cont.)

Independent variable	Shanghai	Nanjing	Hangzhou	Ningbo	Hefei	Fuzhou	Xiamen	Nanchang	Jinan
	Dependent variable: quarterly change in house prices								
Change in population		–							
Change in employment	–	+							
Mortgage rate			–	–					
Unemployment rate				–					
Housing starts									
Income per capita				–					
Observations	31	31	28	31	28	28	28	32	28
R^2	0.363	0.371	0.363	0.455	0.349	0.092	0.241	0.251	0.227
	Dependent variable: quarterly level of house prices								
Change in population		+							
Change in employment				+			–		–
Mortgage rate					+	+	–		+
Unemployment rate					–	+	–		
Housing starts					+				
Income per capita	+	+			+	+		+	
Observations	31	31	28	31	28	28	28	32	28
R^2	0.904	0.907	0.352	0.727	0.948	0.952	0.949	0.898	0.892

Note: A plus sign indicates that the coefficient on the variable is positive and statistically significant at the 5% level, and a minus sign indicates that the coefficient on the variable is negative and statistically significant at the 5% level.

Table 1.11. Regressions of house prices on fundamentals (cont.)

Independent variable	Qingdao	Zhengzhou	Wuhan	Changsha	Guangzhou	Shenzhen	Nanning	Haikou	Chongqing
	Dependent variable: quarterly change in house prices								
Change in population		+							–
Change in employment			+		–				+
Mortgage rate					–				
Unemployment rate	–		+						
Housing starts									
Income per capita			+						
Observations	32	28	30	31	32	29	28	26	30
R^2	0.342	0.290	0.518	0.253	0.326	0.568	0.246	0.307	0.445
	Dependent variable: quarterly level of house prices								
Change in population								+	
Change in employment	+			+				–	
Mortgage rate	+	+	+	+	+	–	+	+	
Unemployment rate		+			–	–		–	
Housing starts									+
Income per capita	+	+	+	+	+	+	+		+
Observations	32	28	30	31	32	29	28	26	30
R^2	0.786	0.965	0.916	0.914	0.978	0.911	0.860	0.912	0.860

Note: A plus sign indicates that the coefficient on the variable is positive and statistically significant at the 5% level, and a minus sign indicates that the coefficient on the variable is negative and statistically significant at the 5% level.

Table 1.11. Regressions of house prices on fundamentals (cont.)

Independent variable	Chengdu	Guiyang	Kunming	Xi'an	Lanzhou	Yinchuan	Urumqi
	Dependent variable: quarterly change in house prices						
Change in population						–	
Change in employment	+				+		–
Mortgage rate							
Unemployment rate		–	+				
Housing starts							
Income per capita			–			–	–
Observations	30	28	28	32	28	25	28
R^2	0.392	0.616	0.559	0.155	0.562	0.610	0.532
	Dependent variable: quarterly level of house prices						
Change in population			+	–			–
Change in employment	+		–		+		
Mortgage rate			+		+		+
Unemployment rate	–		+			–	–
Housing starts							
Income per capita	+	+	+	+	+	+	+
Observations	30	28	28	32	28	25	28
R^2	0.906	0.932	0.929	0.945	0.949	0.912	0.955

Note: A plus sign indicates that the coefficient on the variable is positive and statistically significant at the 5% level, and a minus sign indicates that the coefficient on the variable is negative and statistically significant at the 5% level.

focusing on specific estimates of the coefficients on economic variables. This method needs a reasonable sample period, and seven years is enough data to see trends in the housing market.

In order to pay closer attention to the strength of the real estate sector, the data in the sample up to 2013 is used to estimate the coefficients of the price level equations, and the obtained coefficient estimates are then used to predict the level of house prices from 2014 to 2015. The results of the house price forecast are presented in Figure 1.4. In most cities, forecasts for house prices are very much in line with actual prices. However, in Beijing, Tianjin, Shanghai and Shenzhen, house prices rise markedly, and the predicted house prices based on fundamental factors are significantly lower than the actual house prices in 2015. This suggests that house price growth in these cities has deviated from economic fundamentals. Thus, although the addition of other fundamental variables improves the explanatory power of the model to some extent, the sharp fluctuation in price-to-income ratio and the widespread under forecasting of housing prices still mean that the hypothesis that a real estate bubble exists in these cities cannot be rejected.

To summarize the results, the income level in some cities has limited explanatory power for house price movements, but the addition of other fundamental variables improves the model fit. However, since fundamentals in Hangzhou are insignificant and the R^2 is very low, the Case-Shiller model cannot be used to determine whether there is a real estate bubble in Hangzhou. In Beijing, Tianjin, Shanghai and Shenzhen, price-to-income ratios fluctuate widely, and prices predicted by fundamentals are significantly lower than actual prices. Therefore, it is concluded that a bubble exists in the real estate market of these cities.

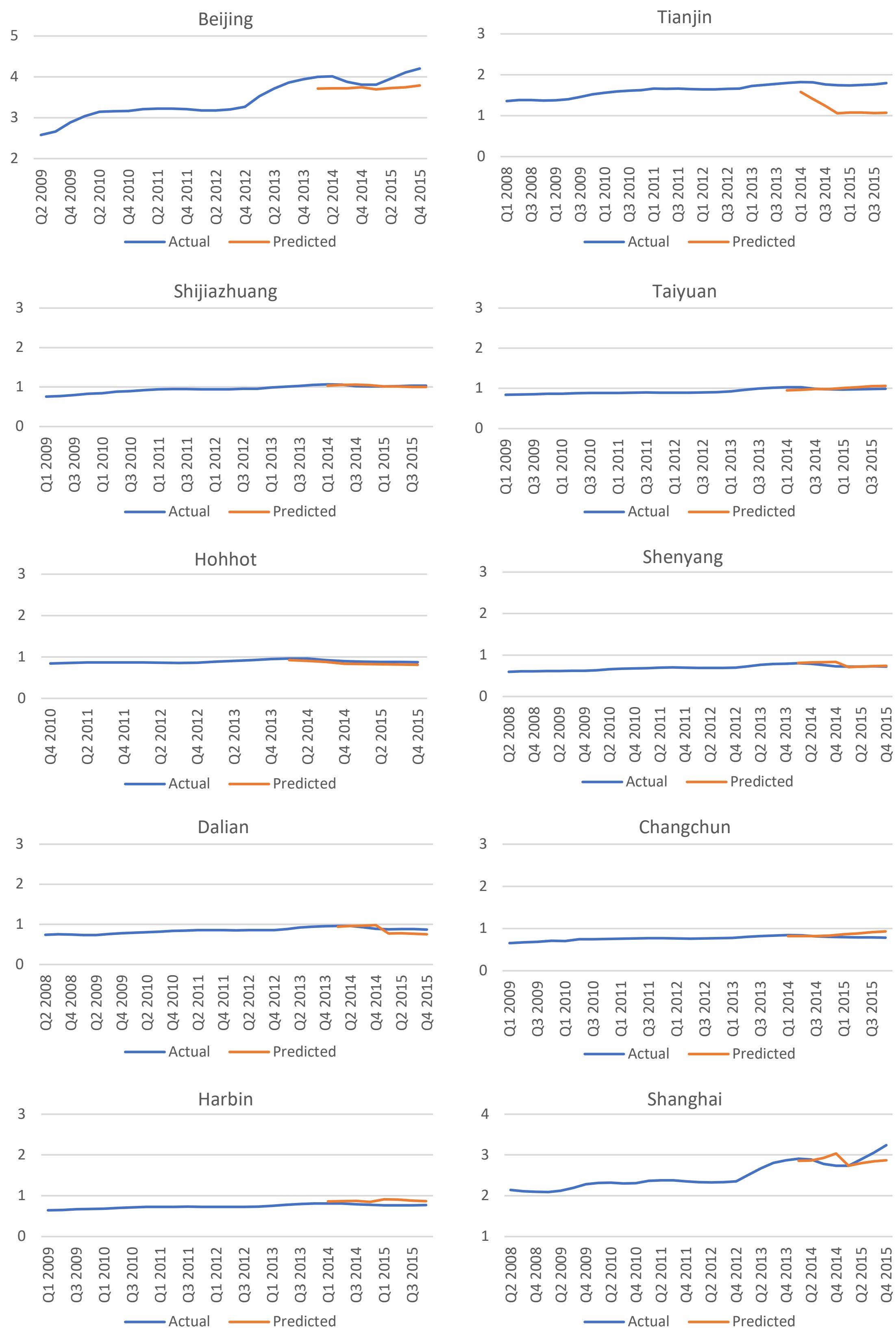

Figure 1.4. Actual and predicted house prices (unit: 10,000 RMB)

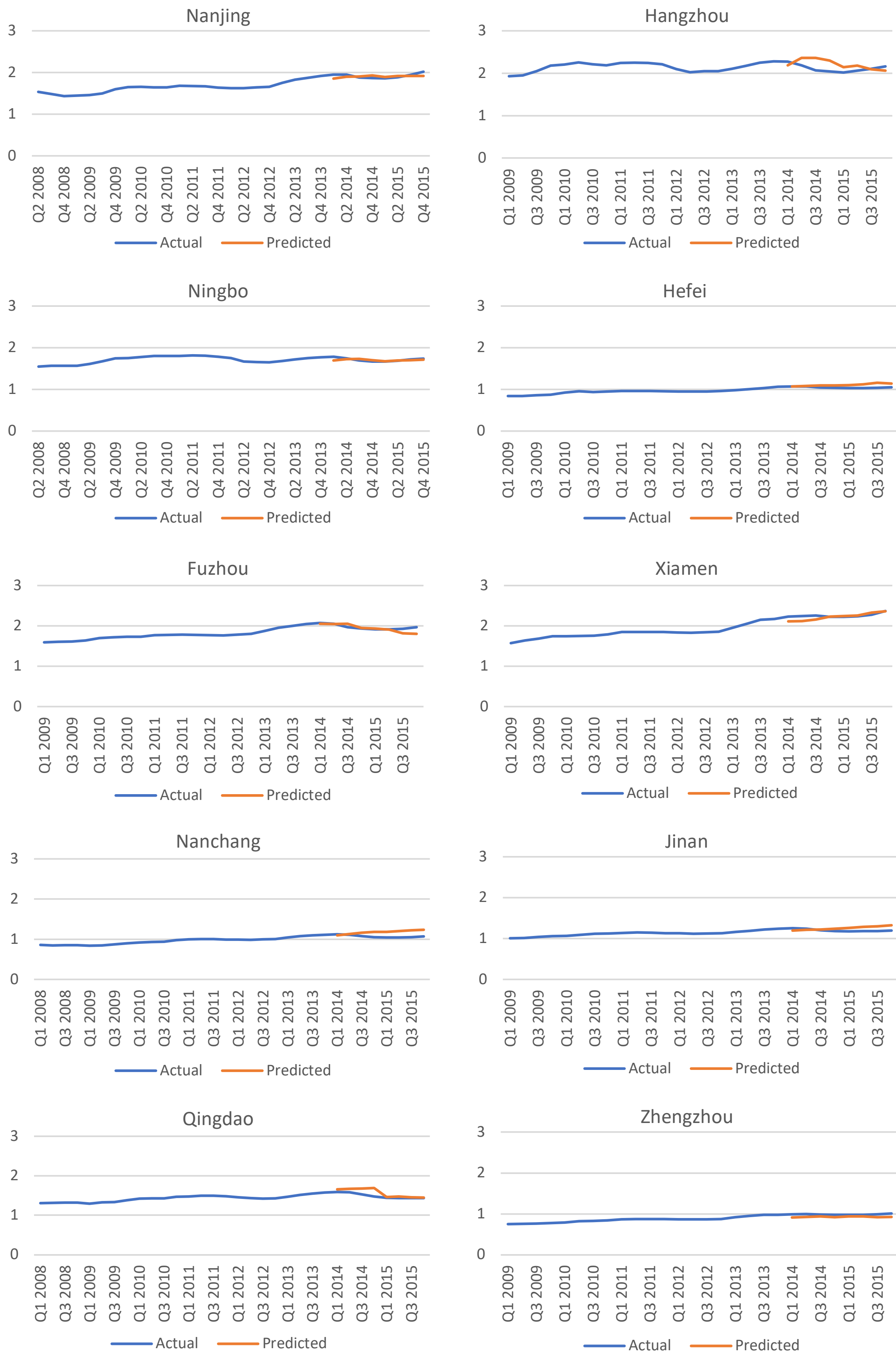

Figure 1.4. Actual and predicted house prices (unit: 10,000 RMB) (cont.)

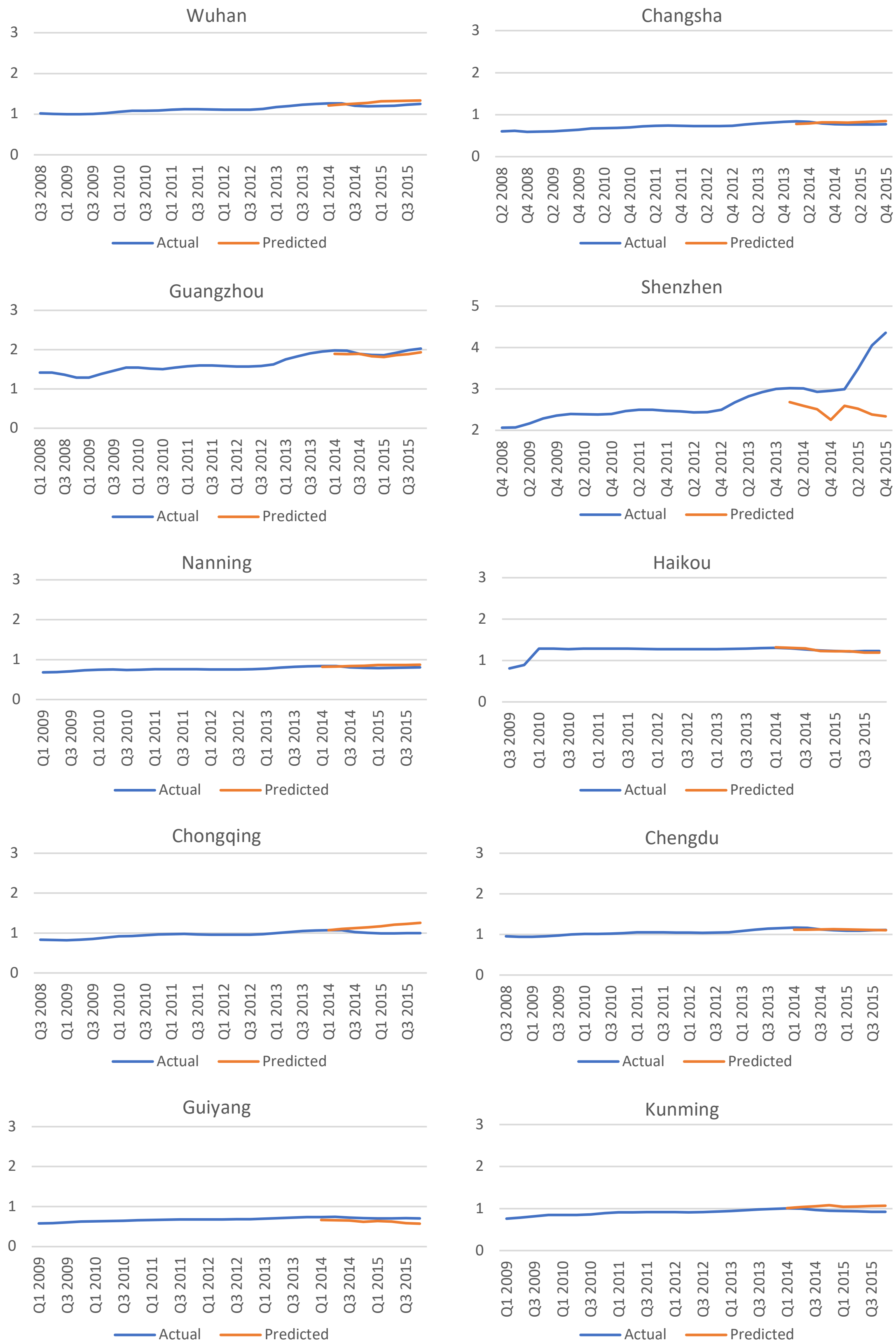

Figure 1.4. Actual and predicted house prices (unit: 10,000 RMB) (cont.)

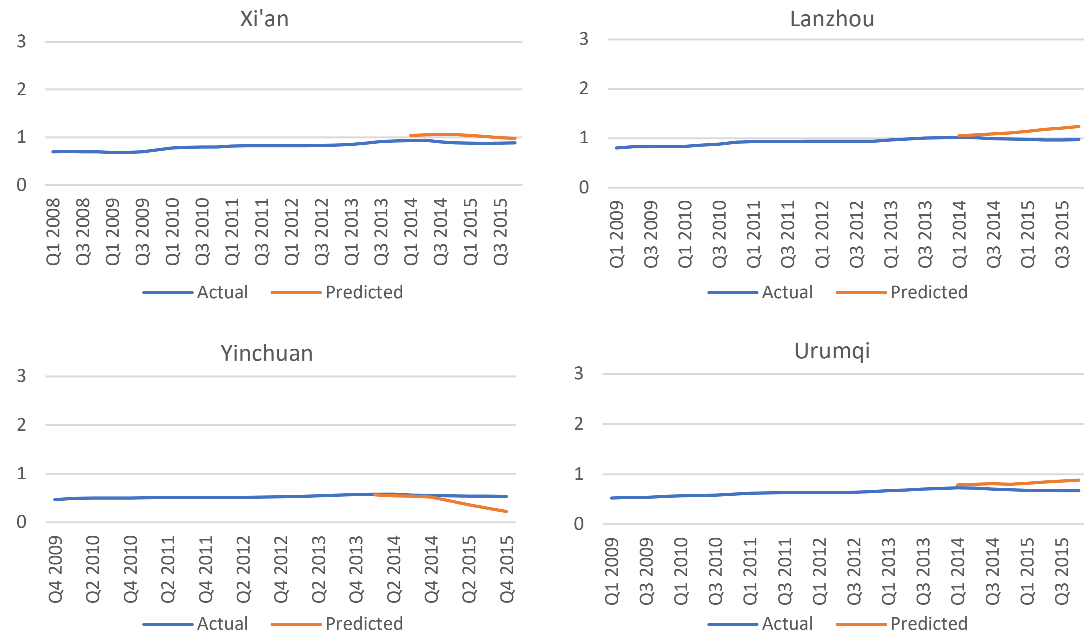

Figure 1.4. Actual and predicted house prices (unit: 10,000 RMB) (cont.)

1.5.5 Summary of the Results of Bubble Detection Models

The results of whether there are real estate bubbles in 34 first- and second-tier cities in China obtained by using the data of the same period and applying the above four bubble detection models are summarized in Table 1.12. The LPPLS model analyses the behaviour of house price series through pure statistical methods. Under its framework, the cities of Hohhot, Nanjing, Nanchang and Haikou show no signs of a bubble. Through the variance decomposition of the price-to-rent ratio, the results of the dynamic Gordon growth model show that in Shijiazhuang, Dalian, Kunming and Yinchuan, the contribution of rational bubble to the fluctuation of house price-to-rent ratio is less than that of fundamental factors, indicating that house prices in these cities have not deviated from economic fundamentals. According to the user cost model, the price-to-rent ratio should be equal to the reciprocal of the user cost of housing under the equilibrium condition of the real estate market. Of all the sample cities, only Hohhot meets this criterion. Finally, the method of Case and Shiller (2003) emphasizes the importance of income in explaining housing price changes. With the exception of Hangzhou, where the model does not fit the data, the study finds that in Beijing, Tianjin, Shanghai and Shenzhen, price-to-income ratios fluctuate wildly, and forecasts based on economic fundamentals significantly understate actual prices. Therefore, the hypothesis that there is a real estate bubble in these four cities cannot be rejected.

Table 1.12. Summary of the results obtained from the four bubble detection models

City	The LPPLS model	The dynamic Gordon growth model	The user cost model	The Case-Shiller model
Beijing	Yes	Yes	Yes	Yes
Tianjin	Yes	Yes	Yes	Yes
Shijiazhuang	Yes	No	Yes	No
Taiyuan	Yes	Yes	Yes	No
Hohhot	No	Yes	No	No
Shenyang	Yes	Yes	Yes	No
Dalian	Yes	No	Yes	No
Changchun	Yes	Yes	Yes	No
Harbin	Yes	Yes	Yes	No
Shanghai	Yes	Yes	Yes	Yes
Nanjing	No	Yes	Yes	No
Hangzhou	Yes	Yes	Yes	-
Ningbo	Yes	Yes	Yes	No
Hefei	Yes	Yes	Yes	No
Fuzhou	Yes	Yes	Yes	No
Xiamen	Yes	Yes	Yes	No
Nanchang	No	Yes	Yes	No
Jinan	Yes	Yes	Yes	No
Qingdao	Yes	Yes	Yes	No
Zhengzhou	Yes	Yes	Yes	No
Wuhan	Yes	Yes	Yes	No
Changsha	Yes	Yes	Yes	No
Guangzhou	Yes	Yes	Yes	No
Shenzhen	Yes	Yes	Yes	Yes
Nanning	Yes	Yes	Yes	No
Haikou	No	Yes	Yes	No
Chongqing	Yes	Yes	Yes	No
Chengdu	Yes	Yes	Yes	No
Guiyang	Yes	Yes	Yes	No
Kunming	Yes	No	Yes	No
Xi'an	Yes	Yes	Yes	No
Lanzhou	Yes	Yes	Yes	No
Yinchuan	Yes	No	Yes	No
Urumqi	Yes	Yes	Yes	No

The user cost of housing seems to be a more sensitive indicator of price bubbles. Under the framework of user cost model, it is concluded that the real estate market of all cities except Hohhot is in a bubble. The LPPLS model, the user cost model and the Case-Shiller model all prove that there is no real estate bubble in Hohhot. In contrast, the Case-Shiller model does not give evidence of bubbles in most cities. The model's results show that home prices in 29 cities are to some extent supported by fundamental factors. In conclusion, for Beijing, Tianjin, Shanghai and Shenzhen, the four bubble detection models all come to the same conclusion that there is a bubble in house prices. For the other cities, different models generate different predictions. There is not a single city in the sample that is recognized by all four models as having no real estate bubble.

1.6 Conclusion

Using data from the Chinese real estate market, this paper compares the results of four widely used bubble detection models and examines whether different assumptions and models give different predictions even when the data are the same.

The LPPLS model is purely statistical in nature and diagnoses bubbles by capturing the super-exponential growth behaviour of house price indices. The results of the model show that cities except Hohhot, Nanjing, Nanchang and Haikou all have unsustainable real estate bubbles. The other three models are based on fundamentals. Based on the dynamic Gordon growth model, it is shown that the rational bubble is the main driving factor of the fluctuation of the price-to-rent ratio in 30 cities except Shijiazhuang, Dalian, Kunming and Yinchuan. The user cost model calculates the cost of home ownership and compares it with the market rent to determine whether house prices are out of line with fundamentals. It is found that only Hohhot satisfies the equilibrium condition of the real estate market in the sample period, and behavioural factors, especially the inflation illusion, have a great influence on the fluctuation of the price-to-rent ratio. This proves that China’s house price boom is more of a behavioural bubble. The method of Case and Shiller (2003) is also used to test whether the rise in house prices deviates from income levels. The results show that income is not a good explanation for house price fluctuations in some cities such as Haikou and Ningbo, but other fundamental variables add greatly to the R^2 of the model. According to forecasts of house prices based on fundamental factors, the actual house prices in Beijing, Tianjin, Shanghai and Shenzhen significantly exceed the predicted house prices after 2014, which means that house price growth is out of line with economic fundamentals. Therefore, it can be concluded that while the model’s ability to predict house prices improves with the addition of other fundamental variables, the hypothesis of real estate bubbles in the above four cities cannot be rejected.

To summarize, in addition to Beijing, Tianjin, Shanghai and Shenzhen, which are identified as having a real estate bubble by all four bubble detection models, the remaining 30 cities are identified as having a bubble by at least one of the models. In response to rapidly rising house prices and a potential price bubble, Chinese government agencies have jointly issued rules on the proportion of down payment since 2005, aiming to discourage speculation and stabilise the real estate market. The next two chapters further investigate whether the loan-to-value ratio policy can restrain the rise of house prices by restricting the availability of loans and thus achieve the purpose of curbing bubbles, and whether the policy can affect the purchasing decisions of households.

Chapter 2

Government Intervention and the Effects of Loan-to-Value Ratio Policy on House Prices

2.1 Introduction

Real estate plays an important role in driving economic growth because it accounts for a large proportion of personal and corporate wealth across all sectors of the economy. For instance, the subprime mortgage crisis in the United States in 2007 did not only plunge the United States into a debt crisis and weaken its economic development, but also triggered the global financial crisis which led to a global economic downturn. One of the main causes of the crisis was that financial institutions took advantage of the housing boom to overdevelop home mortgages. Lenders made loans to high-risk borrowers, and lending standards deteriorated. To stabilize the market, governments around the world have sought policies to curb speculation. In this context, loan-to-value (LTV) ratio policies, which help ensure that home loans are extended to high-quality borrowers by setting down payment thresholds, are increasingly being used (Shim et al., 2013; Akinci and Olmstead-Rumsey, 2018).

In theory, the LTV policy is designed to reduce demand pressures and systemic risks by curbing borrowers' leverage, but its effectiveness also depends on the extent to which credit-constrained households are marginal buyers of homes and the ability of constrained buyers to borrow from sources other than banks (Jácome and Mitra, 2015; Cizel et al., 2019). These reasons provide a rationale for an empirical study of LTV ratio policy. Studies have shown that LTV restrictions can effectively reduce systemic risk and credit growth, but the impact on house price inflation is not clear and has been extensively debated by economists and policy makers. The main challenge is to understand how market indicators would have performed without these policies.

This study fills this gap by applying a standard fixed effects model with variable treatment intensity in the context of China's housing finance system and by adopting the difference-in-differences (DD) technique to confirm the findings. The focus of the study is on China given that it is the largest emerging market globally and because of its distinct city and national level LTV policies which provide a suitable environment for causal analysis. Other leading countries, such as the US and the UK, have yet to impose any caps on LTV ratios at national level.

Although LTV policies announced by the Chinese central government apply to the whole country, cities have some degree of freedom in setting stricter requirements. As a result, LTV ratios are not uniform across China. Therefore, treatment groups and control groups could be selected depending on whether a city's LTV cap had changed after a policy was released. To estimate the impact of LTV policy, the research design is built to compare the outcomes in treatment and control group cities.

A serious challenge in exploring the impact of LTV policy using a fixed effects panel regression model is endogeneity. Although real estate policies are used to control high house prices, the high level of house prices may have a reciprocal effect on real estate policy. To confirm the effectiveness of the policy, independent evidence is provided using a classical DD model at two time points, before and after a release of national LTV policies. Since LTV ratio policies announced by the central government apply all over the country, they are unlikely to be correlated with the local economic environment and the state of the regional property market. The propensity score matching technique is also adopted to artificially construct a control group and a treatment group that meet the parallel trends assumption.

Preliminary results suggest that LTV ceilings have a significant positive influence on price growth rates, which implies that a drop in LTV ceilings would slow down house price growth whereas an increase in the maximum LTV ratio would accelerate the growth of house prices. The asymmetry of the effect of LTV policy is then studied. It seems that tightening LTV policies (that is, reducing maximum allowable LTV levels) tends to have a greater impact on house prices than relaxing such policies with a high degree of statistical significance. The results support the hypothesis that the elasticity of urban housing supply affects the effectiveness of LTV policy.

After the financial crisis, a growing body of studies have investigated the effects of LTV policies. As a form of macroprudential regulation, the policy can achieve better results than monetary or fiscal solutions by acting directly on housing market activities (Crowe et al., 2013). Rubio (2016) incorporates LTV limits in a standard New Keynesian dynamic stochastic general equilibrium model to simulate real estate market activity and explore the policy effect. The results show that LTV ceilings can reduce credit volatility and ensure financial stability; when stricter limits on LTV ratios are established, a stronger policy effect will be produced. However, there is no consensus among scholars on the impact of the policy on housing prices. Ahuja and Nabar (2011), Igan and Kang (2011) and Hwang, Park, and Lee (2013) argue that limits on the LTV ratio restrain the growth of house prices, whereas Neagu et al. (2015), Vandenbussche et al. (2015) and Cerutti et al. (2017) find a limited influence of LTV caps on house prices. The International Monetary Fund (2014) also notes that as house prices rise, the LTV ratio ceiling is likely to become less binding.

This study contributes to the existing literature on the impact of LTV policies from three aspects. Firstly, studies on the impact of LTV policies focus mainly on the situation in developed countries and many of the studies have estimated only the relationship between LTV restrictions and housing market indicators. In contrast, the current study uses the fixed effects regression model and the DD technique to determine the causal effects of LTV policy. These methods have recently become popular in real estate research (Berger et al., 2016; and Sá, 2016).

Secondly, most previous studies have relied on dummy variables to represent LTV measures or constructed numeric variables to count the number of policy actions taken within a given period as a way to show the intensity of policy intervention (Ahuja and Nabar, 2011; Kuttner and Shim, 2012 and 2016; Jung et al., 2017; Akinci and Olmstead-Rumsey, 2018). But these methods cannot capture the change of LTV caps over time and may greatly affect the accuracy of the performance evaluation of this consistent, time-varying strategy. A few other studies use intensity-adjusted LTV action variables to quantify policy efforts (Vandenbussche et al., 2015; and Richter et al., 2019). These studies only capture changes in maximum LTV ratios since they include a large set of economies to perform panel regressions and the initial tightness of LTV regulation cannot be measured and compared across countries. However, Alam et al. (2019) examine the effects of LTV policies on credit and consumption and find that the initial LTV level has an impact on the effectiveness of the policy. Therefore, taking advantage of the local variations in LTV requirements among Chinese cities, this study uses LTV levels as the main independent variable to measure the degree of exposure to the policy with regard to the direction and magnitude of changes in the LTV caps.

Thirdly, the paper also separates the LTV limits for borrowers who do not own properties and for borrowers who already own property to (a) identify the effects of different types of loan caps and (b) understand how LTV policies can facilitate a more effective allocation of resources and a steady development of the real estate market. To the best of the author’s knowledge, these issues have not been studied in previous research studies.

The remainder of this paper is organized as follows. In the next section, the differentiated credit policies adopted by the Chinese government are introduced and compared with the policy designs of other countries. Section 2.3 describes the data and the application of the DD method for policy evaluation. Section 2.4 discusses the empirical methodology for estimating the impact of LTV policy on house prices and reports the results. In Section 2.5, the key findings are summarized, and recommendations for policy formulation are provided.

2.2 Background

The LTV ratio is used in home mortgages to determine the amount necessary for a down payment. Tightening LTV caps mean that borrowers would need to provide larger down payments, which would reduce household leverage and the supply of credit, whereas loosening LTV caps would require smaller down payments, which would increase household leverage and the availability of credit. Although higher LTV caps help people gain access to home ownership, they also increase the likelihood of default. Therefore, both of these aspects should be considered in the policy-making process (Gete and Reher, 2016).

Table 2.1. Changes in provident fund loan terms in Guangzhou on March 20th, 2017

Housing situation			Old policy		New policy		Change
Building area per apartment	Number of properties owned	Housing loan records	LTV caps	Interest rate	LTV caps	Interest rate	
Below 144 m^2 (including)	0	None	70%	Base rate	70%	Base rate	
		Paid off	70%	Base rate	60%	Base rate	Lower LTV
		One outstanding loan	30%	By 10% above the base rate	30%	By 10% above the base rate	
		Two or more outstanding loans	No loan granted				
	1	None or paid off	70%	By 10% above the base rate	50%	By 10% above the base rate	Lower LTV
		Unsettled housing loans in this city	30%	By 10% above the base rate	30%	By 10% above the base rate	
		Unsettled housing loans outside this city	No loan granted				
Above 144 m^2	0	None or paid off	70%	Base rate	30%	Base rate	Lower LTV
		One outstanding loan	30%	By 10% above the base rate	30%	By 10% above the base rate	
		Two or more outstanding loans	No loan granted				
	1	None or paid off	70%	By 10% above the base rate	30%	By 10% above the base rate	Lower LTV
		Unsettled housing loans in this city	30%	By 10% above the base rate	30%	By 10% above the base rate	
		Unsettled housing loans outside this city	No loan granted				

Source: Guangzhou Housing Provident Fund Management Centre.

Operating in parallel with China's housing reform, the system of combining commercial bank mortgage loans with housing provident fund (HPF) loans has been gradually established. These two types of home loans serve the same purpose. In general, HPF loans have lower interest rates and down payment requirements due to their assurance and mutual assistance nature. However, in view of the provident fund's complicated application process, long approval time, and loan amounts that may be too low in relation to house prices, the vast majority of home buyers opt for commercial loans to buy properties or to make up shortfalls in insufficient HPF loans.

The Chinese government also offers a differentiated credit policy to ensure that eligible residents can obtain the required mortgage loans when buying their first, ordinary commercial housing units. This provides more financial support to potential homebuyers who have a more urgent need or demand for houses. First-time buyers[2] can apply for loans from commercial banks or the HPF administration center under preferential government policies. Existing owner-occupiers are often subject to stricter LTV restrictions to reduce the possibility of the banks' money being used for speculative purchases.

Table 2.1 shows the example of changes in credit policy terms in Guangzhou. The details of the differentiated credit policy are well presented—it can be seen that caps on LTV ratios relate to many factors, including the number of properties owned, the building area per apartment, whether previous housing loans have been paid off, etc. Households with more homes and outstanding loans are restricted to lower LTV caps, and in some cases no loan is available. Houses larger than 144 m^2, such as villas and high-end apartments, are identified as non-ordinary residences and are usually subject to tougher LTV restrictions.

[2] The expression "first-time buyers" applies to homebuyers who have never bought a home before and also to homebuyers who buy another home after selling their previous home, so they still only own one home. In China, homebuyers are seen as two groups—those buying their only home and those who own other homes when buying a new home.

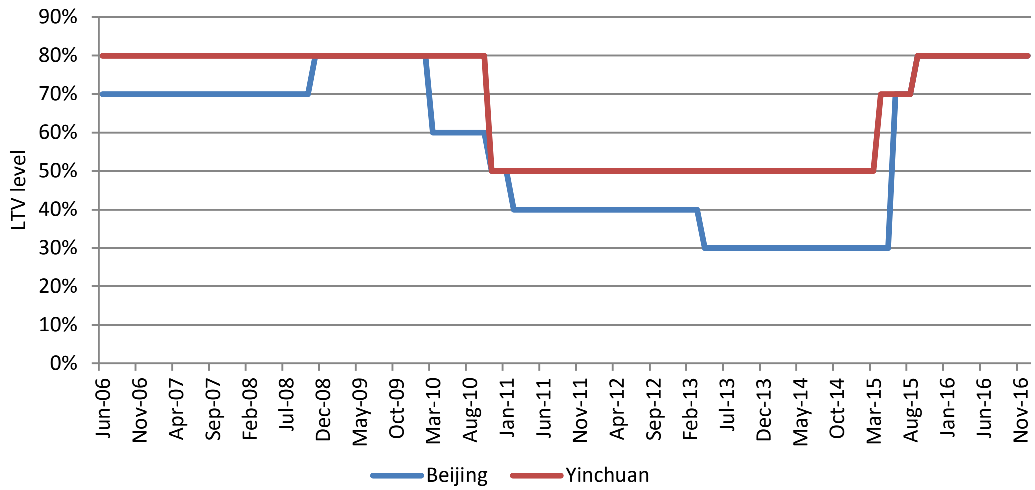

Figure 2.1. Loan-to-value caps of housing provident fund loans for borrowers who own one property and have cleared the corresponding loans in Beijing and Yinchuan

Furthermore, the example of adjustment of HPF policy in Guangzhou also reflects the fact that regional real estate markets are restricted not only by national policies but also by laws and regulations issued by local governments. Beijing has issued the largest number of LTV ratio policies, followed by Shanghai. Other cities with relatively steady price growth have introduced fewer regulations. As shown in Figure 2.1, the government in Beijing issued 10 LTV ratio policies from 2007 to 2016 to control house prices whereas Yinchuan, a provincial capital, implemented only the LTV ratio policies stipulated by the state. The caps on LTV ratios implemented in Beijing changed more frequently and were typically lower than those in Yinchuan. Due to the introduction of local policies, the actual implementation of an LTV ceiling may vary among cities.

In comparison, major developed countries, such as the UK, the US and Australia, do not set legal upper limits for LTV ratios at government level. Instead, mortgage sizes are controlled independently by commercial banks according to their risk control preferences and market principles. In addition to mainland China, the two special administrative regions of China

(Hong Kong and Macau), some developing economy countries, and a handful of small developed countries in Europe have also included LTV ratios, with caps, in their regulatory targets.

For instance, the legal ceilings on LTV ratios imposed by the Singapore government peaked at 90% in July 2005 and were then reduced several times, reaching 60% in January 2011. China's LTV cap level was 80% at its peak in most cities after the 2008 financial crisis and 30% at its lowest in Beijing, Shanghai, Guangzhou and Shenzhen in 2013 for existing owner-occupiers. Owing to the high volatility of China's property market, a lower minimum level was required than in other countries. Another example is South Korea. The Korean government has divided the country into speculative zones and speculation-prone zones and imposed differential LTV limits, depending on mortgage loan maturity, the type of financial institution issuing loans, and the appraised value of the property. In the Hong Kong Special Administrative Region, the government has also adopted a differentiated LTV policy that sets a maximum LTV ratio based on the assessed value of the property. Sometimes, a lower LTV ceiling may be applied to a luxury property. The most distinctive feature of the Hong Kong market is the Mortgage Insurance Programme (MIP), launched in March 1999. Under this program, the Hong Kong Mortgage Corporation provides insurance to banks to enable homebuyers to secure mortgage loans up to a certain level of LTV ratio. This approach has proved to be effective in alleviating the disadvantages of an LTV policy that leads to insufficient liquidity (Wong et al., 2011). Hong Kong's policy also distinguishes between owner-occupied residential properties and non-owner-occupied residential properties to encourage home purchases for the purpose of owner-occupation. LTV policies in developed countries in Europe such as in Norway, Sweden, and the Netherlands are usually set at a uniform and relatively high ceiling.

2.3 Data and Research Design

2.3.1 Data Description

The sample comprises 70 large and medium-sized cities in China across 30 out of 34 provincial administrative regions, including data for 10 years of 2007–2016 at a quarterly frequency. The selection of sample cities is mainly based on the data available from the National Bureau of Statistics of China due to the authority of its data and the representativeness of the selected cities.

2.3.1.1 Loan-to-Value Ratio Limits

Policy releases were collected manually from the official websites of local governments and a dataset containing LTV ratio limits imposed by central and local authorities for 70 major cities in China was constructed. Figure 2.2 gives a visual representation of the changes in national LTV requirements for commercial mortgage loans. Half of these 14 national policy actions are tightening actions and the other half are loosening actions. The Appendix contains more details on the sample of cities and national LTV ratio policies.

In addition to LTV ratio policies announced by the central government, many local authorities have also introduced their own policies that may be even more stringent than national policies. When municipal governments set lower LTV caps, regional housing markets always implement these more restrictive credit limits, rather than the general LTV ceilings set by central authorities. This mechanism makes it possible to use the DD approach to study policy effects.

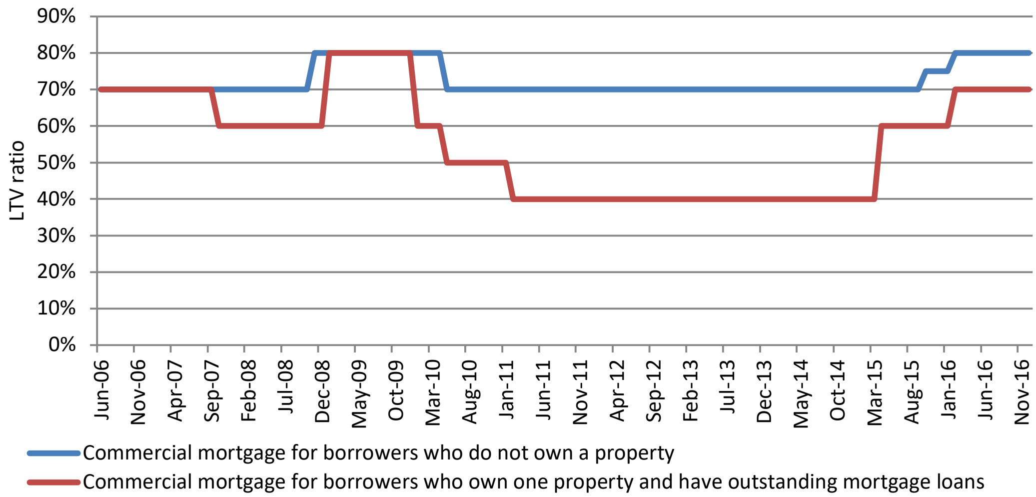

Figure 2.2. The evolution of loan-to-value caps for commercial loans set by national policies

Table 2.2 shows that China's central government typically pays more attention to commercial lending, whereas personal HPF loans with LTV limits are issued more often by local authorities. However, no matter what the sources of loans are, it can be seen that governments at all levels have imposed more and tougher policies on second housing purchases, limiting credit supply for them while supporting reasonable housing demand. When house prices become too volatile, the management of the demand for second homes becomes a high priority.

It is also worth mentioning that in China, researchers usually divide cities into four tiers. Higher-tier cities generally have a higher gross domestic product, larger populations, and a higher level of political administration. In the 70-city sample, tier one is made up of six cities, of which four municipalities—Beijing, Chongqing, Shanghai and Tianjin—are directly controlled by China's Administration Centre; the second category comprises 29 provincial

Table 2.2. The number of national or city-level loan-to-value ratio policies during 2007–2016

Region	LTV caps for a commercial mortgage for households who do not own a property	LTV caps for a commercial mortgage for households who own one property	LTV caps for HPF loans for households who do not own a property	LTV caps for HPF loans for households who own one property
Nationwide	4	7	2	4
Beijing	1	3	1	5
Chongqing	0	0	1	1
Guangzhou	0	1	1	2
Shanghai	1	2	1	3
Shenzhen	0	1	1	1
Tianjin	1	1	4	6
Changchun	0	0	0	1
Chengdu	0	2	2	2
Changsha	0	0	1	0
Dalian	0	0	0	1
Fuzhou	1	0	0	0
Hefei	1	1	1	1
Hohhot	1	1	1	1
Haikou	0	0	1	1
Hangzhou	0	0	3	2
Jinan	1	1	2	2
Ningbo	0	0	0	1
Nanchang	0	1	1	1
Nanjing	0	2	0	0
Shenyang	0	2	1	4
Wuhan	1	2	0	0
Xi’an	0	0	0	1
Xiamen	1	1	1	1
Zhengzhou	0	1	1	2
Wuxi	0	1	1	4
Wenzhou	0	0	1	0
Jinhua	0	0	3	2
Luoyang	0	1	0	0
Pingdingshan	0	1	0	0
Yueyang	0	0	2	1
Nanchong	0	0	1	1

capital cities and sub-provincial capital cities; the third tier comprises 34 prefecture capital cities. Also included is the county-level city Dali, categorized as tier four. Table 2.3 shows that higher-tier cities tend to issue more LTV ratio policies to constrain housing credit growth; this is postulated to be due to sharp rises in their house prices. Thus, at least part of the observed association between house price movements and policy announcements may arise by reverse causality.

Table 2.3. The average number of loan-to-value ratio policy releases by city tiers, 2007–2016

Tiers	LTV caps for a commercial mortgage for households who do not own a property	LTV caps for a commercial mortgage for households who own one property	LTV caps for HPF loans for households who do not own a property	LTV caps for HPF loans for households who own one property
First-tier	0.50	1.33	1.67	3.17
Second-tier	0.21	0.48	0.52	0.69
Third-tier	0	0.09	0.24	0.24

Note: Statistics of fourth-tier cities are not reported since there is only one fourth-tier city in the sample. This city did not introduce an LTV ratio policy during the sample period.

In order to establish the time series variable of the cities' LTV upper limits, the most stringent of the municipal/central government restrictions is used as the binding LTV limit. The time series for LTV is constructed as follows. When the LTV limit changes in the second half of a month, the value of the LTV limit for the current month is set to remain the same and the value of the LTV limit for the next month is set to change in accordance with the new policy stance. When the LTV policy is released in the first half of a month, the value of the LTV limit for that month is set for an immediate change. The resulting monthly LTV limits are then averaged and converted to quarterly data.

2.3.1.2 House Prices and Other Controls

The monthly house price indices come from the National Bureau of Statistics of China. The national consumer price index is subtracted from the house price indices to deflate them into real terms. The time series are then converted from a monthly to a quarterly frequency by averaging the real growth rate of house prices, because much of the information contained in the monthly data is likely to be noisy with many spikes caused by temporary fluctuations. Unlike longer time intervals that tend to smooth the price data and show trends in house price movements, short-term monthly data may not. Particularly as the house purchasing process can take months to complete, policy change is unlikely to have an immediate effect on prices. This is consistent with most of the literature on the effectiveness of LTV ratio policy (Duca et al., 2011; Crowe et al., 2013; Kuttner and Shim, 2016; Tressel and Zhang, 2016; and Akinci and Olmstead-Rumsey, 2018).

The reason for not using annual frequency data is that the effect of LTV ratio policy can be relatively short-lived, and the use of quarterly data is more likely to capture the impact of policies before it wears off. In addition, during some periods, LTV ratio policies were introduced several times throughout the year. If the data were collected annually, only the average impact of these policies on house prices would be observed. Annual intervals can also lead to the policy effects mixed in with other unrecognized factors, which may cause difficulty in isolating the effects of LTV policies.

In the regression analysis, population, income, and unemployment rates are also included to measure real housing demand and control for housing market dynamics in the selected cities in this study. These three macroeconomic indicators are most commonly used as control variables in research on the real estate market (Cao et al. 2015; Berger et al, 2016; and Sá 2016). Since these variables are available only on an annual basis, they are converted to quarterly series by keeping the values constant for all four quarters of the year. Some market factors that could affect housing prices—stock of dwellings, housing starts—are missing in most of the second and third tier cities in the sample so naturally cannot be included in the regression. The data were collected from the Wind database, Qianzhan database, Municipal Statistical Bulletin on Economic and Social Development, Municipal Statistical Yearbook, and work reports of municipal governments. Table 2.4 presents descriptive statistics for the key variables, by city tiers.

Table 2.4. Descriptive statistics (2007–2016)

Tiers	Obs	Mean	Std. Dev.	Min	Max
Panel 1: The real annual growth rate of the new commercial housing sales prices					
First-tier	240	0.043	0.102	0.009	0.077
Second-tier	1160	0.015	0.066	-0.008	0.054
Third-tier	1360	0.000	0.054	-0.017	0.043
Panel 2: The real annual growth rate of the second-hand housing sales prices					
First-tier	240	0.032	0.099	-0.005	0.076
Second-tier	1160	0.001	0.054	-0.014	0.025
Third-tier	1360	-0.011	0.045	-0.036	0.029
Panel 3: Loan-to-value caps applied to first-time home buyers					
First-tier	240	0.720	0.034	0.707	0.728
Second-tier	1160	0.730	0.040	0.712	0.732
Third-tier	1360	0.731	0.040	0.724	0.732
Panel 4: Loan-to-value caps applied to second-time home buyers					
First-tier	240	0.519	0.151	0.473	0.565
Second-tier	1160	0.563	0.141	0.515	0.570
Third-tier	1360	0.568	0.141	0.553	0.572
Panel 5: The annual growth rate of permanent residents					
First-tier	240	0.028	0.016	0.008	0.037
Second-tier	1160	0.012	0.007	-0.002	0.029
Third-tier	1360	0.005	0.005	-0.009	0.021
Panel 6: The annual growth rate of per capita disposable income of urban residents					
First-tier	240	0.105	0.020	0.099	0.109
Second-tier	1160	0.115	0.032	0.103	0.145
Third-tier	1360	0.116	0.032	0.096	0.135
Panel 7: The change in registered urban unemployment rate					
First-tier	240	0.029	0.001	0.014	0.042
Second-tier	1160	0.031	0.004	0.018	0.038
Third-tier	1360	0.032	0.003	0.012	0.044

Notes: 1. 'Mean' reports the average of the city mean for each indicator at a tier level. 'Std. Dev' reports the average of the city standard deviation for each indicator. 'Min' and 'Max' report the minimum and maximum city mean at a tier level, respectively.

2. Statistics of fourth-tier cities are not reported since there is only one fourth-tier city in the sample. This city did not introduce an LTV ratio policy during the sample period.

2.3.2 Difference-in-Differences Model

In China, the release of national policies creates additional local variations in LTV caps. When the central government changes LTV limits for housing loans, some cities comply with the requirements of the national policy, but other cities that have implemented tighter LTV restrictions than the national limits may not change their LTV requirements. This provides a favourable condition for comparing differences between cities, over time, to capture the causal effects of LTV ratio policy using the DD approach.

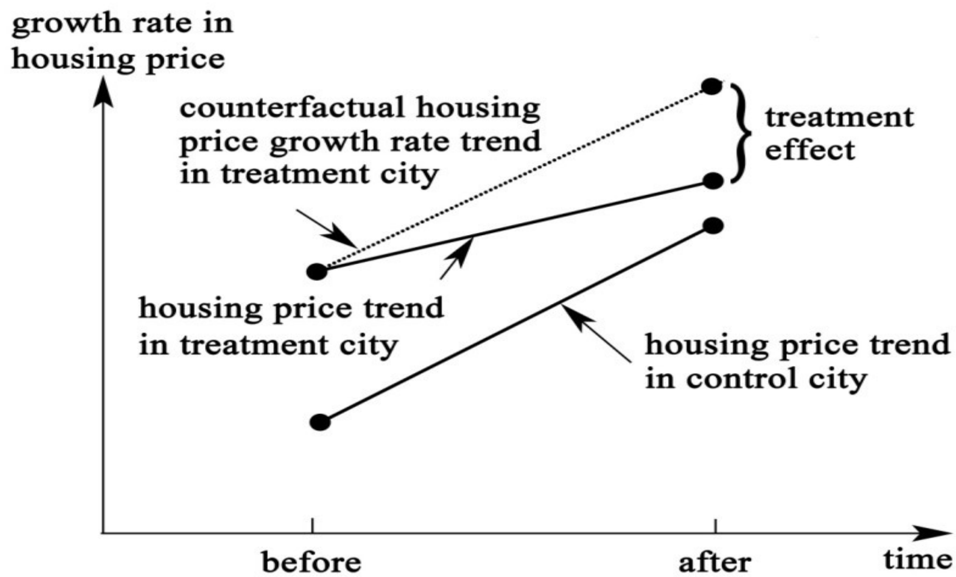

Figure 2.3. Causal effects in the difference-in-differences model

The DD method allows for different treatment intensity across cities. After the issuance of the LTV policy, the cities whose LTV limits remain unchanged are regarded as the control group cities; the cities whose LTV limits change with the new policy requirements are regarded as the treatment group cities. The key identifying assumption is that, without treatment, house price trends would be the same in the control and treated cities. If, for example, after the release of a tightening policy, the growth rate of house prices decreases in the treatment group cities compared to the control group cities, it would be an indication that the policy has effectively slowed down house price growth. The design of DD method is shown in Figure 2.3.

2.3.2.1 Model Framework

Suppose that there are only two cities and two time periods. Let D be equal to 1 for treated units, the cities that actually implement new LTV limits, while for control cities where LTV caps remain unchanged, D is equal to 0. The time t is assigned to 1 for the post-treatment period and assigned to 0 for the pre-treatment period. There are four potential outcomes, $Y_{dc}(t)$, where d denotes whether the treatment is imposed in city c or not. $Y_{1c}(0)$ is the house price growth rate that city c attains before an LTV ratio policy roll-out if the city will change the current LTV ratio at $t = 1$ according to the new policy; $Y_{0c}(0)$ represents the house price growth rate that city c attains before a policy roll-out if the city would then maintain the current LTV level. Similarly, $Y_{1c}(1)$ and $Y_{0c}(1)$ imply the potential house price growth rate in city c after a policy is introduced.

Then the causal effect can be defined as:

$$\tau_{ct} = Y_{1c}(t) - Y_{0c}(t) \tag{2.1}$$

In order to study the situation at $t = 1$, the classic average treatment effect on the treated (ATT) is adopted, and the formula is as follows:

$$\tau_{ATT} = E[Y_1(1) - Y_0(1)|D = 1] \tag{2.2}$$

where $E(\cdot)$ is the conditional expectation operator.

Table 2.5 lists all the potential outcomes that can be observed. The problem is that

$E[Y_{0c}(1)|D = 1]$ is unknown. This is the average potential post-period outcome for treated cities in the absence of the treatment.

Table 2.5 Potential outcomes under the framework of the difference-in-differences model

Units/Periods	Post-period ($t = 1$)	Pre-period ($t = 0$)
Treated cities ($D = 1$)	$E[Y_1(1)|D = 1]$	$E[Y_0(0)|D = 1]$
Control cities ($D = 0$)	$E[Y_0(1)|D = 0]$	$E[Y_0(0)|D = 0]$

One way to solve this problem might be to use the potential outcomes of the treated before and after the policy release, but this approach is not appropriate. Assuming that $E[Y_0(1)|D = 1] = E[Y_0(0)|D = 1]$ and calculating the difference between $E[Y_1(1)|D = 1]$ and $E[Y_0(0)|D = 1]$ only gives the change in house price in the treated city during the whole period, which could be caused by many factors, not necessarily by the policy itself.

Another control strategy would be to use the potential outcomes of both treated and control cities in the post-period. Assume that $E[Y_0(1)|D = 1] = E[Y_0(1)|D = 0]$ and calculate the difference between $E[Y_1(1)|D = 1]$ and $E[Y_0(1)|D = 0]$. However, this approach is also inappropriate because the characteristics of the treated and control cities may be so different from the outset that the outcomes after the treatment occurs cannot be substituted for each other.

The third solution is to difference twice, namely the difference-in-differences method. Take into account the initial difference between the treated city and the control city, and assume that the house price growth in these two cities would follow parallel trends in the absence of the policy roll-out, changing at the same rate from $t = 0$ to $t = 1$, that is, $E[Y_0(1) - Y_0(0)|D = 1] = E[Y_0(1) - Y_0(0)|D = 0]$.

By solving the common trends assumption for the counterfactual $E[Y_0(1)|D=1]$ and replacing in equation (2.2), the total difference is:

$$\tau_{ATT} = \{E[Y_1(1)|D=1] - E[Y_0(0)|D=1]\} - \{E[Y_0(1)|D=0] - E[Y_0(0)|D=0]\} \quad (2.3)$$

2.3.2.2 Model Estimation

The core of DD setup lies in the additive structure for potential outcomes in cities without treatment:

$$E(Y_{0ct}|c,t) = \gamma_c + \lambda_t \quad (2.4)$$

where Y_{0ct} represents the house price index in city c at time t in the absence of the policy release, γ_c is a time-invariant city effect and λ_t denotes a time effect being common across cities.

Let D_{ct} denote a dummy for the treated city after the intervention. Assume that $E(Y_{1c} - Y_{0ct}|c,t)\} = \tau(\text{constant})$, which is the policy effect, then the house price can be expressed as:

$$Y_{ct} = \gamma_c + \lambda_t + \tau D_{ct} + \varepsilon_{ct} \quad (2.5)$$

where ε_{ct} is the error term with zero mean, reflecting the idiosyncratic variation in potential outcomes across cities and time.

The ATT is derived as follows:

$$E(Y_{ct}|c = \text{untreated city}, t = \text{post period}) - E(Y_{ct}|c = \text{untreated city}, t = \text{pre period})$$
$$= \lambda_{\text{post}} - \lambda_{\text{pre}} \quad (2.6)$$

$$E(Y_{ct}|c = \text{treated city}, t = \text{post period}) - E(Y_{ct}|c = \text{treated city}, t = \text{pre period})$$
$$= \lambda_{\text{post}} - \lambda_{\text{pre}} + \tau \quad (2.7)$$

So, the difference-in-differences estimator is:

$$\begin{aligned}[E(Y_{ct}|c = \text{treated city}, t = \text{post period}) - E(Y_{ct}|c = \text{treated city}, t = \text{pre period})] \\ -[E(Y_{ct}|c = \text{untreated city}, t = \text{post period}) \\ -E(Y_{ct}|c = \text{untreated city}, t = \text{pre period})] \\ = \tau \qquad (2.8)\end{aligned}$$

As for the regression version of the DD model, in the simplest case, if there are two cities and two time points, the regression equation would be:

$$Y_{ct} = \alpha + \gamma Treat_c + \lambda Post_t + \tau D_{ct} + \varepsilon_{ct} \qquad (2.9)$$

where $Treat_c$ is a dummy variable equal to one for the treated city and zero for the control city; $Post_t$ is also a dummy variable equal to one after a new policy begins to take effect and zero otherwise. This is the classical DD model. An equivalent formulation could be:

$$Y_{ct} = \alpha + \gamma Treat_c + \lambda Post_t + \tau Treat_c \cdot Post_t + \varepsilon_{ct} \qquad (2.10)$$

However, if there are many cities and time points in the sample, then the regression equation needs to be generalised as:

$$Y_{ct} = \alpha + \gamma_c + \lambda_t + \tau D_{ct} + \varepsilon_{ct} \qquad (2.11)$$

where γ_c represents a full set of city effects and λ_t denotes a full set of time-period dummies controlling for time fixed effects. τ is the DD estimand of interest, which indicates the causal effect of a particular treatment.

2.4 Empirical Methods and Results

2.4.1 Specification

The following model is used to estimate the impact of LTV restrictions on housing prices:

$$HP_{i,t} = \alpha + \sum_{j=1}^{J_\beta} \beta_j LTV_{i,t-j} + \sum_{j=1}^{J_\gamma} \gamma_j X_{i,t-j} + \phi_t + \rho_i + \varepsilon_{i,t} \quad (2.12)$$

where $HP_{i,t}$ denotes the annualized quarterly growth rate in real house prices in city i at time t. The main explanatory variable is the LTV ratio limit ($LTV_{i,t-j}$), used to assess the lagged policy effects in the quarters following tightening and easing actions. This study borrows from Kuttner and Shim (2016) and adopts the general-to-specific approach to determine the appropriate number of lags. In particular, this means starting with four lags and gradually decreasing the lag length until the parameter estimates, individually or jointly, become statistically significant. This process produces a model with four lag periods for the dependent variable and four lag periods for the LTV caps. The coefficient β_j can be interpreted as the percentage change in house prices corresponding to a quarterly change of one percentage point in maximum LTV ratios. Regressions are run separately for LTV ratio policies applicable to borrowers who do not own properties and for borrowers who already own property. This is because the two types of LTV limits tend to be close to each other in terms of release times and are therefore interrelated.

$X_{i,t-j}$ represents a set of controls, including a series of lagged dependent variables and one-year lags of the resident population growth, the per capita disposable income growth and the registered urban unemployment rate. The population growth rate, the income growth rate and the unemployment rate are used to capture local macroeconomic conditions, which may have had an impact on housing demand. Due to data limitations, these three control variables have available annual data only, so their values from the previous year are used for regression, rather than using multiple lags. In addition, lagged house prices variables are also included in the estimation equation due to the inertia in house price growth (Case and Shiller, 1989). A related concern is that the use of the fixed effects estimator in a model with a lagged dependent variable may cause bias. However, Nickell (1981) argues that as the number of time series observations increases, the bias will decrease. Thus, given that the dataset contains observations obtained over 10 years, the magnitude of such bias would be small[3].

The growth rate version of the regression equation is used to avoid the nonstationary problem (Kuttner and Shim, 2016). The purpose of using real house price growth rate is to further eliminate the impact of inflation and ensure the stability of the data. ϕ_t denotes year dummies, incorporating the impact of the influence factors that are related only to different time points and not to the differences in characteristics between cities, such as national trends in time-varying economic variables. Although the regressions are based on quarterly data, year fixed effects are controlled for because economic conditions do not change much from quarter to quarter. City fixed effects ρ_i are also included to control for different trends in house price growth among cities (Sá 2016). According to Angrist and Pischke (2009), a regression DD model with panel data raises serial correlation. For repeated observations on cities, house price in a quarter is highly related to the prior quarter price, and an equivalent relationship holds for residuals. Therefore, clustered standard errors are used, which are heteroskedasticity-robust and clustered by cities to account for correlation within groups.

Moreover, the exposure measure has been increasingly used in studies of policy effects—Mian and Sufi (2012) measured the exposure of U.S. cities to the 2009 cash for clunkers program. This method takes into account the extent to which policies can affect economic

[3] The regressions without lagged dependent variables are also conducted, and the results seem robust. It can be confirmed that LTV restrictions do have a positive overall impact on house price growth within a period of four quarters following policy release. The results can be provided as needed.

variables and is therefore superior to the use of policy dummies in estimating policy effects. In this case, a policy which changes the ceiling on the LTV ratio by 20% is expected to have a larger effect than one which changes the LTV ceiling by 10%. In other words, the effect of each policy release will vary depending on the size of the policy intervention. Using dummy variables to represent policy announcements cannot capture the change in maximum allowable LTV ratios so it is impossible to accurately estimate the regulatory effect of the policy on house prices. The empirical strategy of the current study exploits the variations across Chinese cities in their exposure to the policy as measured by the actual change in LTV caps. If the hypothesis is borne out, the larger the LTV ratio limit adjustment, the greater the exposure will be.

2.4.2 Baseline Regressions

Table 2.6 and Table 2.7 report the implied four-quarter effects of LTV ratio policy applicable to first-time buyers and existing owner-occupiers, respectively, on the real price growth of newly constructed residential buildings made available for sale. The results for second-hand residential buildings are reported in Table A2.3 and Table A2.4 in the appendix.

Provident fund loans and commercial loans have no essential differences except for the lenders. Therefore, the shares (by total value) of these two kinds of home loans in the individual housing loan market are used to calculate a weighted average of LTV restrictions and observe the overall policy effect. The results for commercial (only) loans can be found in the appendix.

Table 2.6. Effects of loan-to-value limits for borrowers who do not own a property

	Real growth in prices of newly built houses			
	(1)	(2)	(3)	(4)
Loan-to-value caps lagged one quarter	0.337***	0.356***	0.220**	0.250***
	(0.075)	(0.072)	(0.092)	(0.087)
Loan-to-value caps lagged two quarter	-0.161***	-0.145***	-0.176***	-0.162**
	(0.043)	(0.040)	(0.064)	(0.061)
Loan-to-value caps lagged three quarter	0.092*	0.110**	0.075	0.094*
	(0.047)	(0.047)	(0.050)	(0.050)
Loan-to-value caps lagged four quarter	-0.057	-0.046	-0.001	0.016
	(0.045)	(0.045)	(0.034)	(0.038)
Real growth in house prices lagged one quarter	1.291***	1.210***	1.430***	1.339***
	(0.072)	(0.066)	(0.045)	(0.043)
Real growth in house prices lagged two quarter	-0.438***	-0.409***	-0.593***	-0.554***
	(0.067)	(0.063)	(0.061)	(0.059)
Real growth in house prices lagged three quarter	-0.051*	-0.042	-0.004	0.011
	(0.031)	(0.031)	(0.036)	(0.035)
Real growth in house prices lagged four quarter	-0.036	-0.080***	-0.034	-0.094***
	(0.025)	(0.023)	(0.033)	(0.030)
Overall policy effect over four quarters	0.212***	0.275***	0.118*	0.198***
	(0.057)	(0.056)	(0.067)	(0.065)
Long-run policy effect	0.906***	0.857***	0.585*	0.661***
	(0.230)	(0.169)	(0.348)	(0.237)
Observations	2799	2799	2799	2799
R^2 within	0.871	0.882	0.915	0.923
City trends	No	Yes	No	Yes
Weights	No	No	Yes	Yes

Notes: 1. Column (1) does not control for city trends or add any weights; column (2) controls for city trends; column (3) is weighted by population of each city; column (4) includes both city trends and weights. Regressions include city fixed effects, year fixed effects, lagged resident population, per capita disposable income of urban households and registered urban unemployment rate as control variables. For simplicity, the regression coefficients of control variables are not reported. Robust standard errors clustered by cities are in parentheses.

2. *** indicates significant at the 1% level; ** indicates significant at the 5% level; * indicates significant at the 10% level.

As shown in Table 2.6, changes in LTV caps for first-time buyers have a large, statistically significant, positive effect on prices in the next quarter after a policy is released, which is as expected. A drop in LTV caps slows down the pace of house price growth, whereas an increase in the maximum LTV ratio accelerates the growth of house prices. The overall effect of LTV limits in the four quarters immediately following policy changes is obtained by estimating the linear combination of coefficients on LTV lags. The results show that the overall policy effect over four quarters is highly statistically significant. According to column (1), on impact, the annualized growth rate in real house prices decreases by about 0.212% in a year in which the LTV cap is reduced by one percentage point. The regression results are robust. The results are not significantly affected by the inclusion of city-specific trends or weighting of the equation by population size. Moreover, the study also examines the long-term impact of the LTV policy. Since the house price in the long run is equal to the equilibrium house price, the regression equation can be written as $HP_i = \sum_{j=1}^{4} \beta_j LTV_{i,t-j} + \sum_{j=1}^{4} \gamma_j HP_i$. By combining the house price on both sides, the effect of the policy on the house price is represented by a nonlinear combination of parameter estimates, that is, $(\sum_{j=1}^{4} \beta_j) / (1 - \sum_{j=1}^{4} \gamma_j)$. The results suggest that a one-percentage-point reduction in the LTV ceiling reduces real house price growth by 0.906% over the long run. Given that the typical adjustment to China's LTV ratio limit is a change of 10 percentage points, this implies a 9.06% reduction in long-term price growth.

The results for LTV restrictions applied to borrowers who own one property, and who wish to buy a second property are presented in Table 2.7. Compared with the estimated coefficients of the LTV caps for first-time buyers, changes in LTV caps for existing property owners have a much smaller, but statistically significant, impact on house price growth. The results show that a one-percentage-point drop in maximum LTV ratios leads to the house price growth rate falling by 0.044% in a year and by 0.195% in the long run. When population weighted urban data are used, the overall effect of four lags of LTV caps and the long-run policy effect are statistically insignificant. A greater weighting to cities with large populations may exacerbate the endogeneity of LTV changes and housing market conditions. Large cities are more likely to reduce the LTV ratio on their own when house prices are already rising rapidly, resulting in a negative correlation between the LTV limit and house prices, which obscures the actual effect of the policy. It can also be seen that the results become more significant with city trends. The inclusion of the interaction term of city and time relaxes the common trends assumption and allows different cities to have non-parallel evolution in house prices in the absence of an LTV

Table 2.7. Effects of loan-to-value limits for borrowers who own one property

	Real growth in prices of newly built houses			
	(1)	(2)	(3)	(4)
Loan-to-value caps lagged one quarter	0.065***	0.067***	0.045***	0.049***
	(0.012)	(0.011)	(0.016)	(0.015)
Loan-to-value caps lagged two quarter	0.030***	0.033***	0.018*	0.022**
	(0.009)	(0.009)	(0.010)	(0.009)
Loan-to-value caps lagged three quarter	-0.086***	-0.065***	-0.079***	-0.061***
	(0.010)	(0.010)	(0.012)	(0.012)
Loan-to-value caps lagged four quarter	0.035**	0.056***	0.037**	0.061***
	(0.017)	(0.015)	(0.015)	(0.017)
Real growth in house prices lagged one quarter	1.302***	1.217***	1.431***	1.338***
	(0.071)	(0.065)	(0.045)	(0.043)
Real growth in house prices lagged two quarter	-0.448***	-0.419***	-0.589***	-0.549***
	(0.063)	(0.059)	(0.055)	(0.052)
Real growth in house prices lagged three quarter	-0.079***	-0.071***	-0.035	-0.024
	(0.025)	(0.025)	(0.030)	(0.030)
Real growth in house prices lagged four quarter	-0.001	-0.043**	-0.005	-0.060**
	(0.023)	(0.021)	(0.028)	(0.028)
Overall policy effect over four quarters	0.044*	0.091***	0.020	0.071***
	(0.025)	(0.019)	(0.024)	(0.024)
Long-run policy effect	0.195*	0.288***	0.103	0.242***
	(0.110)	(0.060)	(0.122)	(0.086)
Observations	2799	2799	2799	2799
R^2 within	0.872	0.884	0.916	0.925
City trends	No	Yes	No	Yes
Weights	No	No	Yes	Yes

Notes: 1. Column (1) does not control for city trends or add any weights; column (2) controls for city trends; column (3) is weighted by population of each city; column (4) includes both city trends and weights. Regressions include city fixed effects, year fixed effects, lagged resident population, per capita disposable income of urban households and registered urban unemployment rate as control variables. For simplicity, the regression coefficients of control variables are not reported. Robust standard errors clustered by cities are in parentheses.

2. *** indicates significant at the 1% level; ** indicates significant at the 5% level; * indicates significant at the 10% level.

ratio policy release.

It makes sense that the regression results show that LTV restrictions on first-time buyers have a bigger impact on prices than restrictions on existing homeowners. This is the case because the greatest obstacle to buying for first-time buyers is obtaining a large enough mortgage (affected by deposit size and available LTV rates), whereas people owning other homes will commonly have sufficient equity in their existing property to ensure that LTV is less of a barrier.

For a better understanding of how the response of house prices to LTV ceiling shock changes over time, the local projections method proposed by Jordà (2005) is used to directly estimate impulse responses at different time points. Unlike a vector autoregression, this method avoids the need to identify all unknown influencing factors and multivariate dynamic processes. The approach was also applied by Favara and Imbs (2015) and by Sá (2016) to analyze the effect of shocks on house price growth. The former studied a shock to credit supply while the latter studied a shock to foreign investment. Local projections are made by estimating sequential regressions of the endogenous variable shifted forward. The dependent variable is used as a lead factor because LTV ratio restrictions only affect future housing transactions from the time they are in place:

$$HP_{i,t+h} = \alpha + \beta^h LTV_{i,t} + \gamma X_{i,t-1} + \phi_t + \rho_i + \varepsilon_{i,t} \tag{2.13}$$

The vector of estimates $\{\beta^h | h = 0,1, \dots\}$ measures the impact of LTV ratio policy on house price growth at horizon h, giving a visual representation of how the effect of an LTV policy shock changes over time. Figure 2.4 presents the impulse responses of the real house price growth rate over a period of eight quarters.

The impacts of these two kinds of LTV restrictions peak in the first quarter after implementation. The effect of an increase in LTV caps on house price growth for first-time buyers is fairly persistent and only fades away two years after the shock. When LTV limits are applied to existing property owners, the regulatory effect on house prices is temporary, fading gradually and becoming insignificant two quarters after the change. Overall, limits on the LTV ratio for borrowers without homes have much bigger and longer-lasting effects on house prices than those applied to people who already own a property.

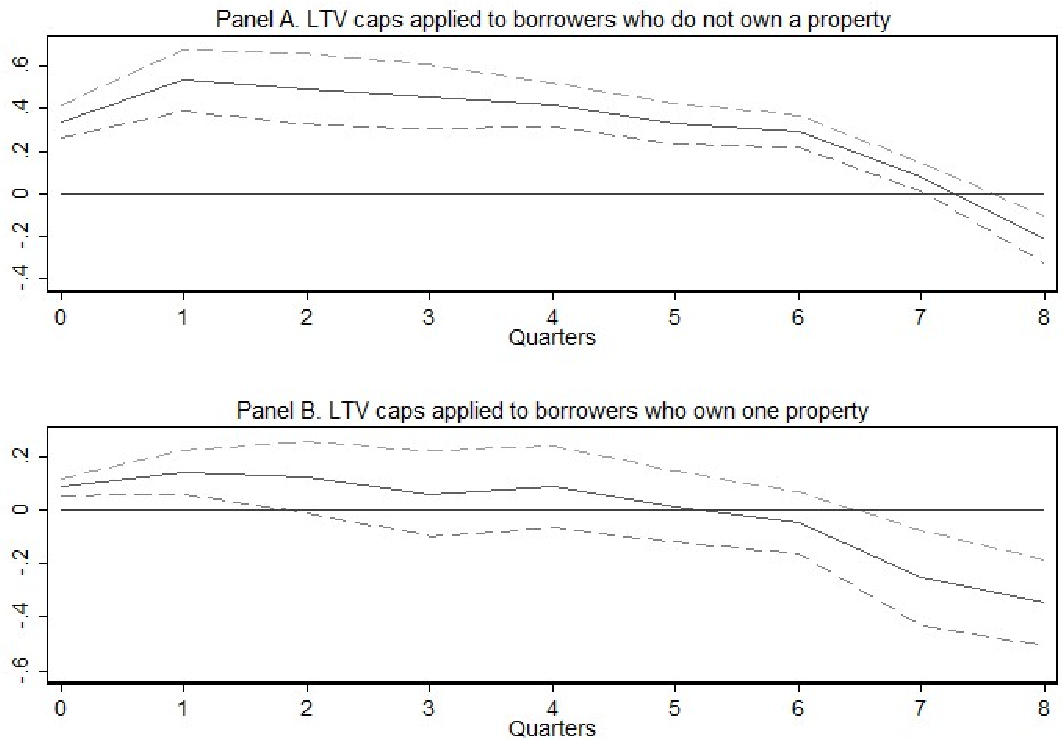

Figure 2.4. Impulse responses of house price growth rate to shock to loan-to-value caps
(dashed lines are 90% confidence bands)

Note: The figure shows estimated coefficients and 90% confidence interval from local projection equations, which investigates the impact of a change in LTV ratio caps on real house price growth for eight quarters after the shock. The sample comprises 70 cities in China for the period 2007–2016. Regressions include city fixed effects, year fixed effects, lagged real house price growth rate, resident population, per capita disposable income of urban households and registered urban unemployment rate as control variables.

2.4.3 Evidence Obtained by Classical Difference-in-Differences Model

The evidence already presented shows that LTV ratio policy has a regulating effect on the growth rate of house prices. However, there may be concerns that the results of the fixed effects model are affected by endogeneity problems causing the parameter estimation to be biased and resulting in the coefficients being deemed unreliable measures of policy effectiveness. Specifically, local governments in cities with rapidly escalating house prices tend to introduce more policies to control housing prices, whereas local governments in cities with slowly rising house prices lack the incentive to frequently adjust LTV ratio caps.

It would be possible to use an instrumental variable to replace the endogenous regressors, but it is difficult to identify an exogenous source of variation for the policy variables. Fortunately, the consequence of endogeneity in this case is that the estimates understate the effectiveness of the policy (Kuttner and Shim, 2016). As long as LTV policy is found to have a restrictive effect on the housing price, it can be concluded that the policy must be effective, and the actual effect can only be greater. Consider a tightening action of the LTV policy, for example. If the tightened LTV requirement had the effect of moderating house prices, it would reduce the rate of growth, other things being equal. But if policymakers were inclined to tighten LTV limits when the housing market was already overextended, the LTV cap and house prices would be inversely correlated, offsetting the observed policy effects. Therefore, the endogeneity bias in the relation between housing price and LTV policy does not change the basic conclusion that LTV restriction effectively controls house price growth.

In order to address the potential impact of endogeneity, the classical DD model is used to conduct a robustness check. To do so, the following equation is applied at two time points before and after a national LTV policy roll-out:

$$HP_{i,t} = \alpha + \gamma Treat_i + \lambda Post_t + \tau Treat_i * Post_t + \varepsilon_{i,t} \tag{2.14}$$

where $Treat_i$ represents a dummy variable which is assigned a value of 1 for the treated cities in which mortgage LTV caps have been changed by the policy, otherwise values are 0; $Post_t$ represents another dummy variable assigned a value of 0 before an LTV policy announcement and 1 after a policy announcement. An interaction term is included to indicate treated cities after the intervention, and coefficient τ is the policy effect of interest.

The model includes only the effect of LTV policies issued by the central government because the country is unlikely to make national-level policies based on the situation of any particular regional real estate market. As a result, serious endogeneity problems are avoided. Table 2.8 and Table 2.9, respectively, show the results for tightening and loosening LTV policies imposed by the Chinese central government for commercial housing loans.

Table 2.8. Difference-in-differences regressions for tightening loan-to-value policies

	Real growth in prices of newly built houses			
	(1)	(2)	(3)	(4)
Treat	-0.079***	-0.080***	-0.040***	-0.039***
	(0.010)	(0.011)	(0.004)	(0.011)
Post	0.004***	0.004***	0.073***	0.073***
	(0.000)	(0.000)	(0.000)	(0.000)
Treat*Post	-0.020***	-0.042***	-0.038***	-0.041***
	(0.004)	(0.012)	(0.009)	(0.005)
Observations	140	38	140	38
R^2 within	0.022	0.397	0.084	0.212

Notes: 1. Columns (1) and (2) give the response of real house price growth rates to the policy which reduced the LTV cap applied to commercial loans for borrowers who do not own a property from 80% to 70% on April 17, 2010, where column (2) adopts the propensity score matching technique; columns (3) and (4) show the response of real house price growth rates to the policy which reduced the LTV cap applied to commercial loans for borrowers who already own one property from 80% to 60% on January 10, 2010. Column (4) adopts the propensity score matching technique. Robust standard errors clustered by cities are in parentheses.

2. *** indicates significant at the 1% level; ** indicates significant at the 5% level; * indicates significant at the 10% level.

Table 2.8 shows the impact of two nationwide policies tightening LTV restrictions on house price growth that were launched on April 17, 2010, and on January 10, 2010, for first-time homebuyers and for existing property owners, respectively. Within the framework of the DD model, the control group consists of cities that had already implemented even tougher LTV restrictions than the new nationwide LTV caps mandated by the policy. For these cities, LTV ratio limits did not change after the nationwide policy was introduced. The treated cities were implementing higher LTV ceilings than the reduced level of maximum LTV ratios set by the new policy, so became subject to the new, lower LTV limits and decreased their LTV ceilings accordingly. In this case, the estimated policy effect $\hat{\tau}$ is expected to be negative (that is, tightening LTV ratio policy reduces the real growth rate of house prices). The results shown in columns (1) and (3) in Table 2.8 confirm this prediction. The negative coefficients on the interaction term are statistically significant at the 1% level.

One concern with regard to the DD approach is whether rising property prices in Chinese cities violate the DD model's assumption about parallel trends. To address this concern, the propensity score matching (PSM) technique is adopted to select the treated cities whose house price growth trend is similar to that of the control cities. This is done so that the cities in the control group and the treatment group had parallel average growth trends in the period before the policy was issued. PSM can help reduce the bias caused by confounding variables that have been observable in an estimate of the treatment effect simply by comparing the results of units receiving treatment with those not receiving treatment. According to the results shown in columns (2) and (4) of Table 2.8, the effect of LTV policy is still highly significant when the sample is controlled for price growth trends.

Another noteworthy aspect is that the subsample selected by the PSM technique is unbalanced. For both tightening LTV policies, only Beijing is used as a control city; all the other cities are treated cities affected by these policies. Because the timing of each of the two policy announcements is very close, the past trajectory of house price growth of the control city has been similar. The same set of treated cities is therefore selected for assessing the impact of these two policies based on the graphs presented in Figure 2.5.

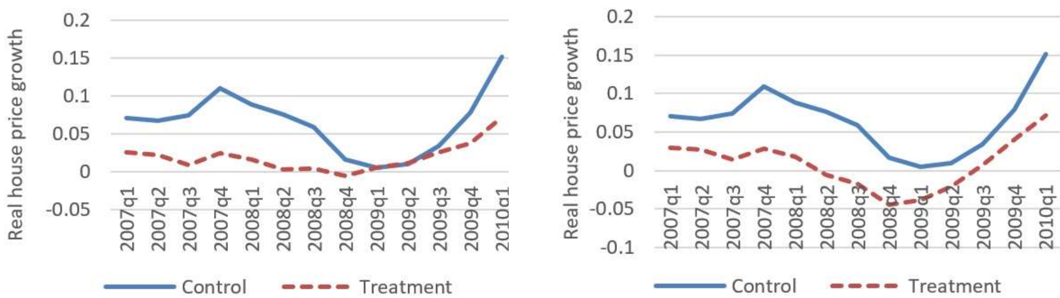

Figure 2.5. Price trends with and without propensity score matching (tightening policies)

Note: The graph on the left shows the price growth rate of the control city, Beijing, and the average growth rate of treated cities based on the whole sample of 70 cities as of the first quarter of 2010; the graph on the right shows the price growth rate of the control city, Beijing, and the average growth rate of the treated cities selected by propensity score matching technique as of the first quarter of 2010.

Table 2.9 shows the DD regression results with dummy variables for national policies on loosening LTV ratios introduced on October 22, 2008 and on February 2, 2016. Loosening policies issued by the central government take into account cities' intention to relax LTV limits. When such a policy is introduced, eligible cities that intend to relax credit restrictions will be able to raise their LTV caps according to the new scheme. For the LTV policy released on October 22, 2008, only Beijing is used as a control city. The Beijing municipal government introduced an LTV limit of 70% for first-time buyers in January 2006 and maintained it until September 2016. This is why Beijing did not change its LTV cap in response to the identified national-level changes. For the policy announced on February 2, 2016, the control group includes four cities—Beijing, Guangzhou, Shenzhen, and Shenyang. These cities had maintained 30%–35% LTV caps on commercial loans for existing property owners since 2013, despite the national-level changes.

Table 2.9. Difference-in-differences regressions for loosening loan-to-value policies

	Real growth in prices of newly built houses			
	(1)	(2)	(3)	(4)
Treat	-0.054***	-0.055***	-0.163*	-0.115
	(0.004)	(0.012)	(0.089)	(0.096)
Post	-0.054***	-0.054***	0.065	0.065
	(0.000)	(0.000)	(0.046)	(0.050)
Treat*Post	0.055***	0.043***	0.015	0.144**
	(0.004)	(0.007)	(0.047)	(0.061)
Observations	140	40	140	30
R^2 within	0.017	0.056	0.294	0.403

Notes: 1. Columns (1) and (2) give the response of real house price growth rates to the policy which increased the LTV cap applied to commercial loans for borrowers who do not own a property from 70% to 80% on October 22, 2008, where column (2) adopts the propensity score matching technique; columns (3) and (4) show the response of real house price growth rates to the policy which increased the LTV cap applied to commercial loans for borrowers who already own one property from 60% to 70% on February 2, 2016. Column (4) adopts the propensity score matching technique. Robust standard errors clustered by cities are in parentheses.

2. *** indicates significant at the 1% level; ** indicates significant at the 5% level; * indicates significant at the 10% level.

Columns (1) and (3) in Table 2.9 report the ordinary results for each of the two national-level changes. It can be seen that the two loosening LTV policies have a positive impact on house price growth (that is, they effectively encourage faster price rises in treated cities). The house price trends of the control group and the treatment group with and without the PSM method before the two loosening policies was issued by the central government are shown in Figure 2.6. The effect of the policy announced on October 22, 2008 is statistically significant at the 1% level. For the LTV policy announced on February 2, 2016, the coefficient of the interaction term in column (3) is not statistically significant; however, it becomes significant at the 5% level when the PSM technique is applied to ensure parallel trends in house price growth between cities to the extent possible.

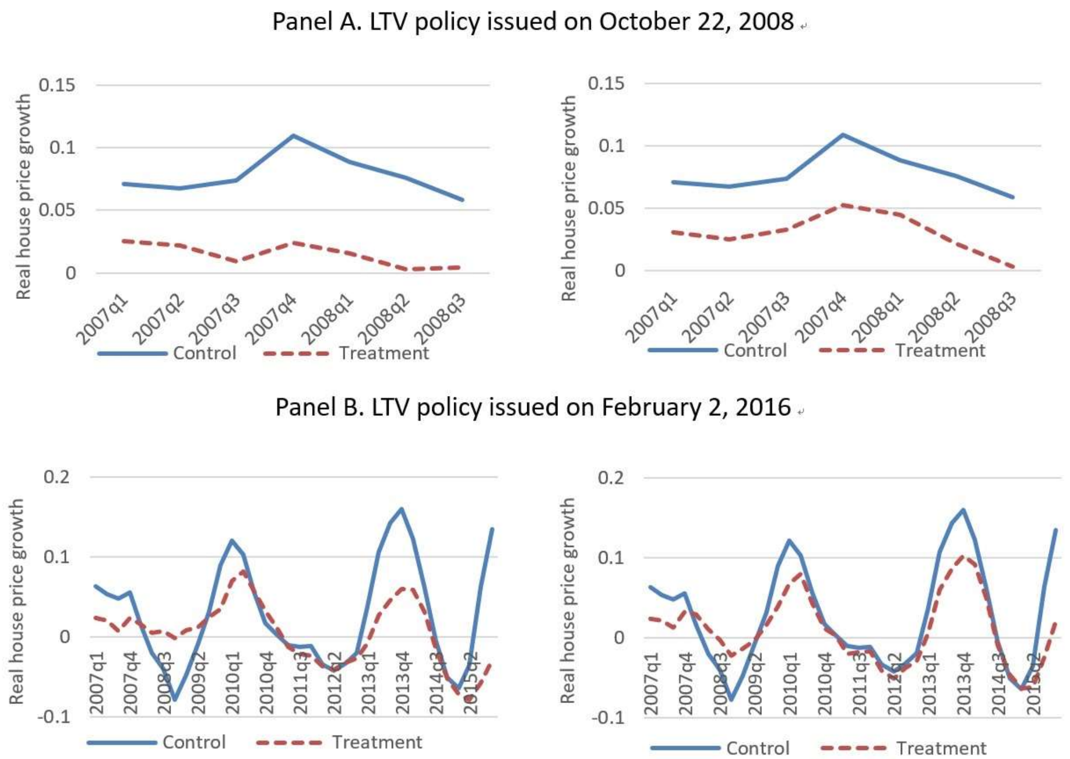

Figure 2.6. Price trends with and without propensity score matching (loosening policies)

Note: The graph on the left shows the average price growth rate of control cities and the average growth rate of treated cities based on the whole sample of 70 cities; the graph on the right shows the average price growth rate of control cities and the average growth rate of the treated cities selected by propensity score matching technique.

Since the central government is likely to pay more attention to the situation of big cities when making national-level policies, a robustness check is conducted by first removing the four first-tier cities—Beijing, Shanghai, Guangzhou and Shenzhen. Then, the median of the difference between national LTV and city LTV is used to distinguish between the control and treatment groups. The cities in which the change in LTV caps is below the median are used as a control group; the cities in which the change in LTV caps is above the median are used as a treatment group. This confirms the earlier findings that LTV policy can play a role in regulating housing prices. The results are reported in Table A2.7 in the appendix.

2.4.4 The Asymmetry of the Policy Effect

Loosening and tightening LTV policies are usually carried out at different stages of the economic cycle so the effects can be asymmetric. On the one hand, when caps on LTV ratios are reduced, the availability of credit for potential homebuyers will be more limited putting real constraints on them. On the other hand, increases in LTV caps tend to occur during economic downturns. Despite the availability of bigger loans, households may be reluctant to buy properties because they feel constrained by factors other than the LTV ratio, for example a future decrease in house prices or low wages that could make paying the mortgages difficult. As a result, LTV cap easing might be less effective than LTV cap tightening. Igan and Kang (2011), McDonald (2015) and Kuttner and Shim (2016) all found that loosening LTV policies have done little to boost the housing market, whereas tightening LTV policies have effectively curbed price growth.

To test this hypothesis, house price growth rate is regressed on the lags of changes in LTV caps using the following model, conducted separately for tightening and loosening policies:

$$HP_{i,t} = \alpha + \sum_{j=1}^{J_\beta} \beta_j \Delta LTV_{i,t-j} + \sum_{j=1}^{J_\gamma} \gamma_j X_{i,t-j} + \phi_t + \rho_i + \varepsilon_{i,t} \tag{2.15}$$

With regard to tightening policies, the policy variable has a negative value in the quarter when LTV caps are reduced, and zero in other periods; for loosening policies, the policy variable is positive in the quarter when LTV caps are raised, and zero in other periods. The results for asymmetric effects are presented in Table 2.10 and Table 2.11.

By using the actual change of LTV caps, more statistically significant results are obtained than in previous studies that used dummies to represent policy changes. The effects of LTV policies on first-time buyers and on existing property owners are examined separately. Overall, LTV limits for first-time buyers have a greater effect on house price growth rate than for existing property owners. In terms of the asymmetry in the policy effect, the estimated impact of tightening LTV restrictions for borrowers who do not own a property is more statistically significant than the impact of loosening LTV restrictions. For the LTV policy which applies to borrowers who own one property, the impact of tightening LTV on house prices is significantly greater than that of loosening LTV over a period of four quarters following policy releases; the coefficient of tightening action is found to be statistically significant at the 1% level, whereas the coefficient of loosening action is not. The results show that LTV policies have been more effective in controlling price growth rates during real estate booms than in lifting the housing market out of downturns, which is consistent with the findings of Igan and Kang (2011); Kuttner and Shim (2016); and McDonald (2015). By tightening LTV limits, policymakers can sharply reduce home purchases during housing booms, especially home purchases by first-time buyers; price growth rates will not fully return to their former levels when restrictions are relaxed.

2.4.5 Supply Constraints

There are reasons to suspect that the degree to which house prices respond to changes in LTV limits may be influenced by supply conditions. When housing supply is subject to many regulatory or geographical restrictions, house prices can rise rapidly due to excessive demand. They cannot be lowered immediately by increasing the supply of property. As a result, in cities where the housing supply is quite inelastic, the implementation of mandatory restrictions on credit availability should reduce the growth rate of house prices to a greater extent.

Table 2.10. Asymmetric effects on house price growth rate of loan-to-value limits for borrowers who do not own a property

	Tightening				Loosening			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Loan-to-value caps lagged one quarter	0.598***	0.559***	0.486***	0.455***	0.129	0.249*	0.006	0.093
	(0.086)	(0.083)	(0.060)	(0.060)	(0.141)	(0.146)	(0.142)	(0.162)
Loan-to-value caps lagged two quarter	0.099**	0.105**	0.063	0.063	0.160*	0.235**	-0.000	0.062
	(0.048)	(0.048)	(0.049)	(0.050)	(0.089)	(0.091)	(0.100)	(0.110)
Loan-to-value caps lagged three quarter	-0.046	-0.069	-0.103***	-0.135***	0.134	0.276**	0.003	0.121
	(0.048)	(0.049)	(0.039)	(0.044)	(0.125)	(0.131)	(0.123)	(0.147)
Loan-to-value caps lagged four quarter	0.304***	0.296***	0.372***	0.345***	0.368***	0.467***	0.224***	0.309***
	(0.088)	(0.090)	(0.052)	(0.057)	(0.113)	(0.122)	(0.084)	(0.099)
Real growth in house prices lagged one quarter	1.289***	1.218***	1.422***	1.344***	1.302***	1.224***	1.426***	1.341***
	(0.074)	(0.070)	(0.044)	(0.041)	(0.069)	(0.063)	(0.039)	(0.037)
Real growth in house prices lagged two quarter	-0.428***	-0.408***	-0.582***	-0.557***	-0.466***	-0.439***	-0.604***	-0.572***
	(0.071)	(0.068)	(0.056)	(0.056)	(0.062)	(0.059)	(0.051)	(0.050)
Real growth in house prices lagged three quarter	-0.070**	-0.057*	-0.027	-0.006	-0.051	-0.037	-0.006	0.017
	(0.028)	(0.029)	(0.035)	(0.034)	(0.032)	(0.033)	(0.036)	(0.034)
Real growth in house prices lagged four quarter	-0.028	-0.069***	-0.015	-0.073**	-0.028	-0.072***	-0.030	-0.091***
	(0.025)	(0.023)	(0.032)	(0.029)	(0.026)	(0.024)	(0.032)	(0.029)
Four-quarter effect of the policy action	0.955***	0.891***	0.817***	0.728***	0.792*	1.227**	0.233	0.585
	(0.093)	(0.106)	(0.110)	(0.135)	(0.440)	(0.468)	(0.412)	(0.488)
Observations	2799	2799	2799	2799	2799	2799	2799	2799
R^2 within	0.874	0.884	0.918	0.926	0.870	0.882	0.915	0.923
City trends	No	Yes	No	Yes	No	Yes	No	Yes
Weights	No	No	Yes	Yes	No	No	Yes	Yes

Notes: 1. The dependent variable is the annualised quarterly growth rate in real house prices. The overall policy effect is the effect in the four quarters following LTV policy releases. The sample comprises 70 cities in China for the period 2007–2016. Regressions include city fixed effects, year fixed effects, lagged resident population, per capita disposable income of urban households and registered urban unemployment rate as control variables. For simplicity, the regression coefficients of control variables are not reported. Robust standard errors clustered by cities are in parentheses.

2. *** indicates significant at the 1% level; ** indicates significant at the 5% level; * indicates significant at the 10% level.

Table 2.11. Asymmetric effects on house price growth rate of loan-to-value limits for borrowers who own one property

	Tightening				Loosening			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Loan-to-value caps lagged one quarter	0.159***	0.142***	0.146***	0.129***	-0.000	-0.002	-0.022	-0.023
	(0.024)	(0.024)	(0.017)	(0.018)	(0.011)	(0.010)	(0.019)	(0.017)
Loan-to-value caps lagged two quarter	0.214***	0.204***	0.178***	0.169***	0.030*	0.032**	-0.005	-0.001
	(0.028)	(0.027)	(0.019)	(0.021)	(0.017)	(0.015)	(0.023)	(0.021)
Loan-to-value caps lagged three quarter	0.084***	0.088***	0.062***	0.068***	-0.044***	-0.044***	-0.067***	-0.068***
	(0.030)	(0.030)	(0.020)	(0.022)	(0.014)	(0.015)	(0.014)	(0.016)
Loan-to-value caps lagged four quarter	0.127***	0.116***	0.081***	0.071***	0.106***	0.099***	0.080***	0.072***
	(0.038)	(0.037)	(0.015)	(0.015)	(0.024)	(0.024)	(0.016)	(0.017)
Real growth in house prices lagged one quarter	1.305***	1.231***	1.421***	1.340***	1.321***	1.247***	1.445***	1.364***
	(0.068)	(0.064)	(0.041)	(0.040)	(0.070)	(0.065)	(0.040)	(0.037)
Real growth in house prices lagged two quarter	-0.432***	-0.409***	-0.560***	-0.533***	-0.492***	-0.469***	-0.627***	-0.602***
	(0.064)	(0.061)	(0.054)	(0.055)	(0.066)	(0.064)	(0.050)	(0.049)
Real growth in house prices lagged three quarter	-0.068**	-0.054*	-0.030	-0.006	-0.040	-0.028	0.001	0.024
	(0.026)	(0.027)	(0.036)	(0.035)	(0.033)	(0.034)	(0.038)	(0.036)
Real growth in house prices lagged four quarter	-0.025	-0.068***	-0.020	-0.080**	-0.026	-0.069***	-0.031	-0.091***
	(0.026)	(0.024)	(0.034)	(0.031)	(0.025)	(0.024)	(0.030)	(0.029)
Four-quarter effect of the policy action	0.584***	0.550***	0.467***	0.438***	0.091*	0.084	-0.014	-0.021
	(0.108)	(0.107)	(0.047)	(0.054)	(0.054)	(0.053)	(0.060)	(0.060)
Observations	2799	2799	2799	2799	2799	2799	2799	2799
R^2 within	0.876	0.885	0.919	0.926	0.872	0.882	0.917	0.924
City trends	No	Yes	No	Yes	No	Yes	No	Yes
Weights	No	No	Yes	Yes	No	No	Yes	Yes

Notes: 1. The dependent variable is the annualised quarterly growth rate in real house prices. The overall policy effect is the effect in the four quarters following LTV policy releases. The sample comprises 70 cities in China for the period 2007–2016. Regressions include city fixed effects, year fixed effects, lagged resident population, per capita disposable income of urban households and registered urban unemployment rate as control variables. For simplicity, the regression coefficients of control variables are not reported. Robust standard errors clustered by cities are in parentheses.

2. *** indicates significant at the 1% level; ** indicates significant at the 5% level; * indicates significant at the 10% level.

To test this hypothesis, estimates of housing supply elasticity of 35 first and second-tier cities in China from earlier studies are used. In a dataset from 1998 to 2009, Wang et al. (2012) stated that the national housing supply elasticity should be somewhere between 2.8 and 5.6, whereas Liu (2014) claimed that China's aggregate supply elasticity is 2.65. Their conclusions suggest that China's housing supply elasticity is significantly lower than the estimated supply elasticity of 7.3 in the United States (Green et al., 2005) during the same time period. This implies that China is more vulnerable to house price fluctuations. The main difference between the two studies is that Wang et al., (2012) included both current and one-year lagged housing price levels as explanatory variables, whereas Liu (2014) used only the lagged growth rate of house prices rather than the price level. This was done to avoid the impact on the estimation of non-stationarity caused by the time trend in price data, and to avoid the problem of endogeneity. For this reason, the model used by Liu seems to be more reliable in the estimation of housing supply elasticity.

The regression equation considering the impact of housing supply elasticity is shown in equation (2.16):

$$HP_{i,t} = \alpha + \beta LTV_{i,t-1} + \delta LTV_{i,t-1} * elasticity_i + \gamma X_{i,t-1} + \phi_t + \rho_i + \varepsilon_{i,t} \quad (2.16)$$

where the product of LTV limit and housing supply elasticity is added. The coefficient on this interaction term is expected to be negative because high elasticity of housing supply is assumed to lessen the effect of LTV policy. Table 2.12 and Table 2.13 present the regression results obtained by using Liu's (2014) estimation of housing supply elasticity in 35 first and second-tier Chinese cities.

Table 2.12. The impact of supply elasticity on the effectiveness of loan-to-value policy for borrowers who do not own a property

	Real growth in prices of newly built houses			
	(1)	(2)	(3)	(4)
Lagged loan-to-value caps	0.525***	0.653***	0.420***	0.554***
	(0.101)	(0.108)	(0.101)	(0.100)
Lagged loan-to-value caps × supply elasticity	-0.019**	-0.025***	-0.014*	-0.022**
	(0.008)	(0.008)	(0.008)	(0.009)
Lagged real house price growth	0.946***	0.880***	0.964***	0.906***
	(0.034)	(0.034)	(0.017)	(0.017)
Observations	1400	1400	1400	1400
R^2 within	0.845	0.858	0.878	0.886
City trends	No	Yes	No	Yes
Weights	No	No	Yes	Yes

Notes: 1. The sample comprises 35 cities in China for the period 2007–2016. Regressions include city fixed effects, year fixed effects, lagged resident population, per capita disposable income of urban households and registered urban unemployment rate as control variables. For simplicity, the regression coefficients of control variables are not reported. Robust standard errors clustered by cities are in parentheses.

2. *** indicates significant at the 1% level; ** indicates significant at the 5% level; * indicates significant at the 10% level.

For LTV caps applied to first-time buyers, the coefficient on the elasticity term is negative and statistically significant in all four regression models as shown in Table 2.12. This suggests that LTV ratio limits have a stronger effect on house prices in cities with a lower elasticity of housing supply. For LTV policies that restrict borrowers who own one property, the estimated coefficient on the elasticity term also has a negative value and becomes statistically significant when controlling for city trends as shown in columns (2) and (4) of Table 2.13.

The analysis in this study draw on studies by Adelino et al., (2012); Favara and Imbs (2015); and Sá (2016). These authors used data from the US and the UK to examine the impact of housing supply elasticity on the transmission of shocks to house prices. They found that house prices respond more strongly to shocks in areas where housing supply is less elastic (that is, high elasticity of supply helps reduce house price fluctuations), which is consistent with the results of this paper.

Table 2.13. The impact of supply elasticity on the effectiveness of loan-to-value policy for borrowers who own one property

	Real growth in prices of newly built houses			
	(1)	(2)	(3)	(4)
Lagged loan-to-value caps	0.135***	0.217***	0.125***	0.201***
	(0.018)	(0.021)	(0.018)	(0.023)
Lagged loan-to-value caps × supply elasticity	-0.001	-0.010***	-0.002	-0.009**
	(0.001)	(0.003)	(0.001)	(0.003)
Lagged real house price growth	0.953***	0.876***	0.966***	0.896***
	(0.035)	(0.033)	(0.015)	(0.017)
Observations	1400	1400	1400	1400
R^2 within	0.846	0.862	0.880	0.891
City trends	No	Yes	No	Yes
Weights	No	No	Yes	Yes

Notes: 1. The sample comprises 35 cities in China for the period 2007–2016. Regressions include city fixed effects, year fixed effects, lagged resident population, per capita disposable income of urban households and registered urban unemployment rate as control variables. For simplicity, the regression coefficients of control variables are not reported. Robust standard errors clustered by cities are in parentheses.

2. *** indicates significant at the 1% level; ** indicates significant at the 5% level; * indicates significant at the 10% level.

2.4.6 The Potential Impact of Home Purchase Restrictions

Grodecka (2020) points out that in the mortgage business, LTV requirements may not be the only constraint on potential homebuyers. Ignoring other potential constraints may lead to an overstatement of LTV’s effectiveness as a macroprudential policy tool. Grodecka developed a multi-constraint framework where borrowers were constrained by LTV limits and debt service-to-income limits and found that if borrowers were subject to both constraints, tightening LTV policy could actually push up house prices without changing the debt ratios. In China, there are no explicit debt service-to-income constraints.

Another widely used real estate policy in China is the home purchase restrictions (HPR) policy, which aims to curb speculative demand and rapidly increasing house prices. The HPR policy limits the number of homes each household can buy, regardless of their financial situation. On April 17, 2010, the State Council issued a notice on resolutely curbing soaring housing prices in some cities, pointing out that local governments may take temporary measures to limit the number of houses people can buy within a certain period. In the same month, Beijing established detailed rules for implementing the restriction, the first city to stipulate that each household could buy only one additional home. Other Chinese cities also began to introduce purchase restrictions. Among the 70 Chinese cities in the sample, 39 cities adopted HPR policies in late 2010 or early 2011. Except for four first-tier cities, including Beijing, Shanghai, Guangzhou, and Shenzhen, other lower tier cities lifted their purchase restrictions in 2014.

Considering the potential impact of the HPR policy, a dummy variable is added to the basic regression equation:

$$HP_{i,t} = \alpha + \sum_{j=1}^{J_\beta} \beta_j LTV_{i,t-j} + \sum_{j=1}^{J_\delta} \delta_j HPR_{i,t-j} + \sum_{j=1}^{J_\gamma} \gamma_j X_{i,t-j} + \phi_t + \rho_i + \varepsilon_{i,t} \quad (2.17)$$

where HPR_i denotes the home purchase restriction. If a city adopts HPR in a certain period, then HPR_i takes the value of 1; otherwise, it is 0. The application of the general-to-specific lag length selection procedure leads to a specification with four lags each of the LTV limit, the HPR policy and real house price growth. The coefficient on the HPR term is expected to be negative because HPR policy prohibits some potential buyers from buying houses, thereby cooling the real estate market and reducing house price growth; when the policy was lifted in 2014, these potential buyers could re-join the buying market thus pushing up prices.

The regression results obtained with and without the HPR dummy are compared and are shown in Table 2.14. The table shows that the estimates of LTV policy effect have hardly changed and remain highly significant after including the dummy variables for HPR policy,

Table 2.14. Potential impact of the home purchase restrictions policy on house price growth rate

	Without HPR				With HPR			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. LTV limits for borrowers who do not own a property								
Overall effect of LTV policy	0.212***	0.275***	0.118*	0.198***	0.206***	0.263***	0.114*	0.182***
	(0.057)	(0.056)	(0.067)	(0.065)	(0.056)	(0.056)	(0.063)	(0.065)
Overall effect of HPR policy					-0.001	-0.011***	0.001	-0.010***
					(0.003)	(0.003)	(0.003)	(0.003)
R^2 within	0.871	0.882	0.915	0.923	0.871	0.883	0.915	0.924
Panel B. LTV limits for borrowers who own one property								
Overall effect of LTV policy	0.044*	0.091***	0.020	0.071***	0.043*	0.085***	0.021	0.062**
	(0.025)	(0.019)	(0.024)	(0.024)	(0.023)	(0.020)	(0.021)	(0.024)
Overall effect of HPR policy					0.002	-0.008***	0.002	-0.008***
					(0.002)	(0.003)	(0.002)	(0.003)
R^2 within	0.872	0.884	0.916	0.925	0.872	0.884	0.916	0.925
Observations	2799	2799	2799	2799	2799	2799	2799	2799
City trends	No	Yes	No	Yes	No	Yes	No	Yes
Weights	No	No	Yes	Yes	No	No	Yes	Yes

Notes: 1. The dependent variable is the annualised quarterly growth rate in real house prices. The overall effect of LTV policy or HPR policy is the effect in the four quarters following policy releases. The sample comprises 70 cities in China for the period 2007–2016. Regressions include city fixed effects, year fixed effects, lagged real house price growth rate, resident population, per capita disposable income of urban households and registered urban unemployment rate as control variables. For simplicity, the regression coefficients of control variables are not reported. Robust standard errors clustered by cities are in parentheses.

2. *** indicates significant at the 1% level; ** indicates significant at the 5% level; * indicates significant at the 10% level.

proving that the original results are robust. Compared with the LTV ratio policy, the purchase restriction has a smaller impact on house prices and does not affect the effectiveness of LTV limits on regulating housing price growth. In columns (6) and (8), where city-specific trends are controlled for, significant negative coefficient on the HPR variable is obtained, implying that the adoption of this policy reduces the growth rate of housing prices.

2.5 Conclusion

This paper identifies the causal effect of the LTV ratio policy on house prices in selected cities in China. It uncovers some interesting results and the main findings are listed below.

First, a fixed effects model is used in panel regressions, including the LTV caps for the four quarters immediately following policy release. The LTV limits for both first-time buyers and for existing property owners are found to have a statistically significant positive impact on house price growth, which suggests that LTV ratio policy plays an important role in regulating house prices. Using the impulse response function, the results show that LTV caps for first-time buyers have a greater and more prolonged influence on house prices than for people who already own one property. In the former case, the effect lasts for about two years. For these two types of LTV ratio policy, their impacts on house prices peak in the first quarter following policy changes.

Second, the asymmetric effect of LTV policy is studied. Tightening actions seem to have a bigger impact on house prices than loosening actions, probably because housing supply is rigid downwards. If the government relaxes LTV constraints, property developers may respond by building more homes. The increase in housing supply will reduce the upward pressure on house prices. When the government tightens LTV constraints, demand for homes decreases, but the housing stock is not destroyed. As a result, price growth tends to slow sharply.

The results demonstrate that the elasticity of housing supply affects the effectiveness of LTV ratio policy. The more elastic the housing supply is, the sooner the price fluctuation can be smoothed out. Therefore, the impact of LTV policy on house prices is smaller in cities with an elastic housing supply. Typically, there is a statistically significant negative coefficient for the interaction term of LTV cap and supply elasticity when controlling for city-specific trends.

Based on the results obtained, the following policy recommendations are proposed. Since the effect of LTV limits for first-time homebuyers can last for almost two years, these policies do not need to be adjusted frequently. On the other hand, the LTV limits applied to existing property owners only have an impact on prices for two quarters, so the government could consider introducing such policies more frequently or combining them with other real estate policies to curb speculation. Also, given that LTV policies are particularly effective in dealing with rising property prices, the government should focus on using them to stabilise prices during the housing boom. Furthermore, as cities with low housing supply elasticity are more affected by house price fluctuations and the implementation of LTV restrictions has a greater effect, local governments in these regions should consider strengthening the use of LTV ratio policies to regulate house prices.

Chapter 3

The Effects of the Loan-to-Value Ratio Policy: Evidence from Micro Data

3.1 Introduction

In the wake of the United States subprime mortgage crisis, many governments have attached great importance to the prevention of real estate credit risk and implemented a series of powerful policies aimed at eliminating the impact of the crisis and regulating the real estate market. Monetary policy, fiscal policy and macroprudential policy are all optional policy measures to achieve these objectives, but each of these measures will impose some costs and distortions on the economy, and its effectiveness and efficiency may be limited in practical implementation.

In response to the crisis, the Federal Reserve aggressively eased monetary policy, cutting interest rates and pumping liquidity into banks in an effort to stimulate the ailing economy and revive the housing market. However, while these measures lowered borrowing costs and boosted demand for loans, they had an impact on the economy as a whole, without taking into account the fact that some regions or sectors may not need stimulus and others may need more. On the other hand, containing a real estate boom by raising interest rates and reducing the money supply could lead to a huge output gap and widespread unemployment, paying a heavy price in terms of increasing systemic vulnerability and distorting macroeconomic indicators. In addition, as the transmission mechanism of monetary policy involves capital markets and various economic sectors, there is great uncertainty about how strongly and how quickly these effects will be transmitted. Those challenges have made monetary policy blunted in dealing with fluctuations in the housing market.

Fiscal tools may also be considered for the purpose of reducing volatility in the housing market, such as a cyclically adjustment to property taxes, transaction taxes or mortgage interest tax deductions. In a housing boom, raising taxes or curbing tax deductions would reduce demand for homes and thus prices, whereas in a housing bust, tax cuts or increased mortgage interest deductions would stimulate demand by reducing the cost of home ownership. Although housing-related fiscal policies can theoretically play a role in controlling house prices, their effects largely depend on a country's institutional setting in policy making, the characteristics of the tax system, the political considerations of local governments and the behaviour of home buyers (Crowe et al., 2013). When house prices rise sharply, households may not respond much to tax changes because the capital gains from rising prices are much greater than the cost of buying a home. Moreover, cyclical tax policies can cause economic distortion and impede the price formation process in the real estate market, which reduces market efficiency.

Another policy option is macroprudential regulation, which could in theory be designed to target households and more directly address the risks associated with housing market turbulence. Thus, the cost of more targeted measures such as LTV limits is lower than that of monetary or fiscal policy. As a widely used macroprudential tool, the maximum allowed LTV ratio affects housing demand by limiting the amount of mortgage available to homebuyers.

When house prices grow very fast, a lower LTV ratio could limit purchases made by liquidity-constrained households, dampening total market demand for housing and thus driving down prices. On the other hand, when the real estate market is depressed or housing inventories are overstocked, raising the LTV ratio could boost sales by providing more financing for households to buy homes. Studies have shown that the LTV ratio cap has advantages in promoting financial stability and improving social welfare over policies such as quantitative easing (Rubio, 2016; and Alpanda and Zubairy, 2017). This macroprudential tool facilitates the reallocation of assets to more productive firms and individuals and makes the financial system more resilient by reducing banks' exposure to credit risk. By restricting the leverage that homebuyers can use, banks will have greater assurance that borrowers are able and will continue to repay their loans, minimizing the risks and losses from mortgage defaults and preserving financial stability. Compared with monetary and fiscal policies, LTV rule for mortgages is a more effective and less costly way to reduce household indebtedness (Crowe et al., 2013; and Alpanda and Zubairy, 2017).

While the LTV ratio policy sets a limit on mortgage leverage in an effort to reduce housing demand pressures and financial system risk, its effect depends on the extent to which restrictions on bank loans have created financial hardship for potential homebuyers. Besides, soaring house prices could also ease restrictions on LTV, as homeowners can borrow more against the higher market value of their property. Therefore, it is necessary to evaluate the effect of LTV ratio policy in practical application. However, related studies are still in their infancy, most of which are based on the analysis of macro data or cross-country comparisons and have inherent endogeneity problems. Using data on China's housing market and a difference-in-differences technique, Chapter 2 finds that LTVs have a significant effect on the intensive margin, that is, house prices. The results show that caps on LTV ratios have been effective in tackling rising house prices, especially when applied to borrowers who only own one home. In this chapter, a fixed effects panel regression model is applied to further examine the policy impact on the extensive margin, that is, on the decision to buy a property, for single homeowners[4], which requires micro data. China's real estate market is selected to study the impact of LTV policy, because there are differences in LTV caps implemented in different regions of China, which enables a causal analysis of policy effects. Both central and local governments can impose restrictions on LTV ratios, and local property markets always enforce the tougher restrictions between national LTV requirements and local LTV requirements. As a result, the timing and intensity of LTV adjustments in China vary from region to region.

Some studies at the micro level show that LTV restrictions can affect home buying behaviour (Igan and Kang, 2011; Ho and Zhou, 2016; and Van Bekkum et al., 2019). Using calibrated general equilibrium models, Bajari et al. (2013) suggest that a tightening of LTV limits causes households to delay buying properties and relaxing credit limits encourages households to buy immediately, whereas Halket and Vasudev (2014) argue that a loosening action mainly makes people more inclined to buy larger houses instead of stimulating them to buy earlier, thus only resulting in small changes in homeownership. On the other hand, Tzur-Ilan (2020) adopts a difference-in-differences matching method to identify households with similar characteristics and compares the purchase decisions of households that are restricted by LTV limits with those that are not. She finds that property transactions in Israel

[4] The expression "single homeowners" refers to households that own only one home. In contrast, the expression "multiple homeowners" refers to households that own more than one home.

did not decline after LTV restrictions were introduced but borrowers with limited access to credit bought cheaper and smaller homes, moved further away from central business districts and opted for areas with poorer socio-economic conditions. In light of the above arguments, this paper explores the impact of LTV ratio policy on home ownership and the asymmetry of policy effect from an empirical perspective.

It has been shown that single homeowners, who are typically liquidity-constrained households and have relatively poor economic conditions, tend to be hit harder by an LTV policy shock (Ho and Zhou, 2016; Armstrong et al., 2019; Caloia, 2019; and Van Bekkum et al., 2019). In the specific context of China, the government implements differentiated home mortgage policies, and the LTV caps for single homeowners are generally higher than or equal to those for multiple homeowners. In the previous chapter, the analysis of the impact of China's LTV policies along the intensive margin also proves that LTV limits applied to borrowers buying their only home have a bigger and more lasting impact on the housing market. Therefore, this paper focuses on the buying decisions of such households. Data on LTV ratio limits for single homeowners from 2007–2016 are used in combination with publicly-available data from China Household Finance Survey which contains information on socio-demographic factors. The results demonstrate that an increase in LTV caps would make households more likely to buy homes, and vice versa. There is no statistically significant difference between the magnitude of impact of tightening and loosening LTV constraints on home ownership.

The paper then estimates the distributional effects of LTV policies, that is, how restrictions on access to credit affect heterogeneous households. Those most likely to be influenced are heavily indebted households or potential homebuyers seeking high LTV mortgages. In the literature on the impact of financial sector regulation, specific distributional consequences that arose from the use of policy instruments are largely neglected. However, because of the imperfection of financial markets in reality, it is impossible to be completely immune to household-specific shocks, and the distributional effects of macroeconomic fluctuations and related policy responses are magnified. These phenomena may be more pronounced in emerging economies where financial markets are still underdeveloped (Prasad 2013). Therefore, in the assessment of LTV policy, its distributional consequences, not just the aggregate consequences for the economy, must be carefully considered in order to gain a fuller understanding of the likely impact of the policy and to pay greater attention to household welfare.

Caloia (2019) proves that a tightening of the LTV standard for mortgage applicants is prompting more households to borrow at the limit. Van Bekkum et al. (2019) find a similar distributional shift in mortgage transactions by LTV. They also show that in the Netherlands, a drop in the LTV cap has led to fewer households seizing home ownership, with a massive decline among financially strapped households. Some other studies also look at the welfare implications arisen from an LTV policy across income groups and age groups, such as Bajari et al. (2013), Guler et al. (2016), Ho and Zhou (2016) and Tzur-Ilan (2020). On the basis of previous studies, more demographic and personality factors, such as gender, education level, area of residence, risk preference, attention to economic and financial information, are included in this study to evaluate the distributional impact of LTV policy from multiple directions. It is found that the policy is more restrictive to households of older adults, which is consistent with the results of Igan and Kang (2011). In addition, the results indicate that LTV restrictions are more effective at reducing the probability of buying a home for less-educated households and for households in which the head and spouse have more siblings. Policy shocks in LTV ratios have a greater impact for households that are willing to take financial risks.

To the best of the author's knowledge, this paper is the first empirical study to cover both loosening and tightening LTV actions to fully examine the policy effects at the household level, allowing LTV limits to vary over time, whereas other empirical research related to the micro impact of LTV policy on households' credit and housing choices has only focused on the introduction of stricter LTV limits. In order to estimate the practical effects of LTV policy, Igan and Kang (2011), Godoy de Araujo et al. (2020) and Tzur-Ilan (2020) distinguish households that are restricted by tougher LTV limits from the ones that are not, and then compare the outcomes of the two groups to determine the sample average treatment effect. The key to applying this method is to ensure that the counterfactual outcomes of the treatment group can be well represented by the outcomes of the control group. Although they attempt to select treated and untreated households with similar characteristics, the matched households could still be very different in many unobservable ways. Rather than trying to match individual households, a logistic model is used to examine the impact of LTV ratio policies on the probability of buying a property where the policy applies. Based on regional variation in LTV caps in China, a fixed-effects analysis is conducted on panel data, comparing the outcomes of the provinces in which LTV requirements were changed with those in which LTV requirements remained constant.

Another contribution of this paper is the use of exposure measures reflecting the intensity of LTV interventions in the market. Previous empirical studies on the micro-implications of LTV policies use binary variables to indicate policy release, which could not quantify the intensity of policy actions and therefore could not provide detailed suggestions for future policies. Kelly et al. (2018) also point out that the magnitude of the policy effect is closely related to the stringency of LTV requirements and the timing of policy announcements.

The rest of the paper proceeds as follows. The next section provides detailed information on the data set. In Section 3, the empirical methods used to analyse the impact of LTV limits on home-purchase decisions are described and the results are presented. Section 4 concludes.

3.2 Data and Summary Statistics

The empirical analysis uses secondary data obtained from China Household Finance Survey (CHFS) which is jointly carried out by the Southwestern University of Finance and Economics and the People’s Bank of China. CHFS has collected information about household finance biennially since 2011, for example, housing assets and financial wealth, liabilities and credit constraints, income and consumption, demographic characteristics and employment. Specifically, it provides real estate information including home ownership, number of houses owned, floor area, housing acquisition cost and current value, home loan tenure and loan amount, and so on. As of 2017, CHFS covers 58,434 households nationwide, reflecting the basic situation of household finance in China comprehensively and objectively.

In primary data collection, the survey adopts a design method of three-stage, stratified sampling and probability proportional to size (PPS), collects and updates sample data through field trips and quarterly return visits by telephone, to ensure scientific and accurate source data. To be more precise, primary sampling units are selected randomly from cities/counties across the country; in the second stage, residential/village committees are directly sampled from cities/counties; finally, households are drawn from residential/village committees. PPS sampling method is used in each stage of sampling, whose weight is the number of households of a sampling unit. It plays a significant role in the selection of sample clusters. This is a method of sampling in which each unit has a probability of being selected in proportion to its size. The larger the size of a sampling unit is, the greater the chance of being selected becomes.

Table 3.1. Number of surveyed households

	Households that have participated since 2011	Households that have participated since 2013	Households that have participated since 2015	Households that have participated since 2017	Total
CHFS 2011	8438	-	-	-	8438
CHFS 2013	6846	21295	-	-	28141
CHFS 2015	5753	16022	15514	-	37289
CHFS 2017	4752	12084	9988	13187	40011

Source: China Household Finance Survey

The fieldwork for the first wave of the CHFS was carried out in 2011. The survey consists of observations on 8,438 households across 25 provincial-level administrative divisions (excluding Xinjiang, Tibet, Inner Mongolia, Ningxia, Fujian, Hainan, Hong Kong, Macao and Taiwan), 82 counties (municipal districts, county-level cities), and 320 village (neighbourhood) committees. In 2013, on the basis of tracking the 2011 sample, CHFS greatly expanded the sample to 29 provincial-level administrative divisions (excluding Xinjiang, Tibet, Hong Kong, Macao and Taiwan), 267 counties (municipal districts, county-level cities), and 1,048 village (neighbourhood) committees, with a total of 28,141 households. In 2015, CHFS expanded the sample again, covering 29 provinces (autonomous regions, municipalities directly under the central government), 351 counties (municipal districts, county-level cities) and 1,396 village (neighbourhood) committees, with a total of 37,289 households. The fourth wave of the survey in 2017 covered 29 provinces (autonomous regions, municipalities directly under the central government), 355 counties (municipal districts, county-level cities) and 1,428 village (neighbourhood) committees, with a sample size of 40,011 households.

The survey has a considerable sample size and good statistical representativeness. According to the Research Report of China Household Finance Survey, the demographics of the CHFS data are consistent with those released by the National Bureau of Statistics (NBS) in terms of household size, population age structure, sex ratio and per capita income. Amongst the numbers that have been published, the average income from the CHFS is slightly higher than that from the NBS. In addition, the distributions of income for the two data sets are further compared. As it can be seen from Figure 3.1, except for the top 10% of households, the distributions of per capita disposable income of urban residents in CHFS and NBS data sets are similar.

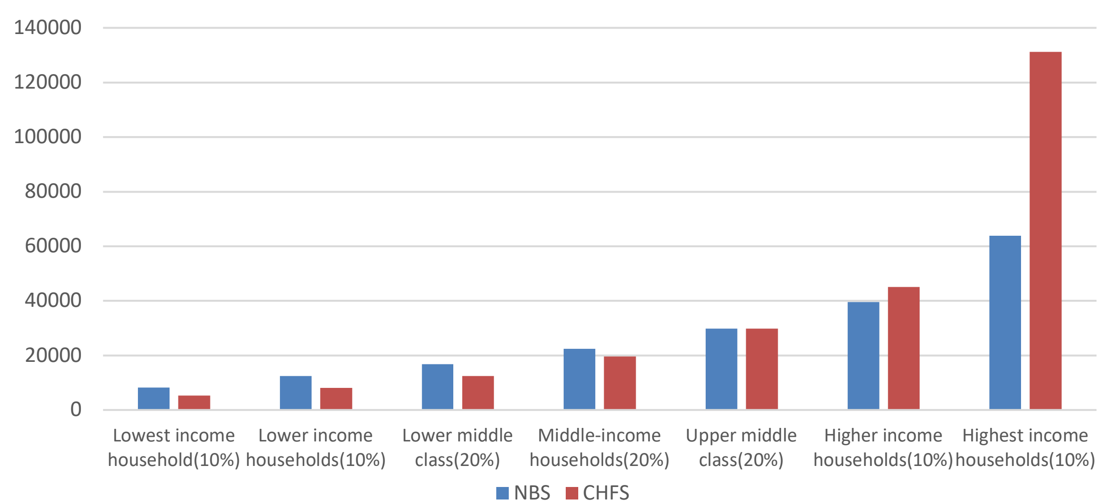

Figure 3.1. Per capita disposable income of urban residents in 2012 (unit: RMB)

Source: Author’s calculations based on data from China Household Finance Survey; the National Bureau of Statistics of China

LTV caps were collected manually from government policy statements issued by China's central and local authorities. The LTV limit of each province is a weighted average of the LTV limits of the cities located in that province, using the populations as weights.

3.2.1 Construction of Panel Data Set

The survey data for 2011, 2013, 2015 and 2017 are combined into one data file and sorted in panel data format.

Since households report the year in which they bought properties in each wave of the survey, the household ID and year are used to reorganize the cross-sectional survey data collected each year into a panel form. In this format, a data set of home purchases in China from 2007 to 2016 is established, which allows to assess the impact of LTV limits during housing booms and busts. However, the information contained in this data set may not be very accurate, as households can make errors when recalling past purchase experience. An ideal data set would consist of an annual survey covering the entire sample period, but based on the available data, this is the best that can be done.

Another noteworthy aspect is that the data set is unbalanced. In subsequent waves of CHFS, some households that had previously participated in the investigation were not included, while many new households were randomly selected to be interviewed. Households that had not bought any property are excluded from the data set because the focus is on households that were involved in the housing market and could be affected by mortgage lending limits. The observations on households are limited to the time period of the sample (2007–2016) from the year in which they bought their first home. In this study, heads of households are restricted to the working-age population aged 25-64 because of their high demand and affordability for housing.

3.2.2 Summary Statistics

Table 3.2 and Table 3.3 present the home purchases of the sample households included in the CHFS surveys and their breakdown by year. According to the number of houses owned, household types fall into three main categories: households that do not own their own homes, single homeowners and multiple homeowners. Single homeowners are those who owned only one home during the sample period, while multiple homeowners are those who owned more than one home during the sample period.

Table 3.2. Number of households by household type

	Households without houses	Single homeowners	Multiple homeowners	Total
Households that have taken part in the CHFS since 2011	514	5960	1964	8438
Households that have taken part in the CHFS since 2013	1470	15166	4659	21295
Households that have taken part in the CHFS since 2015	1332	10927	3255	15514
Households that have taken part in the CHFS since 2017	1810	9447	1930	13187
Total	5126	41500	11808	58434

Source: China Household Finance Survey

From Table 3.2, it can be seen that in each wave of the survey, single homeowners make up the largest proportion of the sample, accounting for about 70% of the total observations. And as mentioned above, LTV restrictions tend to have a greater impact on single homeowners due to their weak economic position relative to that of multiple homeowners. Therefore, the research focus of this paper is the change in the behaviour of this type of households.

Table 3.3. Number of houses purchased during 2007–2016

Year	Single homeowners	Multiple homeowners	Total
2007	1870	533	2403
2008	1936	657	2593
2009	1842	748	2590
2010	1736	805	2541
2011	1312	689	2001
2012	1598	936	2534
2013	1194	950	2144
2014	845	705	1550
2015	858	791	1649
2016	740	881	1621
Total	13931	7695	21626

Source: China Household Finance Survey

By breaking down the survey respondents' home purchases by year, Table 3.3 shows that the number of homes bought by single homeowners has fallen sharply since 2011, while the number of homes bought by multiple homeowners did not drop as much in 2011, and has since rebounded. Considering the changes of LTV ratio caps over time as shown in Figure 3.2, it can be found that the number of housing transactions made by single homeowners is roughly positively correlated with the maximum allowable LTV ratios. LTV limits had been tightened since 2010, followed by a decline in property transactions starting in 2011.

The weighted average LTV limits of 29 provinces, autonomous regions and municipalities in China are calculated. Figure 3.2 illustrates the changes of LTV ceilings for single homeowners in Beijing and Ningxia as an example. China's home finance system consists of the commercial home mortgage business and the Housing Provident Finance (HPF) Scheme. Compared with commercial loans, HPF loans have the advantages of lower interest rates and higher LTV caps, but they are also beset with the problems of complicated application process, long approval time and low loan amounts. Firstly, the weighted average LTV limits of the two types of housing loans in 70 large and medium-sized cities are calculated according to their market share (by total value). Then, for the four municipalities of Beijing, Shanghai, Tianjin, and Chongqing, they are cities in the same rank as provinces, so their LTV limits are directly the ones calculated in the first step. For other provinces and autonomous regions, the obtained LTV limits of cities in the same province are used to calculate the average LTV limit of that province, taking population as the weight and assuming that other cities in the province also follow the same path. As can be seen from Figure 3.2, after the financial crisis of 2007–08, the restrictions on maximum LTVs were relaxed for some time in order to stimulate the real estate market, and from 2010, LTV restrictions were tightened again to curb the excessive growth of house prices. In addition, as a city where housing prices are rising rapidly, Beijing has introduced many local LTV policies, and its LTV ceiling is usually lower than that of Ningxia province.

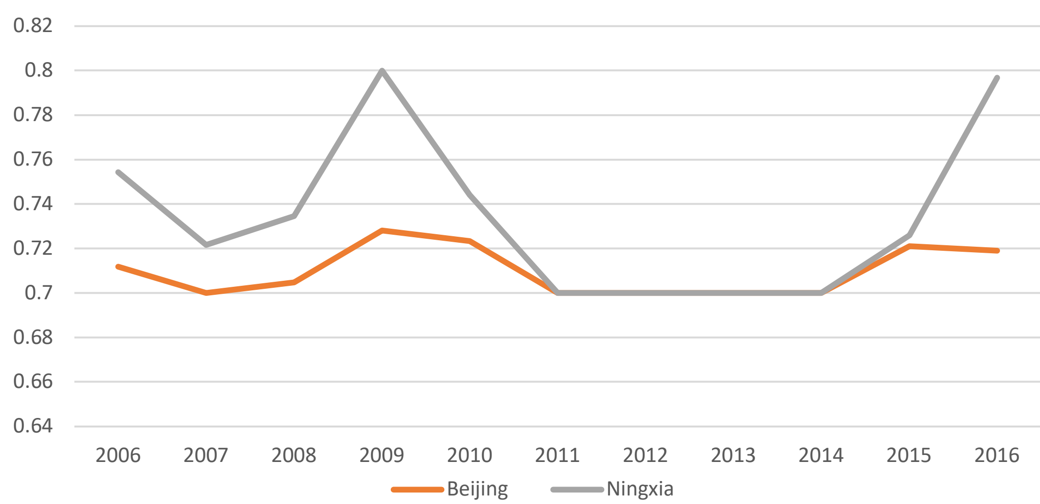

Figure 3.2. Changes in loan-to-value caps for single homeowners

Source: Author’s calculations based on official documents from government

The sample is limited to ages 25–64 and comprises 38,377 households. Table 3.4 tabulates descriptive statistics of the provincial LTV restrictions lagged by one year, the demographic variables for single homeowners and some attributes of the house that is bought. The definitions and descriptions of all variables are listed in Table A3.1 in the appendix.

Table 3.4. Descriptive statistics for key variables (2007–2016)

Variables	Obs	Mean	Std. Dev.	Min	Max
LTV cap	290	0.725	0.031	0.679	0.8
Deciding to buy	273358	0.043	0.203	0	1
Size of the house	10489	127.87	77.844	30	1000
Distance to city centre	986	40.677	47.718	0	720
Age	273358	47.087	10.13	25	64
Gender	273353	0.77	0.421	0	1
Education	273057	3.497	1.620	1	9
Siblings	209624	5.874	3.243	0	25
Type of hukou	267421	0.554	0.497	0	1
Area of residence	273358	0.326	0.469	0	1
Financial literacy	268909	3.941	1.109	1	5
Risk preference	255591	3.976	1.207	1	5

Source: Author's calculations based on policy documents about LTV lending criteria and data from China Household Finance Survey

LTVs fluctuated between 67.9% and 80% across 29 provincial-level administrative divisions over the 10-year period. The same LTV ceiling applies to households living in the same province. Households are observed each year, with a total of 273,358 observations in the sample. Households' decisions to buy are represented by a categorical variable that takes the value 1 if the household bought a house in a year, and 0 otherwise. On average, the probability of buying a home is 4.3%.

A total of 11,717 households headed by people aged between 25 and 64 purchased their only home during the sample period, of which 11,560 reported the size of their homes. The data collected by the questionnaire showed that the house size ranged from 12,000 square meters to just 1 square meter. Therefore, the largest 5% and the smallest 5% of houses were excluded in this study to eliminate outliers, and the average house size was 127.87 square meters. The distance from the house to the city/county centre is the number of minutes it takes to commute. A value of 0 indicates that the house is located in the centre of the city/county, while the furthest houses take up to 12 hours to reach the city/county centre. The average commute time is 41 minutes. Since only the 2011 survey questionnaire asked about the commuting time of the house from the city or county centre, the data volume of this variable was limited. There were 986 households that reported information on this variable.

Gender is defined as a dummy variable that has the value 1 for male householders, and 0 for female householders. Overall, male householders make up 77% of the sample. There are nine levels of education, with 1 representing no schooling and 9 representing a PhD. Statistics show that the number of households with a junior high school education level is the largest, followed by those with a primary school education level and those with a senior high school education level. The next variable is the number of siblings of the head of the household and his or her spouse. On average, the head of a household and his or her spouse have about six siblings.

In addition, China has adopted a unique system of household registration called hukou. It divides Chinese citizens into two categories: agricultural hukou holders or non-agricultural hukou holders. Hukou was originally classified by occupation, but as the system evolved, the distinction was not necessarily related to the holders' actual occupation. A dummy variable for household registration type is created, with a value of 1 if the head of household holds agricultural hukou status, and 0 if the head of household holds non-agricultural hukou status. The proportions of the two types of hukou holders in the sample are roughly equivalent. Another dummy is used to represent the area of usual residence of the household, with 1 indicating the rural area and 0 indicating the urban area. About 32.6% of observations are from rural areas.

CHFS also collects information on households' financial knowledge and subjective attitudes. One of the survey questions is how concerned the household is with economic and financial information on a scale of 1 to 5, with 1 being extremely concerned and 5 being not at all concerned. About 41% of respondents answered 5, and the average answer is 3.94. Another question has to do with the household's willingness to take financial risks in order to earn a corresponding level of return. On a scale of 1 to 5, with 1 representing "high-risk, high-return project" and 5 representing "unwilling to take any risks", households were asked to choose which project they would most like to invest in. Around 48% of respondents answered 5, and the average answer to this question is 3.98, suggesting that most households in the sample are risk averse.

3.3 Research Design and Empirical Results

3.3.1 Specification

The empirical strategy is designed to use cross-province variation in exposure to LTVs to assess the policy impact on home-purchase decision. The extent to which provinces are exposed to LTV ratio policies is measured by the actual changes in LTV caps. Specifically, provinces that experience larger changes in their maximum LTV ratios have greater exposure to the policy. This design allows for different treatment intensities and compares the buying behaviour of households in low and high LTV exposure provinces. The following logistic regression model is employed to explore the marginal effects of LTV adjustments:

$$buy_{i,p,t} = \alpha + \beta LTV_{p,t-1} + \phi_t + \rho_p + \varepsilon_{i,p,t} \tag{3.1}$$

where $buy_{i,p,t}$ denotes the home purchases made by single homeowners. It values 1 if household i in province p bought a house in year t, and otherwise values 0. $LTV_{p,t-1}$ is the LTV limit imposed in province p. The one-year lagged LTV is used because the survey data do not provide details such as at what point in the year the house was bought. Therefore, using the LTV for the current year risks relating the purchase to a future LTV. The coefficient β captures the effect of LTV policy. The marginal effect of the policy variable after logistic regression is estimated, which can be interpreted as the average percentage change in the probability of buying a house when the maximum LTV ratio increases by one percentage point.

Year dummies (ϕ_t) capture the impact of aggregate trends that change over time but are independent of the characteristics of the provinces. Province dummies (ρ_p) are included to control for factors that do not change over time but are related to the characteristics of each province. Controlling for the year fixed effects and the province fixed effects constructs compelling counterfactuals that validate the causal inference for policy evaluation. Moreover, since repeated observations on households in panel data cause serial correlation in residuals, heteroskedasticity-robust standard errors are calculated. They are clustered by province to account for correlation within groups.

The influence of LTV policy on household purchase decision is identified from spatial correlations between the LTV restrictions and changes in the probability of buying a house across provinces. Identification relies on variation in the LTV caps across provinces and time.

Next, the possible asymmetric effects of LTV tightening and loosening are studied. The tightening of LTV limits is likely to have a higher impact on house-buying decisions because it imposes a strict restriction on households' credit availability, which in turn limits their ability to buy. By building a theoretical model, Halket and Vasudev (2014) find evidence that a tightening of LTV limits on property loans reduces demand for owner occupied housing but a loosening of LTV limits fails to prompt households to buy houses, whereas Bajari et al. (2013) argue that a relaxed LTV policy effectively stimulates households to buy immediately. To discuss this controversial issue, the following model is estimated to examine the asymmetry of LTV policy effects:

$$buy_{i,p,t} = \alpha + \beta LTV_{p,t-1} + \gamma LTV_{p,t-1} * tightened_{p,t-1} + \phi_t + \rho_p + \varepsilon_{i,p,t} \tag{3.2}$$

where $tightened_{p,t-1}$ is coded as a binary variable, with 1 for tightened LTV limits and 0 otherwise. If the coefficient γ is positive and statistically significant, then the effect of LTV tightening is greater than that of LTV loosening.

Furthermore, the effectiveness of policy implementation also depends on the behaviour and characteristics of affected households. The estimation of the distributional impact of LTV policy is an important issue to be studied, which contributes to the growing literature on welfare evaluations. With a rich data set containing information on demographic factors, levels of financial literacy and subjective assessments of Chinese households, this study explores the impact of household level heterogeneity on the efficacy of LTV ratio caps across household age, gender, education level, number of siblings, registered residence type, area of residence, as well as risk preference, attention to economic and financial information. An interaction between the LTV and the demographic variable is included to see whether the LTV effect varies by any observable characteristics of households:

$$buy_{i,p,t} = \alpha + \beta LTV_{p,t-1} + \delta demogr_{i,p,t} + \theta LTV_{p,t-1} * demogr_{i,p,t} + \phi_t + \rho_p + \varepsilon_{i,p,t} \tag{3.3}$$

where $demogr_{i,p,t}$ is a set of household demographic factors. The coefficient θ indicates whether and how the impact of LTV restrictions on the buy decision depends on household demographic characteristics.

3.3.2 Baseline Regressions

Table 3.5 reports the results of estimating models (3.1) and (3.2). The preliminary results in column (1) suggest that there is a positive correlation between the LTV restriction and the probability of home purchase. The marginal effect of LTV variation is highly significant and has the expected sign: a more plentiful supply of credit would encourage households to buy, whereas a tighter restriction on credit would reduce home purchases. On impact, when the LTV cap increases by one percentage point, the probability of buying a house increases on average by 0.184%, holding other factors constant. That means changing the maximum LTV ratio by ten percentage points, as China's central and local governments typically do, would change the likelihood of buying a home by 1.84%. Compared with the average purchase probability of 4.3% presented in the sample, the change in the purchase probability caused by LTV accounts for a large proportion. The results indicate that the statutory LTV limits for

Table 3.5. Effects of loan-to-value limits on buying decision

	Deciding to buy	
	(1)	(2)
Lagged LTV limits	0.184***	0.180***
	(0.066)	(0.064)
LTV tightening		0.003
		(0. 008)
Observations	273358	273358
Number of clusters	29	29
R^2 within	0.014	0.014

Notes: 1. The sample includes 29 provincial-level administrative divisions in China for the period 2007–2016. The marginal effects of explanatory variables after logistic regression are shown in the table. Regressions include province and year fixed effects. Standard errors are clustered by province.

2. *** indicates significant at the 1% level; ** indicates significant at the 5% level; * indicates significant at the 10% level.

mortgage applications have a big impact on households' buying decisions, both statistically and economically. This is in line with Ho and Zhou (2016), who argue that adjustments at the extensive margin play a major role in judging the impact of LTV policy.

The estimates of column (2) of Table 3.5 are obtained from model (3.2) and show that there is no asymmetry in the effect of LTV ratio policy on home purchase. The estimated coefficient on the interaction term between the LTV limit and the dummy variable representing the tightening policy release is positive, but compared with the estimate of the LTV term, it is small in magnitude and does not reach statistical significance, indicating that there is no distinct difference between the effects of LTV tightening and LTV easing. The no asymmetry finding is in line with Bajari et al. (2013), that is, the relaxation of LTV rules also plays a significant role in influencing the purchase behaviour of households.

3.3.3 Distributional Effects of Loan-to-Value Policy

This section investigates the differing policy impacts across households with different characteristics. The distributional effects of LTV ratio caps typically arise from the differences in the actual financial constraints they impose on households with different characteristics and may also be related to households' appetite for financial risk or their attention to economic and financial information. The distribution of policy impact can take various forms and can be measured across a range of dimensions, such as income, age, education and area of residence. To assess the distributional effects of the LTV restriction along different dimensions, model (3.3) is estimated, using one demographic variable at a time.

Since the LTV ratio is a restriction on household mortgage borrowing, richer households are expected to be less likely to change their purchase decision when LTV caps change. The difficulty in studying the distributive effects by income is that income data are not necessarily measured at the same time as the housing decision as CHFS has only been conducting surveys every two years since 2011. To address this problem, the study took the average of the total income reported in CHFS surveys in 2011, 2013, 2015 and 2017 to represent the income level of the household. This can reveal which income class the household belongs to and thus

Table 3.6. Effects of loan-to-value limits by income level

	Deciding to buy	
	(1)	(2)
LTV (lag)	0.196***	0.230***
	(0.066)	(0.066)
Income	0.001***	
	(0.000)	
Interaction between LTV and income	-0.001***	
	(0.000)	
Income dummy		0.078***
		(0.020)
Interaction between LTV and income dummy		-0.091***
		(0.028)
Observations	272287	272287
Number of clusters	29	29
R^2 within	0.016	0.016

Notes: 1. The sample includes 29 provincial-level administrative divisions in China for the period 2007–2016. The marginal effects of explanatory variables after logistic regression are shown in the table. Regressions include province and year fixed effects. Standard errors are clustered by province.

2. *** indicates significant at the 1% level; ** indicates significant at the 5% level; * indicates significant at the 10% level.

distinguish between upper-income households and lower-income households. The results of LTV policy effects by income distribution are shown in Table 3.6.

The income variable in the first column of Table 3.6 represents the total income of the household, and the unit is ten thousand yuan. It can be seen that the income level is positively correlated with the probability of buying a house, that is, households with higher income are more likely to buy a house. The coefficient on the interaction term between income and LTV is negative and statistically significant, indicating that the higher the household income level is, the less restrictive effect LTV policy will have on its purchase decision. A dummy variable is then created to distinguish between high- and low-income households. It is equal to 1 if the household's income is greater than the median income of the sample, and 0 if the household's income is less than or equal to the median income of the sample. The results in the second column of Table 3.6 imply that when LTV is reduced by ten percentage points, the probability

Table 3.7. Effects of loan-to-value limits across gender and age groups

	Deciding to buy	
	(1)	(2)
LTV (lag)	0.201***	0.204***
	(0.068)	(0.068)
Gender	0.014	
	(0.024)	
Interaction between LTV and gender	-0.022	
	(0.034)	
Age (25–34)		0.133***
		(0.027)
Age (35–44)		0.039
		(0.027)
Age (45–54)		0.013
		(0.027)
Interaction between LTV and age (25–34)		-0.111***
		(0.037)
Interaction between LTV and age (35–44)		-0.017
		(0.037)
Interaction between LTV and age (45–54)		-0.002
		(0.036)
Observations	273353	273358
Number of clusters	29	29
R^2 within	0.014	0.037

Notes: 1. The sample includes 29 provincial-level administrative divisions in China for the period 2007–2016. The marginal effects of explanatory variables after logistic regression are shown in the table. Regressions include province and year fixed effects. Standard errors are clustered by province.

2. *** indicates significant at the 1% level; ** indicates significant at the 5% level; * indicates significant at the 10% level.

of a low-income household buying a home decreases by 2.3%, while the probability of a high-income household buying a home decreases by only 1.39%.

Table 3.7 reports whether the policy impact on household buying decision varies by gender and age. The estimate of the interaction term between the LTV limit and the demographic variable represents the additional effect of LTV policy for that population group. The results show that there is no significant difference in the impact of LTV limits for male and female heads of households, but the policy does have a greater impact on certain age groups. Households are divided into four groups, with heads aged 25 to 34, 35 to 44, 45 to 54, and 55 to 64. The results show that, at the 95% significance level, the effect of LTV policy for the young age group is significantly smaller. When the LTV ceiling is raised by ten percentage points, the probability of buying a home increases by 0.93% for people aged 25 to 34, and 2.04% for older adults. This may be because young people buying their first home are in urgent need of a house to live a satisfying life, so they are less price sensitive, while older people can decide whether to move, so LTV restrictions are more likely to delay their decision. Besides, the direct effect of the 25–34 age group on the buy decision is positive and statistically significant, supporting the fact that younger households are more willing to buy and therefore less affected by LTV restrictions. These results are consistent with those of Igan and Kang (2011), which showed that tighter LTV policies resulted in a sharp fall in home ownership among people over 35 years of age, with little effect for young adult households.

While the tightening of LTV requirements has proved capable of preventing or containing bubbles, a common concern is whether it will inadvertently target young households, who tend to be less affluent, and exclude them from the property market. However, the results of this study suggest that, at least in China’s practice, restrictions on LTV ratios have not largely prevented younger households from buying homes but have had a greater impact on older households’ decision to buy homes. This reflects the fact that, in addition to limiting people’s ability to buy houses by restraining excessive leverage, LTV policies may also be working through the expectations channel.

Existing research shows that expectations often play a key role in shaping the dynamics of real estate bubbles (Case and Shiller, 2003; and Allen and Carletti, 2011). During housing booms, people tend to translate higher actual growth in house prices into higher expected growth in house prices, and the expectation of higher returns on real estate drives more households to decide to buy homes. This self-reinforcing mechanism of house price expectations provides the fuel for the formation of housing bubbles. In this case, tightening LTV has been shown to dampen potential homebuyers' expectations of future house price increases and alter their investment decisions, which is more common in older adult households (Igan and Kang, 2011). Believing that LTV restrictions will be relaxed in the future and that the tight LTV restrictions currently in place will keep a lid on price rises, older

Table 3.8. Effects of loan-to-value limits by education level and the number of siblings

	Deciding to buy	
	(1)	(2)
LTV (lag)	0.188***	0.199***
	(0.064)	(0.059)
Education	0.071***	
	(0.027)	
Interaction between LTV and education	-0.069*	
	(0.038)	
Two siblings or less		0.069**
		(0.028)
Interaction between LTV and sibling		-0.074*
		(0.039)
Observations	273057	209624
Number of clusters	29	29
R^2 within	0.019	0.020

Notes: 1. The sample includes 29 provincial-level administrative divisions in China for the period 2007–2016. The marginal effects of explanatory variables after logistic regression are shown in the table. Regressions include province and year fixed effects. Standard errors are clustered by province.

2. *** indicates significant at the 1% level; ** indicates significant at the 5% level; * indicates significant at the 10% level.

households are willing to wait until a better time to buy. This leads to a decline in demand for houses, relieving upward pressure on house prices.

Table 3.8 reports the marginal effects of LTV limits on household purchase decision by education level and by number of siblings. A dummy variable is created to distinguish the highly educated households from the less educated households, where 1 represents households with college/vocational education or above and 0 represents households with education below college/vocational school. The results indicate that in the case of a ten-percentage point increase in the maximum LTV ratio, on average, the marginal increase in the probability of higher education households buying a home is 0.69% smaller than that of lower education households. This may be due to the fact that better-educated households tend to have higher incomes, so they are less financially constrained to buy a home and thus less affected by LTV policies.

Families with higher socioeconomic status tend to have fewer children. If the head of a household and his or her spouse have fewer siblings, that means they are likely to come from families that are financially stronger and may therefore be less affected by LTV restrictions when they buy a home. To test this hypothesis, a dummy variable is created to distinguish between households where the head and spouse have fewer siblings and households where the head and spouse have more siblings. It has a value of 1 for households where the head of the household and his or her spouse have two or fewer siblings, and 0 for households where the head of the household and his or her spouse have more than two siblings. The estimates in column (2) of table 3.8 show that households where the head and spouse have fewer siblings are significantly more likely to buy a home. When the maximum LTV ratio is changed

Table 3.9. Effects of loan-to-value limits by type of hukou and area of residence

	Deciding to buy	
	(1)	(2)
LTV (lag)	0.214***	0.189***
	(0.082)	(0.070)
Type of hukou	0.038	
	(0.029)	
Interaction between LTV and type of hukou	-0.054	
	(0.041)	
Area of residence		0.006
		(0.029)
Interaction between LTV and area of residence		-0.025
		(0.041)
Observations	267421	273358
Number of clusters	29	29
R^2 within	0.014	0.016

Notes: 1. The sample includes 29 provincial-level administrative divisions in China for the period 2007–2016. The marginal effects of explanatory variables after logistic regression are shown in the table. Regressions include province and year fixed effects. Standard errors are clustered by province.

2. *** indicates significant at the 1% level; ** indicates significant at the 5% level; * indicates significant at the 10% level.

by ten percentage points, the marginal impact of LTV policy on the buy decision is 0.74% smaller for such households, and the result is statistically significant at the 90% significance level.

Table 3.9 reports the distributional effects of LTV limits across households with different hukou types and households living in different residence areas. Type of hukou is a dummy variable, with a value of 1 indicating that the head of household holds agricultural hukou and a value of 0 indicating that the head of household holds non-agricultural hukou. The estimate of the interaction term between the LTV limit and the type of hukou is small and not statistically significant, which implies that there is no significant difference in LTV policy effects on house purchase decision between agricultural and non-agricultural hukou holders. As household registration has been gradually decoupled from what people actually do over the past two decades, it may no longer reflect household income levels or purchasing power. The results in column (2) show the distributional effects of LTV policy along the area of residence. Area of residence is also a dummy variable representing the area of usual residence of a household. A value of 1 means that the household lives in rural areas, and a value of 0 means that the household lives in urban areas. There is no statistically significant difference in the effect of LTV restriction on the buy decision for urban and rural residents. While house prices are lower in rural areas than in cities, so are income levels for rural residents. Therefore, rural

Table 3.10. Effects of loan-to-value limits by financial literacy and risk preference

	Deciding to buy	
	(1)	(2)
LTV (lag)	0.195***	0.209***
	(0.068)	(0.062)
Financial literacy	0.034	
	(0.021)	
Interaction between LTV and financial literacy	-0.039	
	(0.029)	
Risk preference		0.056**
		(0.023)
Interaction between LTV and risk preference		-0.059*
		(0.032)
Observations	268909	255591
Number of clusters	29	29
R^2 within	0.014	0.017

Notes: 1. The sample includes 29 provincial-level administrative divisions in China for the period 2007–2016. The marginal effects of explanatory variables after logistic regression are shown in the table. Regressions include province and year fixed effects. Standard errors are clustered by province.

2. *** indicates significant at the 1% level; ** indicates significant at the 5% level; * indicates significant at the 10% level.

and urban households alike rely on mortgages to buy homes and are similarly affected by LTV policies.

Table 3.10 shows how the impact of LTV restrictions on home-buying decision varies with the degree to which households pay attention to economic and financial information and the degree to which households are risk seeking. The opinion variables, financial literacy and risk preference, are categorical variables on a 1 to 5 scale, with 1 indicating the highest level and

5 indicating the lowest level. To test the distributional consequences across different groups of households, binary variables are created to distinguish between households that care about economic and financial information to some extent and those that don't care at all, and households that are willing to take financial risks to some extent and those that are not at all willing. It is assumed that households' focus on economic and financial information and their subjective attitude to risk preference are time invariant.

The results suggest that there is no statistically significant difference in the impact of LTV policy on the buy decision between households that paid attention to economic and financial information and households that paid no attention to such information at all. Regardless of a household's level of financial knowledge, the LTV limit, as a real restriction on the household's housing credit, can effectively affect its purchase decision. Even households that are ignorant of the LTV policy will be informed of the current maximum allowable LTV ratio when they want to buy a home and apply for a home mortgage.

The results in column (2) of Table 3.10 show that households that are willing to take risks have a greater probability of buying houses, and LTV restrictions have a smaller marginal impact on their purchasing decisions. On impact, a ten-percentage point increase in the LTV ceiling would increase the probability of buying a home by 2.09% for a household willing to take no risk at all, while a household willing to take some risk would increase the probability of buying a home by just 1.5%. The same is true when the LTV ceiling is lowered. This finding reflects the effect of LTV policy on households' purchasing decisions through the expectations channel. The tightening of LTV policy reduces households' expectation of future house price growth, whereas the loosening of LTV policy heightens households' expectation of future house price growth. However, the expectations channel has less impact on households willing to take risks, since their desire for higher returns may outweigh the measure of investment risk. These households are more likely to engage in real estate transactions and ignore the possible impact of LTV policy on the future dynamics of the real estate market, as long as there is a certain possibility of earning profits from buying a house.

3.3.4 Other Attributes of the House

After examining the effect of LTV ratio policy on the decision of whether to buy a house, this section looks at whether the type of house the household buys is affected by LTV ratio. Some studies show that at the micro level the LTV changes can alter the size of the house that is bought and the distance from the house to the central business district (Halket and Vasudev, 2014; and Tzur-Ilan, 2020). Using data from CHFS on the size of the house that is bought and the proximity of the house from the city or county centre, this paper investigates whether these two attributes of the homes that household buy are affected by LTV limits.

A dummy variable is created to indicate whether the size of the house being bought is large or small. The variable takes a value of 1 if the household buys a house above the median house size in the sample for that province, and 0 if the household buys a house below or equal to the median house size. The following logistic regression model is used to study the marginal effects of LTV changes on house size:

$$size_{i,p,t} = \alpha + \beta LTV_{p,t-1} + \phi_t + \rho_p + \varepsilon_{i,p,t} \tag{3.4}$$

where $size_{i,p,t}$ is the dummy variable that represents the size of the house that household i in province p bought in year t is large or small.

Table 3.11 reports the results of estimating model (3.4). The coefficient on LTV is statistically insignificant, indicating that the LTV ratio has no effect on the size of houses people buy, but it is also possible that this result is due to the fact that the homes were not taken into account for their distance from the city or county centre. In general, homes farther away from the city centre may be larger in size. When the LTV ceiling is raised, people with more credit support are likely to buy bigger homes in the remote areas or smaller homes closer to the city centre. When the LTV ceiling is lowered, people may choose to buy a more remote house of the ideal size. Therefore, on the basis of model (3.4), the distance from the house to the centre of the city or county is controlled for. The regression equation is shown as follows:

$$size_{i,p,t} = \alpha + \beta LTV_{p,t-1} + \gamma DIST_{i,p,t} + \phi_t + \rho_p + \varepsilon_{i,p,t} \tag{3.5}$$

where $DIST_{i,p,t}$ is the number of hours it takes to get from the house to the city or county centre.

Table 3.11. Effects of loan-to-value limits on size of housing

	The dummy variable of housing size	
	(1)	(2)
LTV (lag)	-0.241	0.479
	(0.698)	(1.970)
Distance		0.106**
		(0.054)
Observations	10489	883
Number of clusters	29	25
R^2 within	0.004	0.076

Note: 1. The marginal effects of explanatory variables after logistic regression are shown in the table. Regressions include province and year fixed effects. Standard errors are clustered by province.

2. *** indicates significant at the 1% level; ** indicates significant at the 5% level; * indicates significant at the 10% level.

The results are reported in column (2) of Table 3.11. When controlling for the distance of the house from the city or county centre, the estimated coefficient on the LTV term is still not statistically significant but has the right sign, while the coefficient on the distance term is positive and significant at the 0.05 level. Thus, the LTV policy affects people's decision on whether to buy a house but has no significant impact on the size of the house they buy. The regression results confirm that the farther away the house is from the city or county centre, the larger the size of the house. Next, the study looks at whether LTV limits affect how close a household buys a home to the city or county centre.

Model (3.6) is used to test the hypothesis that an increase in the LTV limit would cause households to choose homes closer to the city or county centre and a decrease in the LTV limit would cause households to choose homes farther away from the city or county centre.

$$distance_{i,p,t} = \alpha + \beta LTV_{p,t-1} + \phi_t + \rho_p + \varepsilon_{i,p,t} \tag{3.6}$$

where $distance_{i,p,t}$ is a dummy variable. It is assigned the value 1 if the time it takes to travel from the home purchased by the household to the city/county centre exceeds the median time it takes to travel from the homes purchased to their city/county centre in that province in the sample, and 0 if the time it takes to travel from the home purchased by the household to the city/county centre is less than or equals to the median time it takes to travel from the homes purchased to their city/county centre in that province.

Table 3.12. Effects of loan-to-value limits on the time required to travel from the house to the city/county centre

	Distance (dummy)
LTV (lag)	-4.496
	(2.809)
Observations	986
Number of clusters	25
R^2 within	0.024

Note: 1. The marginal effects of explanatory variables after logistic regression are shown in the table. Regressions include province and year fixed effects. Standard errors are clustered by province.

2. *** indicates significant at the 1% level; ** indicates significant at the 5% level; * indicates significant at the 10% level.

The results of the impact of LTV restrictions on the proximity of purchased homes to city or county centres are reported in Table 3.12. The coefficient on the LTV limit is not statistically significant, suggesting that the change in LTV has no effect on how far the household decided to buy a home from the city or county centre.

In summary, the LTV policy affects a household's decision whether or not to buy a home, but it has no significant effect on the size of the home purchased or its proximity to the city or county centre. When the LTV limit tightens, people put off buying homes either because they are constrained by credit or because they have lower expectations of future house price rises, but there is no evidence that potential buyers switch to smaller homes or homes farther away from the city or county centre. When the LTV limit loosens, people are more likely to buy a home, but the policy action does not increase the likelihood that they would choose a larger home or one closer to the city or county centre.

3.4 Conclusion

This paper studies several important implications of LTV regulation by using the micro data on household finance and wealth in China. It reveals some interesting results. The LTV restrictions are found to have a positive effect on household buying decision. A lower LTV ceiling would make households less likely to buy a home, whereas an increase in the maximum LTV ratio would encourage households to do so. Changes in the demand for housing could affect prices. The results also suggest that the effect of LTV policy is symmetrical for the purchase decision. Easing LTV restrictions on home loans seems to spur home buying as much as tightening constrains it.

Combined with the findings of Chapter 2, that tightening LTVs tends to have a bigger impact on house prices than easing, this suggests that when the government eases LTV limits to stimulate the housing market, households start buying immediately, but the increase in house price growth is less than the decrease in house price growth caused by tightening actions. The asymmetric response of house prices may be caused by the downward rigidity of housing supply. Because of the durability of housing, housing stock is unlikely to decrease when LTV ratio restrictions are tightened to reduce housing demand. A decrease in housing demand and a fixed housing supply will lead to a sharp decline in price growth. On the other hand, as the government loosens restrictions on LTV to stimulate housing demand, property developers may respond by building more homes. The increase in supply reduces the upward pressure on house prices, so the effect of loosening LTVs on house prices is smaller. Aastveit and Anundsen (2017) find similar asymmetric responses of house prices to expansionary and contractionary monetary shocks and point out that this is related to the elasticity of housing supply.

Another concern about limiting LTV ratios is that government involvement in housing finance could have unintended consequences for the living conditions and quality of life of certain groups. For example, the burden of financial constraints imposed by a reduced LTV cap may hit young people hardest. However, this paper does not find evidence that this is a problem in China's practice. The results show that older-adult households are more affected by the LTV policy than young adult households. This reflects the fact that LTV ratio limit adjustments influence people's buying decisions through the expectations channel. Lower expectations of future price increases make older people more likely to delay buying.

The distributional effects of LTV limits are then assessed along other dimensions. The findings suggest that LTV limits are more effective at reducing the probability of buying a home for less-educated households and for households in which the head and spouse have more siblings. These households tend to be more financially strapped and thus rely more heavily on home mortgages. The results also uncover that for households willing to take financial risks, the impact of the LTV ratio policy is relatively small. Since such households are less concerned about investment risk, LTV restrictions have a limited effect on their buying decisions through the expectations channel.

Finally, this study examines whether the type of house the person buys is affected by the LTV ratio. There is no evidence that loosening the LTV limit incentivizes buyers to choose larger homes, or that tightening the LTV limit causes them to switch to smaller homes, at least in China. In addition, changes in LTV have no significant effect on the distance between homes people buy and the city centre. Therefore, it can be concluded that the LTV ratio policy affects people’s decision on whether to buy a house but has little effect on the attributes of the house they buy. By limiting people’s access to housing credit and influencing people’s expectations of future house price growth, LTV policies provide a viable option for dealing with real estate boom and bust cycles.

Conclusion

Significant achievements have been made in the research on the detection of price bubbles and on the role of macroprudential measures in coping with the boom of real estate market. Regarding the first issue, researchers have developed purely statistical methods to analyse whether house price growth shows an unsustainable pattern of acceleration, as well as ways to determine whether the housing market has deviated from economic fundamentals by exploring the relationship between house prices and rents or incomes. In addition, several post-crisis studies have shown that restrictions on housing credit conditions are more effective than traditional monetary and fiscal policies in reducing credit volatility, achieving financial stability, and promoting social welfare.

Based on previous studies, this thesis further compares the results of four commonly used bubble detection models in the context of China's real estate market and explores the impact of LTV regulations on house price growth and house purchase decisions. Firstly, it is found that different bubble detection models and assumptions may give different predictions even with the same data. For 30 first- and second-tier cities in China, the conclusions drawn by LPPLS model, dynamic Gordon growth model, user cost model and Case-Shiller model are not consistent. The results of some models suggest that there is no real estate bubble, while the results of others support the existence of bubbles in these cities. There are also cases where the Case-Shiller model does not fit the data, making it impossible to make any statement about bubbles from the model. For Beijing, Tianjin, Shanghai and Shenzhen, on the other hand, the results of all four models point to bubbles in their property markets. In this regard, this study provides evidence about the prevalence of real estate bubbles in China's upper-tier cities, especially first-tier cities. Therefore, the Chinese government must closely monitor the development of the local real estate market and take policy actions to curb the rapidly rising house prices.

Secondly, it is found that the LTV ratio policy has a significant positive effect on the growth rate of house prices. In other words, a lower LTV ceiling would slow house price growth, while an increase in the LTV ceiling would accelerate house price growth. The LTV cap for first-time home buyers, in particular, has a bigger and more lasting effect on house prices than the LTV cap for existing owners. The results obtained from the baseline model hold when national-level LTV policies and propensity score matching techniques are used to reduce endogeneity problems and the effects of other real estate policies are taken into account. Moreover, the regulatory impact of the LTV policy is found to be asymmetrical, with tightening appearing to have a greater impact on house prices than easing. In addition to depending on the direction of policy decisions, the response of house prices to changes in LTV limits also depends on city-specific housing supply elasticities.

Lastly, limits on LTV ratios also play an important role in influencing household purchasing decisions. Lowering the LTV limit would cause households to delay buying homes, while raising it would encourage them to do so. Based on the observable sociodemographic characteristics and the survey results of households' latent attitudes and preferences, this study shows that LTV policies have heterogeneous effects across multiple dimensions. In general, households with higher income and education levels are less affected by LTVs. For households willing to take financial risks, the LTV ratio policy has a limited impact on their purchasing decisions through the expectations channel. The study finds no evidence that LTV restrictions primarily discourage young households from buying homes, at least in China. On the other hand, with regard to the effect of the policy on other attributes of the house, the results suggest that changes to the LTV ratio restriction rules have no statistically significant effect on the size of the house that is bought and the distance of the house from the city/county centre.

Further policy implications come from these key findings. As a cyclical macro-prudential policy, LTV regulation can effectively stabilize housing prices, especially in the boom phase of the real estate cycle. When the LTV ratio limit is tightened, demand for homes decreases as households face financial constraints. That, coupled with downward housing supply rigidities, will slow the growth of house prices. When the LTV ratio limit is relaxed, households will buy homes immediately, but the increase in house price inflation will not be as large as the decrease in house price inflation caused by tightening actions because the supply of housing will increase accordingly.

Another topic for future research is to explore how expectations in the housing market are shaped and the impact of macro-prudential policies on those expectations. The results of this study reveal the role of the expectations channel in the implementation of LTV restrictions. Over the past two decades, market expectations have been widely recognized as one of the key factors affecting the real estate cycle, and some bubble detection models also emphasize the importance of expectations during the real estate boom. Several earlier empirical studies described in Chapter 1 have shown that people's long-term expectations of future house price increases can explain the formation of a price bubble in the real estate market. But it is not clear why the public had extravagant expectations about the long-term trend in house prices at the start of the housing boom, or how government intervention affected those expectations. These are important questions to be examined in the future real estate market research.

Appendices

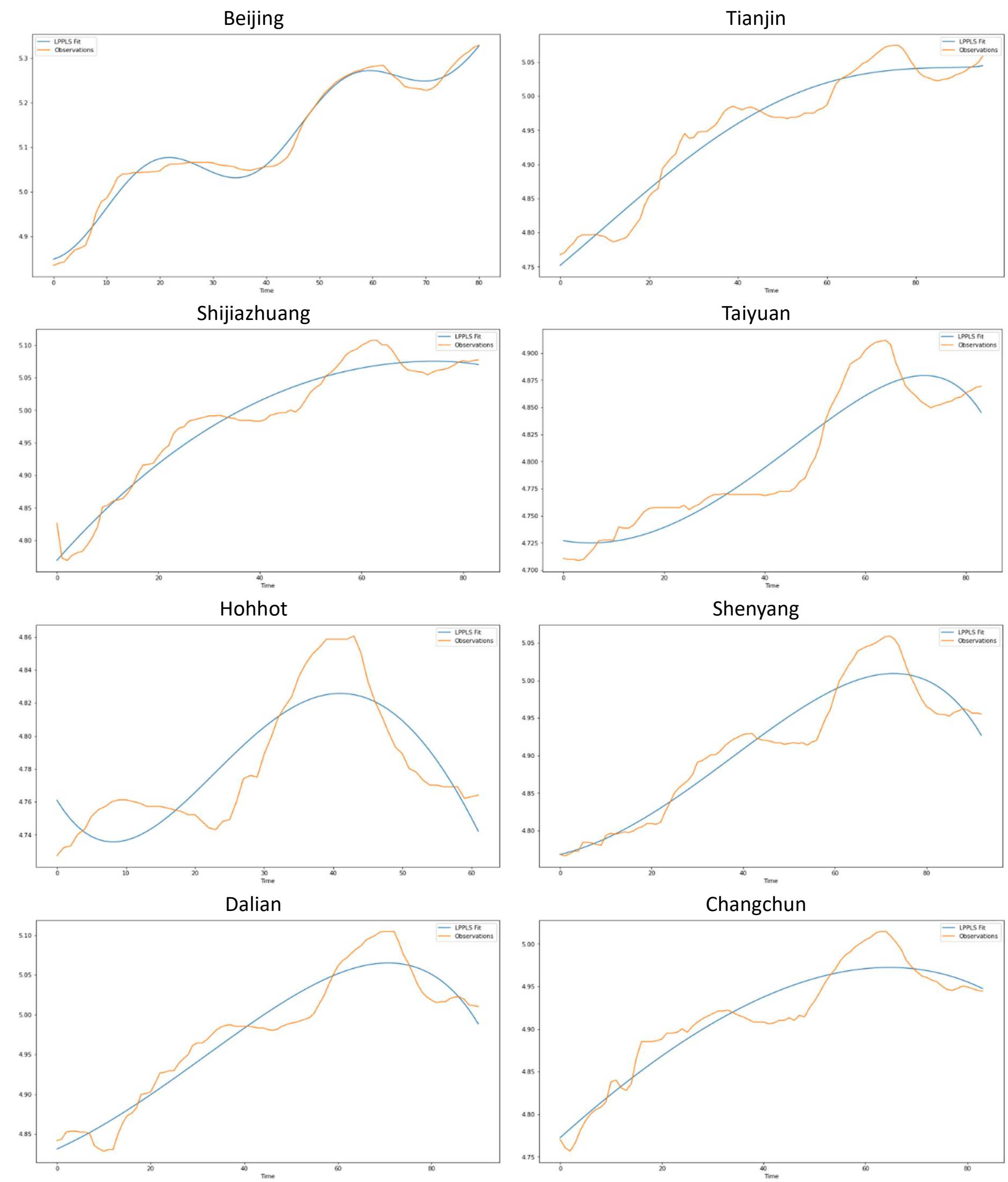

Figure A1.1. Monthly house price indices by city, 2008–2015

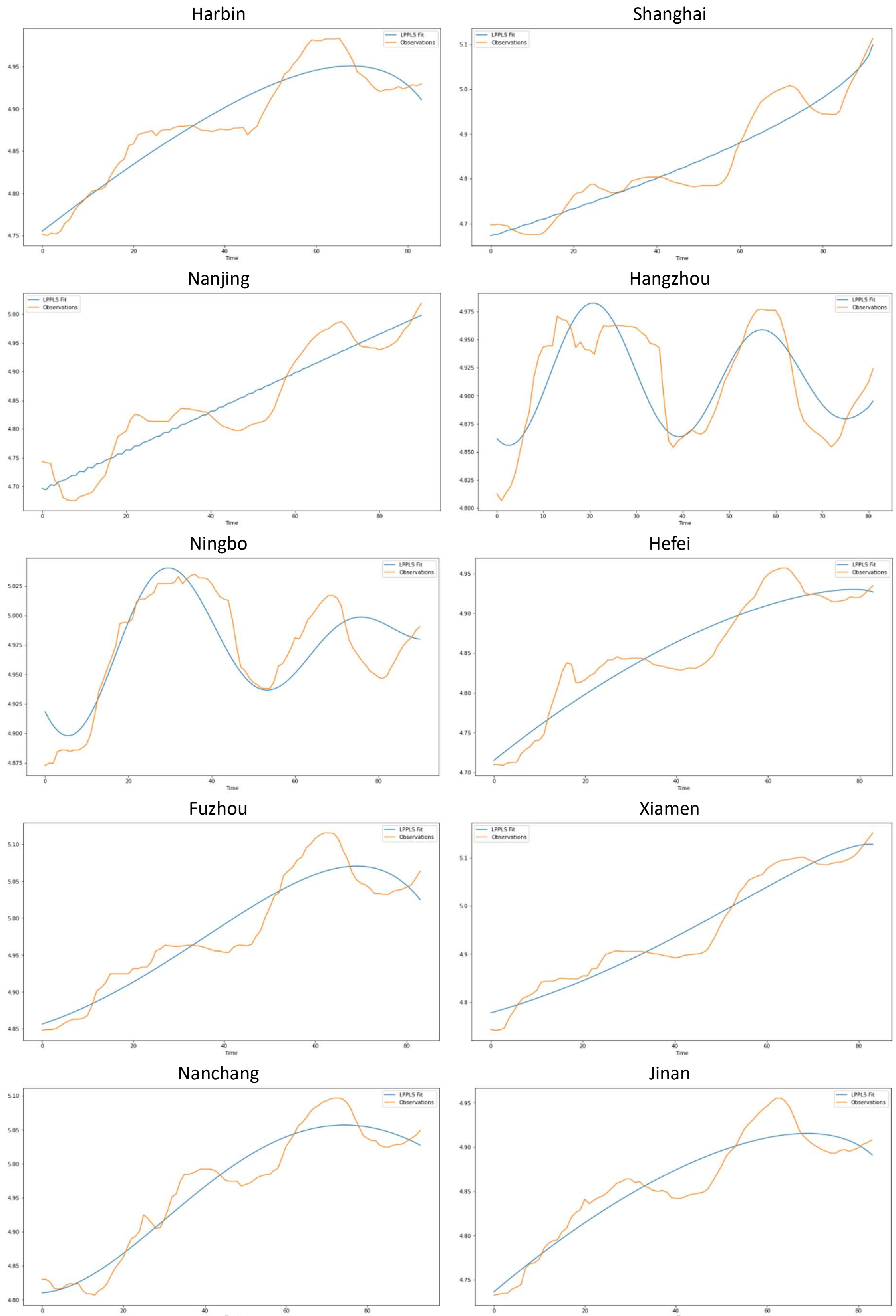

Figure A1.1. Monthly house price indices by city, 2008–2015 (cont.)

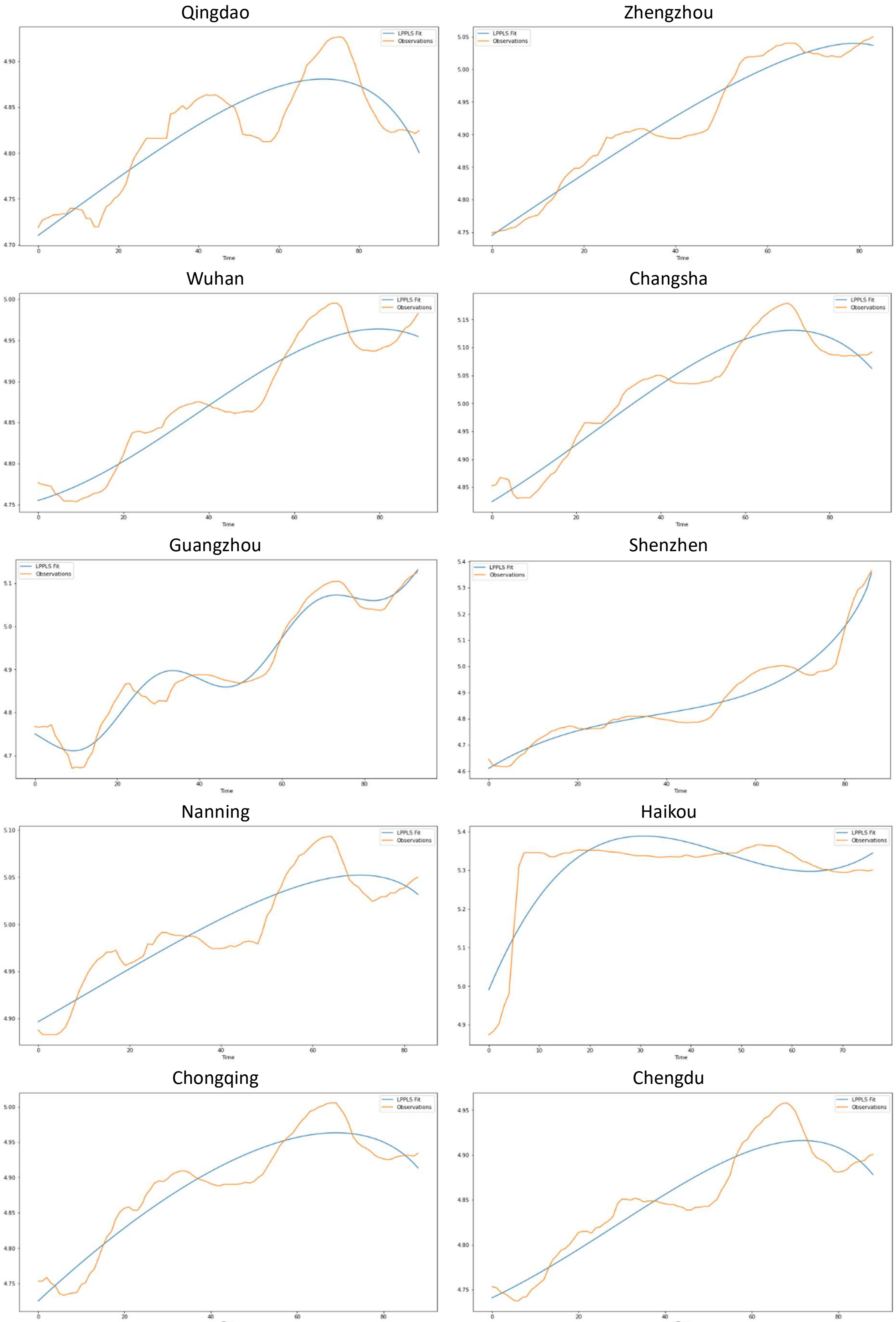

Figure A1.1. Monthly house price indices by city, 2008–2015 (cont.)

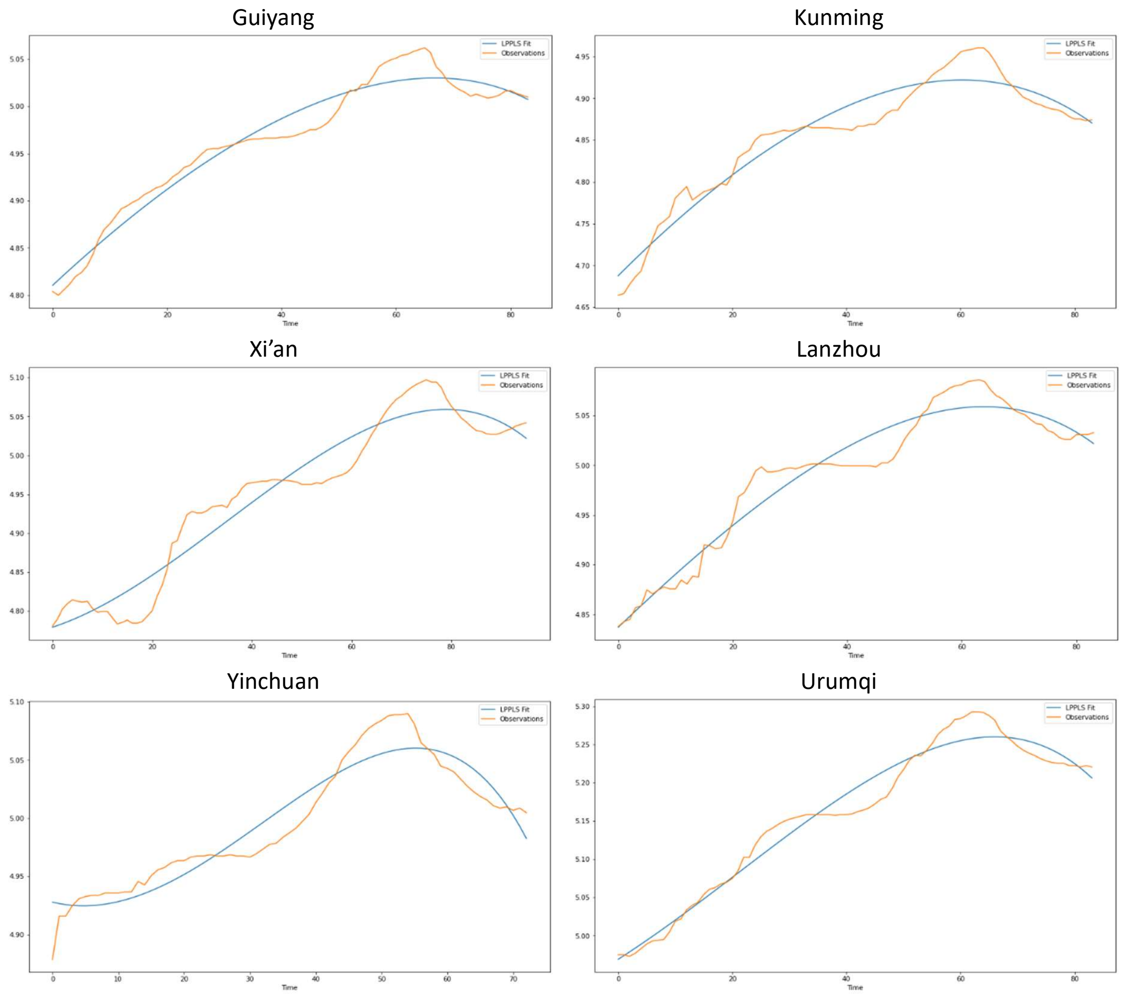

Figure A1.1. Monthly house price indices by city, 2008–2015 (cont.)

Table A1.1. Descriptive statistics of user costs by city, 2008–2015

City	Obs	Mean	Std. Dev	Min	Max
Beijing	81	0.044	0.006	0.031	0.053
Tianjin	96	0.051	0.008	0.031	0.062
Shijiazhuang	84	0.053	0.007	0.037	0.063
Taiyuan	84	0.066	0.007	0.049	0.075
Hohhot	62	0.077	0.006	0.064	0.086
Shenyang	93	0.068	0.008	0.048	0.078
Dalian	91	0.064	0.008	0.044	0.074
Changchun	84	0.059	0.007	0.042	0.068
Harbin	84	0.060	0.007	0.043	0.069
Shanghai	93	0.082	0.008	0.062	0.093
Nanjing	91	0.070	0.008	0.050	0.080
Hangzhou	82	0.098	0.006	0.084	0.107
Ningbo	91	0.080	0.008	0.060	0.091
Hefei	84	0.062	0.007	0.045	0.071
Fuzhou	84	0.066	0.007	0.049	0.075
Xiamen	84	0.055	0.007	0.038	0.064
Nanchang	94	0.057	0.008	0.037	0.067
Jinan	84	0.056	0.007	0.039	0.066
Qingdao	96	0.074	0.008	0.054	0.085
Zhengzhou	84	0.048	0.007	0.031	0.057
Wuhan	90	0.055	0.008	0.035	0.066
Changsha	91	0.056	0.008	0.036	0.067
Guangzhou	94	0.083	0.008	0.063	0.093
Shenzhen	87	0.095	0.008	0.075	0.105
Nanning	84	0.063	0.007	0.046	0.073
Haikou	77	0.141	0.006	0.128	0.150
Chongqing	89	0.067	0.008	0.046	0.077
Chengdu	89	0.066	0.008	0.045	0.076
Guiyang	84	0.049	0.007	0.032	0.058
Kunming	84	0.071	0.007	0.054	0.081
Xi’an	96	0.057	0.008	0.036	0.067
Lanzhou	84	0.049	0.007	0.032	0.058
Yinchuan	73	0.064	0.006	0.051	0.073
Urumqi	84	0.054	0.007	0.038	0.064

Source: Author’s calculations.

Table A1.2. Regressions of house prices on fundamentals

Independent variable	Beijing	Tianjin	Shijiazhuang	Taiyuan	Hohhot	Shenyang	Dalian	Changchun	Harbin
	Dependent variable: quarterly change in house prices								
Change in population	-13.381**	-15.186	1.133	0.087	4.436**	-18.957**	-20.760**	-3.842	4.628
	(4.739)	(11.566)	(1.479)	(0.244)	(2.012)	(8.172)	(8.448)	(3.327)	(2.817)
Change in employment	-2.791	7.095	2.852**	-0.545*	-9.820***	1.596***	0.066	0.625**	0.355
	(2.645)	(5.978)	(1.326)	(0.270)	(3.111)	(0.331)	(0.123)	(0.291)	(0.419)
Mortgage rate	-7.510***	-0.624	-2.502**	0.900	0.761	0.625	0.489	0.769	-1.431
	(1.659)	(0.635)	(1.093)	(0.834)	(0.723)	(0.487)	(0.670)	(0.897)	(0.985)
Unemployment rate	-37.336***	17.775	39.460**	2.771	13.786***	5.434	-2.912	7.169	5.823
	(9.465)	(13.162)	(16.063)	(4.058)	(3.239)	(4.427)	(2.721)	(4.214)	(3.819)
Housing starts	-5.242	-2.567	37.324	-9.204	-1.723	5.760	42.520*	36.050**	12.967
	(24.544)	(7.173)	(22.772)	(43.576)	(14.670)	(8.145)	(23.440)	(15.546)	(15.936)
Income per capita	-10.933***	-4.001	9.661**	0.462	1.111	-0.292	-1.348**	-2.167**	-2.120
	(2.994)	(2.736)	(3.986)	(1.011)	(0.900)	(0.825)	(0.582)	(0.928)	(2.462)
Observations	27	32	28	28	21	31	31	28	28
R^2	0.545	0.388	0.531	0.194	0.758	0.625	0.403	0.432	0.417
	Dependent variable: quarterly level of house prices								
Change in population	0.181	-0.591*	0.072***	0.006	-0.076**	0.377***	-0.092	0.053	0.017
	(0.298)	(0.344)	(0.018)	(0.004)	(0.026)	(0.117)	(0.116)	(0.043)	(0.026)
Change in employment	-0.094	0.379**	0.009	-0.010**	0.136***	0.013**	0.008***	0.003	-0.004
	(0.166)	(0.178)	(0.016)	(0.004)	(0.041)	(0.005)	(0.002)	(0.004)	(0.004)
Mortgage rate	-0.101	0.031	0.055***	0.040***	0.008	0.018**	0.011	0.032**	0.046***
	(0.104)	(0.019)	(0.013)	(0.013)	(0.009)	(0.007)	(0.009)	(0.012)	(0.009)
Unemployment rate	-1.445**	0.887**	-0.195	0.160**	0.229***	-0.117*	0.021	-0.028	0.188***
	(0.596)	(0.392)	(0.198)	(0.065)	(0.042)	(0.063)	(0.037)	(0.054)	(0.035)
Housing starts	1.830	0.131	0.730**	0.072	-0.043	0.047	0.535	0.111	0.304**
	(1.544)	(0.213)	(0.281)	(0.699)	(0.192)	(0.116)	(0.322)	(0.200)	(0.144)
Income per capita	0.514**	0.203**	0.186***	0.141***	0.115***	0.101***	0.119***	0.092***	-0.012
	(0.188)	(0.081)	(0.049)	(0.016)	(0.012)	(0.012)	(0.008)	(0.012)	(0.022)
Observations	27	32	28	28	21	31	31	28	28
R^2	0.934	0.941	0.957	0.870	0.905	0.922	0.923	0.870	0.952

Table A1.2. Regressions of house prices on fundamentals (cont.)

Independent variable	Shanghai	Nanjing	Hangzhou	Ningbo	Hefei	Fuzhou	Xiamen	Nanchang	Jinan
	Dependent variable: quarterly change in house prices								
Change in population	-0.139	-7.414**	-1.478	-2.377	-2.228	1.117	-0.174	0.237	-5.496
	(3.874)	(2.788)	(1.927)	(1.758)	(1.566)	(2.424)	(0.838)	(0.689)	(4.279)
Change in employment	-0.688**	1.849**	-5.625	0.035	1.904	-0.791	-0.687	-0.038	-6.867
	(0.292)	(0.791)	(8.337)	(0.958)	(1.379)	(0.775)	(0.665)	(2.852)	(6.329)
Mortgage rate	-0.791	-0.812	-6.216**	-1.219**	-1.433	-1.124	-0.578	-1.305*	-1.094
	(0.870)	(0.859)	(2.463)	(0.532)	(0.869)	(1.367)	(0.918)	(0.666)	(0.691)
Unemployment rate	6.533	1.895	-1.692	-4.729**	1.429	-3.159	3.516	-6.331	0.726
	(18.807)	(3.108)	(4.226)	(2.288)	(2.275)	(4.549)	(3.539)	(6.997)	(1.894)
Housing starts	-2.549	15.167	5.841	-0.482	68.795*	27.237	102.552	-2.634	-8.317
	(40.839)	(41.055)	(50.161)	(49.185)	(38.761)	(46.472)	(109.137)	(56.012)	(36.916)
Income per capita	0.991	0.784	-5.730*	-4.872**	-0.509	-2.454	0.503	-2.006	-0.376
	(1.807)	(1.663)	(3.222)	(1.753)	(1.959)	(2.966)	(2.700)	(1.636)	(2.154)
Observations	31	31	28	31	28	28	28	32	28
R^2	0.363	0.371	0.363	0.455	0.349	0.092	0.241	0.251	0.227
	Dependent variable: quarterly level of house prices								
Change in population	0.235	0.240***	0.137*	-0.056	0.016	0.033	-0.027	0.011	0.010
	(0.174)	(0.075)	(0.068)	(0.053)	(0.017)	(0.044)	(0.025)	(0.013)	(0.074)
Change in employment	0.022*	-0.031	-0.372	0.107***	-0.014	-0.000	-0.052**	0.091	-0.272**
	(0.013)	(0.021)	(0.295)	(0.029)	(0.015)	(0.014)	(0.020)	(0.054)	(0.110)
Mortgage rate	-0.049	-0.006	-0.001	-0.014	0.039***	0.153***	-0.146***	0.024*	0.040***
	(0.039)	(0.023)	(0.087)	(0.016)	(0.010)	(0.025)	(0.028)	(0.013)	(0.012)
Unemployment rate	0.047	0.010	0.120	0.033	-0.111***	0.435***	-0.474***	0.024	-0.065*
	(0.846)	(0.084)	(0.149)	(0.069)	(0.025)	(0.083)	(0.107)	(0.133)	(0.033)
Housing starts	1.474	1.483	3.365*	2.384	1.226***	0.645	-5.138	0.046	0.430
	(1.837)	(1.106)	(1.774)	(1.490)	(0.430)	(0.851)	(3.298)	(1.064)	(0.642)
Income per capita	0.439***	0.237***	-0.083	0.058	0.050**	0.549***	0.033	0.178***	0.021
	(0.081)	(0.045)	(0.114)	(0.053)	(0.022)	(0.054)	(0.082)	(0.031)	(0.037)
Observations	31	31	28	31	28	28	28	32	28
R^2	0.904	0.907	0.352	0.727	0.948	0.952	0.949	0.898	0.892

Table A1.2. Regressions of house prices on fundamentals (cont.)

Independent variable	Qingdao	Zhengzhou	Wuhan	Changsha	Guangzhou	Shenzhen	Nanning	Haikou	Chongqing
	Dependent variable: quarterly change in house prices								
Change in population	1.837	0.899**	-0.154	-0.352	-2.162	2.708	7.713*	3.702	-24.661**
	(2.433)	(0.421)	(0.535)	(1.166)	(1.714)	(4.023)	(4.045)	(4.202)	(11.577)
Change in employment	-1.343	1.749*	5.115***	6.472	-5.508**	0.955	0.011	1.632	8.142**
	(2.242)	(0.926)	(1.754)	(5.681)	(2.292)	(0.666)	(0.046)	(2.856)	(3.333)
Mortgage rate	-0.200	0.475	-0.788	-0.560	-2.530**	-3.650	0.448	-2.952	-0.962
	(0.482)	(0.658)	(0.487)	(0.919)	(1.139)	(3.650)	(0.744)	(4.439)	(0.780)
Unemployment rate	-16.791**	0.917	10.488***	1.858	-19.180*	2.302	-2.823	12.807	5.958
	(7.041)	(1.338)	(3.133)	(4.882)	(11.206)	(9.192)	(3.725)	(17.621)	(5.096)
Housing starts	-24.889	-7.927	-1.506	27.680	-34.220	141.193	21.899	-254.030	3.791
	(30.354)	(22.061)	(14.092)	(37.120)	(57.087)	(154.458)	(51.707)	(470.336)	(9.935)
Income per capita	0.276	2.632*	6.862***	1.930	-3.235*	2.544	-3.426	9.495	1.827
	(0.658)	(1.444)	(1.974)	(3.348)	(1.711)	(1.840)	(3.180)	(21.197)	(2.767)
Observations	32	28	30	31	32	29	28	26	30
R^2	0.342	0.290	0.518	0.253	0.326	0.568	0.246	0.307	0.445
	Dependent variable: quarterly level of house prices								
Change in population	0.130*	0.006	0.016	0.005	0.002	-0.110	0.069	0.178***	0.003
	(0.063)	(0.006)	(0.012)	(0.014)	(0.022)	(0.206)	(0.045)	(0.020)	(0.238)
Change in employment	0.185***	-0.007	0.054	0.186**	-0.032	0.034	-0.001	-0.037**	0.008
	(0.058)	(0.012)	(0.040)	(0.070)	(0.030)	(0.034)	(0.001)	(0.013)	(0.069)
Mortgage rate	0.039***	0.021**	0.034***	0.032**	0.032**	-0.762***	0.031***	0.129***	0.026
	(0.013)	(0.009)	(0.011)	(0.011)	(0.015)	(0.186)	(0.008)	(0.021)	(0.016)
Unemployment rate	0.152	0.055***	0.025	0.058	-1.062***	-1.089**	0.033	-0.417***	0.001
	(0.183)	(0.018)	(0.071)	(0.060)	(0.147)	(0.470)	(0.041)	(0.083)	(0.105)
Housing starts	-0.196	0.410	0.459	0.388	1.190	-7.968	0.292	0.675	0.705***
	(0.789)	(0.289)	(0.319)	(0.458)	(0.749)	(7.890)	(0.573)	(2.220)	(0.205)
Income per capita	0.100***	0.205***	0.155***	0.184***	0.264***	0.647***	0.110***	-0.143	0.132**
	(0.017)	(0.019)	(0.045)	(0.041)	(0.022)	(0.094)	(0.035)	(0.100)	(0.057)
Observations	32	28	30	31	32	29	28	26	30
R^2	0.786	0.965	0.916	0.914	0.978	0.911	0.860	0.912	0.860

Table A1.2. Regressions of house prices on fundamentals (cont.)

Independent variable	Chengdu	Guiyang	Kunming	Xi’an	Lanzhou	Yinchuan	Urumqi
	Dependent variable: quarterly change in house prices						
Change in population	-0.269	6.774*	-1.341	-3.167	-0.108	-1.037**	-1.816
	(0.546)	(3.741)	(7.643)	(18.316)	(0.494)	(0.380)	(1.546)
Change in employment	2.987***	2.010*	0.735	1.292	1.137**	-0.505*	-0.764**
	(0.982)	(1.030)	(3.588)	(2.336)	(0.464)	(0.267)	(0.298)
Mortgage rate	-1.161*	-0.148	0.442	-0.588	-0.531	-1.680	0.280
	(0.594)	(0.625)	(0.729)	(0.696)	(0.495)	(1.317)	(0.729)
Unemployment rate	-2.734	-6.711**	6.575**	-1.672	-0.257	-8.039	-3.631*
	(2.288)	(2.562)	(2.582)	(4.231)	(0.945)	(5.778)	(2.012)
Housing starts	8.538	4.019	20.580	9.885	-0.956	-16.504	-0.514
	(19.760)	(24.326)	(19.416)	(31.091)	(43.145)	(33.409)	(28.204)
Income per capita	0.093	-3.129*	-4.235***	-1.441	-1.702	-5.510***	-2.203**
	(0.778)	(1.570)	(1.478)	(2.835)	(1.230)	(1.276)	(0.885)
Observations	30	28	28	32	28	25	28
R^2	0.392	0.616	0.559	0.155	0.562	0.610	0.532
	Dependent variable: quarterly level of house prices						
Change in population	-0.000	-0.063	0.380***	-0.484**	-0.003	0.006*	-0.064***
	(0.010)	(0.054)	(0.111)	(0.188)	(0.007)	(0.003)	(0.018)
Change in employment	0.037**	-0.019	-0.150***	-0.041*	0.023***	0.002	0.006*
	(0.017)	(0.015)	(0.052)	(0.024)	(0.007)	(0.002)	(0.004)
Mortgage rate	0.008	0.013	0.055***	0.010	0.071***	0.004	0.082***
	(0.011)	(0.009)	(0.011)	(0.007)	(0.008)	(0.011)	(0.009)
Unemployment rate	-0.130***	-0.075*	0.098**	0.020	0.024	-0.155***	-0.098***
	(0.041)	(0.037)	(0.037)	(0.043)	(0.014)	(0.047)	(0.024)
Housing starts	-0.082	0.143	0.237	-0.146	0.341	0.129	0.690*
	(0.351)	(0.352)	(0.282)	(0.318)	(0.654)	(0.272)	(0.336)
Income per capita	0.117***	0.077***	0.109***	0.094***	0.167***	0.071***	0.068***
	(0.014)	(0.023)	(0.021)	(0.029)	(0.019)	(0.010)	(0.011)
Observations	30	28	28	32	28	25	28
R^2	0.906	0.932	0.929	0.945	0.949	0.912	0.955

Table A2.1. Chinese cities in the sample

City	Tier	Region	City	Tier	Region
Beijing	First-tier	North	Anqing	Third-tier	East
Chongqing	First-tier	Southwest	Bengbu	Third-tier	East
Guangzhou	First-tier	Centre	Beihai	Third-tier	Centre
Shanghai	First-tier	East	Baotou	Third-tier	North
Shenzhen	First-tier	Centre	Changde	Third-tier	Centre
Tianjin	First-tier	North	Dandong	Third-tier	North
Changchun	Second-tier	North	Ganzhou	Third-tier	East
Chengdu	Second-tier	Southwest	Guilin	Third-tier	Centre
Changsha	Second-tier	Centre	Huizhou	Third-tier	Centre
Dalian	Second-tier	North	Jinhua	Third-tier	East
Fuzhou	Second-tier	East	Jining	Third-tier	East
Guiyang	Second-tier	Southwest	Jiujiang	Third-tier	East
Harbin	Second-tier	North	Jilin	Third-tier	North
Hefei	Second-tier	East	Jinzhou	Third-tier	North
Hohhot	Second-tier	North	Luzhou	Third-tier	Southwest
Haikou	Second-tier	Centre	Luoyang	Third-tier	Centre
Hangzhou	Second-tier	East	Mudanjiang	Third-tier	North
Jinan	Second-tier	East	Nanchong	Third-tier	Southwest
Kunming	Second-tier	Southwest	Pingdingshan	Third-tier	Centre
Lanzhou	Second-tier	North	Qinhuangdao	Third-tier	North
Ningbo	Second-tier	East	Quanzhou	Third-tier	East
Nanchang	Second-tier	East	Sanya	Third-tier	Centre
Nanjing	Second-tier	East	Shaoguan	Third-tier	Centre
Nanning	Second-tier	Centre	Tangshan	Third-tier	North
Qingdao	Second-tier	East	Wuxi	Third-tier	East
Shijiazhuang	Second-tier	North	Wenzhou	Third-tier	East
Shenyang	Second-tier	North	Xiangyang	Third-tier	Centre
Taiyuan	Second-tier	North	Xuzhou	Third-tier	East
Wuhan	Second-tier	Centre	Yichang	Third-tier	Centre
Urumchi	Second-tier	North	Yantai	Third-tier	East
Xi’an	Second-tier	North	Yueyang	Third-tier	Centre
Xiamen	Second-tier	East	Yangzhou	Third-tier	East
Yinchuan	Second-tier	North	Zhanjiang	Third-tier	Centre
Zhengzhou	Second-tier	Centre	Zunyi	Third-tier	Southwest
Xining	Second-tier	North	Dali	Fourth-tier	Southwest

Table A2.2. Introduction to national loan-to-value policy from 2007 to 2016

Release date	Release agency	Main content	Policy descriptions
27-09-2007	People's Bank of China (PBOC) and China Banking Regulatory Commission (CBRC)	Commercial banks should require no less than 20% of the transaction price as a down payment for those purchasing their first house (less than 90 m^2). If the floor area is equal to or above 90 m^2, the down payment shall not be less than 30%. For those using commercial loans to purchase houses, the minimum down payment ratio of the loans for the second or above house shall not be lower than 40%, and the loan interest rate shall not be lower than 1.1 times the benchmark interest rate.	Increasing the down payment ratio and the interest rate for commercial housing loans.
22-10-2008	Ministry of Finance and State Administration of Taxation	The minimum down payment ratio for all commercial personal housing loans for first homes has been reduced to 20%. The lower limit of commercial personal housing loan interest rate can be expanded to be 0.7 times the benchmark lending rate. The interest rates on all types of individual housing provident fund (HPF) loans are reduced by 0.27 percentage points.	The down payment for first homes being lowered for the first time in several years.
21-12-2008	General Office of the State Council	For residents who have raised loans to buy houses whose per capita housing area is lower than the local average level and who need to buy a second dwelling for their own use and to improve their living conditions, the preferential policy for first-time buyers can be applied. For the purchase of a second or above house, the loan interest rate shall be reasonably determined by commercial banks on the basis of the benchmark interest rate.	To increase credit support for self-occupied housing consumption and improve living conditions, thus comprehensively stimulating the housing market.
10-01-2010	General Office of the State Council	For those households who have used loans to buy houses and apply again to buy a second or above house (including borrowers, spouses, and minor children), the proportion of the down payment shall not be less than 40% and the loan interest rate shall be strictly determined according to the risk pricing.	Reiterating the minimum down payment of 40% for commercial mortgages for second homes.
17-04-2010	The State Council	For the first self-occupied housing (more than 90 m^2), the down payment ratio shall not be less than 30%; the ratio for second houses shall not be less than 50%. The lending rate shall not be less than 1.1 times the benchmark interest rate. For those who purchase a third or above house with mortgage loans, the proportion of the down payment and the corresponding interest rate shall be greatly increased, as determined by the commercial banks independently according to the risk management principle.	Increasing the down payment ratio for commercial loans.
29-09-2010	People's Bank of China and China Banking Regulatory Commission	Commercial banks shall suspend loans for buying a third or above home. Non-local residents who cannot provide proof of local tax payment or social insurance payment for more than one year shall be suspended from being granted house purchase loans. For the purchase of commercial housing, the down payment ratio will be adjusted to 30% or more; for buying second homes, the rule of no less than 50% down payment and no less than 1.1 times the benchmark interest rate is strictly enforced.	Further increasing the down payment ratio for commercial loans.
04-11-2010	PBOC, CBRC, Ministry of Finance and Ministry of Housing and Urban-Rural Development (MOHURD)	The down payment of HPF loans for the purchase of first common self-housing (less than or equal to 90 m^2) shall not be less than 20%; for the rest (above 90 m^2), the down payment shall not be less than 30%. The second HPF loan is only for households whose existing per capita housing construction area is lower than the local average level, and the use of the loan is limited to the purchase of ordinary self-housing to improve living conditions. The down payment ratio of HPF loans for second houses shall not be lower than 50%, and the loan interest rate shall not be lower than 1.1 times that of first housing in the same period.	Increasing the down payment ratio for HPF loans.

Table A2.2. Introduction to national loan-to-value policy from 2007 to 2016 (cont.)

Release date	Release agency	Main content	Policy descriptions
26-01-2011	General Office of the State Council	For households buying second homes, the down payment ratio is not less than 60%, and the loan interest rate is not less than 1.1 times the benchmark interest rate. Branches of the People's Bank of China may, based on national uniform credit policies, increase the down payment and interest rate of second housing loans based on local price control targets and policy requirements. Banking supervision departments should strengthen supervision and inspection of commercial banks' implementation of differentiated housing credit policies.	Strengthening differentiated housing credit policies and raising the down payment ratio for second homes.
01-03-2013	General Office of the State Council	In cities where housing prices are rising too quickly, local branches of the People's Bank of China can further increase the down payment ratio and loan interest rate on second home loans according to the price control target and policy requirements of the People's Government of the city.	Continuing to strictly manage housing consumption loans.
30-09-2014	People's Bank of China and China Banking Regulatory Commission	For households who purchase their first ordinary self-owned house, the minimum down payment ratio is 30%; the lower limit of loan interest rate is 0.7 times the benchmark interest rate, as determined independently by banking financial institutions. For those who own a house and have cleared previous loans, buying a second common commercial housing unit to improve living conditions, the same policy as for first-time buyers will be implemented. Except for Beijing, Shanghai, Guangzhou, Shenzhen, and Sanya where restrictions on purchases remain in place, the lending restrictions on the third or above house are lifted.	Easing lending restrictions.
30-03-2015	PBOC, CBRC, MOHURD	In order to improve living conditions, when households who own one house and whose corresponding purchase loans have not been cleared apply for commercial personal housing loans to purchase ordinary self-owned houses, the minimum down payment ratio shall be adjusted to no less than 40%. The minimum down payment for an HPF loan to purchase the first ordinary self-housing is 20%. When those who own a house and have already paid off their loan apply for an HPF loan, a minimum down payment of 30% applies.	Gradually relaxing credit limit policy. Reducing down payments for second home loans.
31-08-2015	PBOC, MOHURD, and Ministry of Housing	For households that own one house and have already cleared the corresponding housing purchase loans, if they apply for HPF loans to buy another house to improve living conditions, the minimum down payment proportion will be reduced from 30% to 20%. Beijing, Shanghai, Guangzhou, and Shenzhen can independently decide on the minimum down payment ratio for the application of HPF for the purchase of second housing on the basis of national unified policies and in combination with local conditions.	Further decreasing the down payment ratio for HPF loans for second homes.
30-09-2015	People's Bank of China and China Banking Regulatory Commission	In cities that do not implement house purchasing restrictions, the minimum down payment ratio will be adjusted to no less than 25% for commercial loans for buying the first ordinary house. In cities where house purchasing restrictions are in place, the minimum down payment ratio is 30% for households purchasing houses for the first time or who currently do not own a house. The minimum payment for commercial personal housing loans for second homes is 40%.	Reducing the down payment ratios for first homes.
02-02-2016	People's Bank of China and China Banking Regulatory Commission	In the cities that do not implement house purchasing restrictions, in principle, the minimum down payment proportion of commercial loans for first houses is 25%, and cities can lower this by 5%. For households that own a house and have not cleared the corresponding purchase loan, if they apply for a commercial personal housing loan again to purchase ordinary housing to improve living conditions, the minimum down payment proportion will be adjusted to no less than 30%.	Further decreasing down payment ratio for commercial mortgages.

Table A2.3. Effects of loan-to-value limits for borrowers who do not own a property

	Real growth in prices of second-hand houses			
	(1)	(2)	(3)	(4)
Loan-to-value caps lagged one quarter	0.243***	0.256***	0.167**	0.171**
	(0.068)	(0.067)	(0.067)	(0.070)
Loan-to-value caps lagged two quarter	-0.125***	-0.107**	-0.152***	-0.129**
	(0.041)	(0.042)	(0.051)	(0.049)
Loan-to-value caps lagged three quarter	0.006	0.016	0.005	0.010
	(0.048)	(0.048)	(0.046)	(0.046)
Loan-to-value caps lagged four quarter	-0.002	-0.004	0.034	0.035
	(0.040)	(0.039)	(0.027)	(0.030)
Real growth in house prices lagged one quarter	1.199***	1.129***	1.328***	1.255***
	(0.079)	(0.074)	(0.064)	(0.061)
Real growth in house prices lagged two quarter	-0.309***	-0.289***	-0.423***	-0.402***
	(0.082)	(0.078)	(0.085)	(0.082)
Real growth in house prices lagged three quarter	-0.084***	-0.100***	-0.062	-0.063
	(0.030)	(0.035)	(0.043)	(0.043)
Real growth in house prices lagged four quarter	-0.024	-0.031	-0.029	-0.056
	(0.021)	(0.028)	(0.044)	(0.041)
Overall policy effect over four quarters	0.123**	0.161***	0.053	0.087
	(0.053)	(0.054)	(0.062)	(0.068)
Long-run policy effect	0.565**	0.553***	0.287	0.326
	(0.232)	(0.171)	(0.341)	(0.259)
Observations	2799	2799	2799	2799
R^2 within	0.841	0.854	0.899	0.907
City trends	No	Yes	No	Yes
Weights	No	No	Yes	Yes

Notes: 1. Column (1) does not control for city trends or add any weights; column (2) controls for city trends; column (3) is weighted by population of each city; column (4) includes both city trends and weights. Regressions include city fixed effects, year fixed effects, lagged resident population, per capita disposable income of urban households and registered urban unemployment rate as control variables. For simplicity, the regression coefficients of control variables are not reported. Robust standard errors clustered by cities are in parentheses.

2. *** indicates significant at the 1% level; ** indicates significant at the 5% level; * indicates significant at the 10% level.

Table A2.4. Effects of loan-to-value limits for borrowers who own one property

	Real growth in prices of second-hand houses			
	(1)	(2)	(3)	(4)
Loan-to-value caps lagged one quarter	0.041***	0.048***	0.024**	0.033***
	(0.012)	(0.011)	(0.012)	(0.010)
Loan-to-value caps lagged two quarter	0.042***	0.045***	0.031***	0.035***
	(0.010)	(0.010)	(0.010)	(0.009)
Loan-to-value caps lagged three quarter	-0.090***	-0.076***	-0.095***	-0.082***
	(0.014)	(0.013)	(0.017)	(0.017)
Loan-to-value caps lagged four quarter	0.011	0.025	0.017	0.028
	(0.017)	(0.016)	(0.017)	(0.019)
Real growth in house prices lagged one quarter	1.198***	1.124***	1.324***	1.250***
	(0.079)	(0.075)	(0.065)	(0.064)
Real growth in house prices lagged two quarter	-0.315***	-0.293***	-0.429***	-0.402***
	(0.082)	(0.077)	(0.085)	(0.082)
Real growth in house prices lagged three quarter	-0.084***	-0.102***	-0.067	-0.071*
	(0.028)	(0.032)	(0.041)	(0.040)
Real growth in house prices lagged four quarter	-0.017	-0.022	-0.020	-0.041
	(0.017)	(0.024)	(0.042)	(0.041)
Overall policy effect over four quarters	0.004	0.043**	-0.023	0.013
	(0.024)	(0.020)	(0.025)	(0.027)
Long-run policy effect	0.017	0.145**	-0.119	0.050
	(0.110)	(0.065)	(0.122)	(0.103)
Observations	2799	2799	2799	2799
R^2 within	0.843	0.856	0.901	0.909
City trends	No	Yes	No	Yes
Weights	No	No	Yes	Yes

Notes: 1. Column (1) does not control for city trends or add any weights; column (2) controls for city trends; column (3) is weighted by population of each city; column (4) includes both city trends and weights. Regressions include city fixed effects, year fixed effects, lagged resident population, per capita disposable income of urban households and registered urban unemployment rate as control variables. For simplicity, the regression coefficients of control variables are not reported. Robust standard errors clustered by cities are in parentheses.

2. *** indicates significant at the 1% level; ** indicates significant at the 5% level; * indicates significant at the 10% level.

Table A2.5. Effects of loan-to-value limits on commercial loans for borrowers who do not own a property

	Real growth in prices of newly built houses			
	(1)	(2)	(3)	(4)
Loan-to-value caps lagged one quarter	0.284***	0.318***	0.189**	0.217***
	(0.067)	(0.067)	(0.078)	(0.080)
Loan-to-value caps lagged two quarter	-0.180***	-0.168***	-0.184***	-0.168***
	(0.037)	(0.036)	(0.054)	(0.052)
Loan-to-value caps lagged three quarter	0.158***	0.170***	0.149***	0.160***
	(0.035)	(0.035)	(0.036)	(0.037)
Loan-to-value caps lagged four quarter	-0.080**	-0.066**	-0.047**	-0.031
	(0.031)	(0.032)	(0.023)	(0.025)
Real growth in house prices lagged one quarter	1.294***	1.208***	1.432***	1.340***
	(0.072)	(0.066)	(0.045)	(0.042)
Real growth in house prices lagged two quarter	-0.442***	-0.408***	-0.599***	-0.559***
	(0.068)	(0.064)	(0.060)	(0.059)
Real growth in house prices lagged three quarter	-0.055*	-0.048	-0.002	0.013
	(0.031)	(0.031)	(0.036)	(0.035)
Real growth in house prices lagged four quarter	-0.037	-0.082***	-0.036	-0.097***
	(0.026)	(0.024)	(0.033)	(0.030)
Overall policy effect over four quarters	0.181***	0.253***	0.107*	0.177***
	(0.053)	(0.052)	(0.060)	(0.066)
Long-run policy effect	0.754***	0.769***	0.522*	0.583**
	(0.202)	(0.154)	(0.303)	(0.230)
Observations	2799	2799	2799	2799
R^2 within	0.870	0.882	0.915	0.923
City trends	No	Yes	No	Yes
Weights	No	No	Yes	Yes

Notes: 1. Column (1) does not control for city trends or add any weights; column (2) controls for city trends; column (3) is weighted by population of each city; column (4) includes both city trends and weights. Regressions include city fixed effects, year fixed effects, lagged resident population, per capita disposable income of urban households and registered urban unemployment rate as control variables. For simplicity, the regression coefficients of control variables are not reported. Robust standard errors clustered by cities are in parentheses.

2. *** indicates significant at the 1% level; ** indicates significant at the 5% level; * indicates significant at the 10% level.

Table A2.6. Effects of loan-to-value limits on commercial loans for borrowers who own one property

	Real growth in prices of newly built houses			
	(1)	(2)	(3)	(4)
Loan-to-value caps lagged one quarter	0.055***	0.058***	0.037***	0.041***
	(0.011)	(0.011)	(0.013)	(0.013)
Loan-to-value caps lagged two quarter	0.026***	0.031***	0.014*	0.020**
	(0.010)	(0.009)	(0.008)	(0.008)
Loan-to-value caps lagged three quarter	-0.071***	-0.056***	-0.069***	-0.057***
	(0.009)	(0.009)	(0.009)	(0.010)
Loan-to-value caps lagged four quarter	0.018	0.040**	0.022	0.041**
	(0.020)	(0.018)	(0.015)	(0.019)
Real growth in house prices lagged one quarter	1.301***	1.217***	1.431***	1.342***
	(0.072)	(0.066)	(0.044)	(0.043)
Real growth in house prices lagged two quarter	-0.448***	-0.417***	-0.591***	-0.552***
	(0.063)	(0.059)	(0.055)	(0.053)
Real growth in house prices lagged three quarter	-0.078***	-0.070***	-0.034	-0.021
	(0.025)	(0.025)	(0.031)	(0.031)
Real growth in house prices lagged four quarter	-0.006	-0.048**	-0.010	-0.064**
	(0.024)	(0.022)	(0.029)	(0.029)
Overall policy effect over four quarters	0.029	0.073***	0.004	0.044
	(0.025)	(0.021)	(0.024)	(0.028)
Long-run policy effect	0.125	0.229***	0.021	0.150
	(0.111)	(0.070)	(0.117)	(0.099)
Observations	2799	2799	2799	2799
R^2 within	0.872	0.883	0.916	0.924
City trends	No	Yes	No	Yes
Weights	No	No	Yes	Yes

Notes: 1. Column (1) does not control for city trends or add any weights; column (2) controls for city trends; column (3) is weighted by population of each city; column (4) includes both city trends and weights. Regressions include city fixed effects, year fixed effects, lagged resident population, per capita disposable income of urban households and registered urban unemployment rate as control variables. For simplicity, the regression coefficients of control variables are not reported. Robust standard errors clustered by cities are in parentheses.

2. *** indicates significant at the 1% level; ** indicates significant at the 5% level; * indicates significant at the 10% level.

Table A2.7. Difference-in-differences regressions with dummy variables for loosening loan-to-value policies (excluding Beijing, Shanghai, Guangzhou, Shenzhen)

	Real growth in prices of newly built houses	
	(1)	(2)
Treat	-0.034***	-0.001
	(0.005)	(0.006)
Post	0.018**	0.031***
	(0.006)	(0.000)
Treat*Post	0.012*	0.047**
	(0.006)	(0.022)
Observations	34	38
R^2 within	0.215	0.198

Notes: 1. Column (1) gives the response of real house price growth rates to the policy which increased the LTV cap applied to commercial loans for borrowers who do not own a property from 70% to 80% on October 22, 2008; column (2) shows the response of real house price growth rates to the policy which increased the LTV cap applied to commercial loans for borrowers who already own one property from 60% to 70% on February 2, 2016. The propensity score matching technique is adopted to select the treated cities whose house price growth trend was similar to that of the control cities. Robust standard errors clustered by cities are in parentheses.

2. *** indicates significant at the 1% level; ** indicates significant at the 5% level; * indicates significant at the 10% level.

Table A3.1. Definitions and descriptions of key variables

Variables	Value	Meaning
LTV cap	Decimal numbers between 0 and 1	Actual level of the largest allowable LTV ratio
Deciding to buy	0	Not bought a house
	1	bought a house
Size of the house	Positive real number	The size of the house that is bought (unit: square meters)
Distance to city centre	Positive real number	The number of minutes required to commute from the house to the city/county centre
Age	Integral numbers between 25 and 64	Age of head of household
Gender	0	Female
	1	Male
Education	1	No schooling at all
	2	Primary school
	3	Junior high
	4	High school
	5	Technical high school
	6	College/Vocational school
	7	Bachelor’s degree
	8	Master’s degree
	9	Doctorate degree
Siblings	Integers starting at 0	Number of siblings of head of household and spouse
Type of hukou	0	Non-agricultural residency
	1	Agricultural residency
Area of residence	0	Urban area
	1	Rural area
Financial literacy	1	Very concerned with financial information
	2	Quite concerned with financial information
	3	Fairly concerned with financial information
	4	Seldom concerned with financial information
	5	Never concerned with financial information
Risk preference	1	High-risk, high-return project
	2	Slightly high-risk, slightly high-return project
	3	Medium risk, medium return project
	4	Slightly low-risk, slightly low-return project
	5	Unwilling to take any risks

Bibliography

[1] Aastveit, K.A. and Anundsen, A. K. (2017). ‘Asymmetric Effects of Monetary Policy in Regional Housing Markets’, Working Papers No 7/2017, Centre for Applied Macro- and Petroleum economics (CAMP), BI Norwegian Business School.

[2] Adelino, M., Schoar, A. and Severino, F. (2012). ‘Credit Supply and House Prices: Evidence from Mortgage Market Segmentation’, NBER Working Paper No. 17832.

[3] Ahuja, A. and Nabar, M. (2011). ‘Safeguarding Banks and Containing Property Booms: Cross-Country Evidence on Macroprudential Policies and Lessons from Hong Kong SAR’, IMF Working Paper No. 11/284.

[4] Akinci, O. and Olmstead-Rumsey, J. (2018). ‘How Effective are Macroprudential Policies? An Empirical Investigation’, *Journal of Financial Intermediation*, vol 33, pp. 33–57.

[5] Alam, Z., Alter, A., Eiseman, J., Gelos, G., Kang, H., Narita, M., Nier, E. and Wang, N. (2019). ‘Digging Deeper—Evidence on the Effects of Macroprudential Policies from a New Database’, IMF Working Paper No. 19/66.

[6] Aliber, R. Z., Kindleberger, C. P. and Overton, T. (2015). *Manias, Panics, and Crashes: A History of Financial Crises*, Palgrave Macmillan UK.

[7] Allen, F. and Carletti, E. (2011). ‘What Should Central Banks Do about Real Estate Prices?’, IDEAS Working Paper Series from RePEc.

[8] Alpanda, S. and Zubairy, S. (2017). ‘Addressing Household Indebtedness: Monetary, Fiscal or Macroprudential Policy?’, *European Economic Review*, vol. 92, pp. 47–73.

[9] Angrist, J.D. and Pischke, J.-S. (2009). *Mostly Harmless Econometrics: An Empiricist’s*

Companion, Princeton: Princeton University Press.

[10] Armstrong, J., Skilling, H. and Yao, F. (2019). 'Loan-to-Value Ratio Restrictions and House Prices: Micro Evidence from New Zealand', *Journal of Housing Economics*, vol. 44, pp. 88–98.

[11] Bajari, P., Chan, P., Krueger, D. and Miller, D. (2013). 'A Dynamic Model of Housing Demand: Estimation and Policy Implications', *International Economic Review*, vol. 54(2), pp. 409–442.

[12] Berger, D., Turner, N. and Zwick, E. (2016). 'Stimulating Housing Markets', Chicago Booth Research Paper No. 16-16; Kreisman Working Papers Series in Housing Law and Policy No. 40.

[13] Brée, D. S. and Joseph, N. L. (2013). 'Testing for Financial Crashes Using the Log Periodic Power Law Model', *International Review of Financial Analysis*, vol. 30, pp. 287–297.

[14] Brunnermeier, M. K. and Julliard, C. (2008). 'Money Illusion and Housing Frenzies', *Review of Financial Studies*, vol. 21(1), pp. 135–180.

[15] Brunnermeier, M. K. and Oehmke, M. (2013). 'Bubbles, Financial Crises, and Systemic Risk', Handbook of the Economics of Finance. Amsterdam: Elsevier.

[16] Caloia, F. G. (2019). 'Leverage Constraints, House Prices and Household Debt: Evidence from the Netherlands', Working Paper.

[17] Campbell, S. D., Davis, M. A., Gallin, J. and Martin, R. F. (2009). 'What Moves Housing Markets: A Variance Decomposition of the Rent–Price Ratio', *Journal of Urban Economics*, vol. 66, pp. 90–102.

[18] Cao, J., Huang, B. and Lai, R. N. (2015). 'On the Effectiveness of Housing Purchase Restriction Policy in China: A Difference in Difference Approach', SSRN Electronic Journal No. 2584275.

[19] Case, K. E. and Shiller, R. J. (1989). 'The Efficiency of the Market for Single-Family Homes',

The American Economic Review, vol. 79(1), pp. 125–137.

[20] Case, K. E. and Shiller, R. J. (2003). 'Is There a Bubble in the Housing Market?', Brookings papers on economic activity, Issue 2, pp. 299–362.

[21] Cerutti, E., Claessens, S. and Laeven, L. (2017). 'The Use and Effectiveness of Macroprudential Policies: New Evidence', *Journal of Financial Stability*, vol. 28, pp. 203–224.

[22] Chen, J., Chen, Y. and Liu, R. (2009). '所有权成本、投资者预期与住宅价格波动：关于国内四大城市住宅市场的经验研究', *The Journal of World Economy*, vol. (10), pp. 14–24.

[23] Cieslak, A. and Povala, P. (2015). 'Expected Returns in Treasury Bonds', *The Review of Financial Studies*, vol. 28(10), pp. 2859–2901.

[24] Cizel, J., Frost, J., Houben, A. and Wierts, P. (2019). 'Effective Macroprudential Policy: Cross-Sector Substitution from Price and Quantity Measures', *Journal of Money, Credit and Banking*, vol. 51(5), pp. 1209–1235.

[25] Crowe, C., Dell'Ariccia, G., Igan, D. and Rabanal, P. (2013). 'How to Deal with Real Estate Booms: Lessons from Country Experiences', *Journal of Financial Stability*, vol. 9(3), pp. 300–319.

[26] Deng, Y., Gyourko, J. and Wu, J. (2017). 'Evaluating Risk across Chinese Housing Markets', VOX CHINA, August 2.

[27] Deng, Y., Wei, S-J. and Wu, J. (2015). 'Estimating the Unofficial Income of Officials from Housing Purchases: The Case of China', Working Paper, National University of Singapore.

[28] Duca, J. V., Muellbauer, J. and Murphy, A. (2011). 'House Prices and Credit Constraints: Making Sense of the US Experience', *The Economic Journal*, vol. 121, pp. 533–551.

[29] Favara, G. and Imbs, J. (2015). 'Credit Supply and the Price of Housing', *The American*

Economic Review, vol. 105(3), pp. 958–992.

[30] 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*, vol. 125(1), pp. 140–223.

[31] Gelain, P., Lansing, K. J. and Natvik, G. J. (2018). 'Explaining the Boom-Bust Cycle in the U.S. Housing Market: A Reverse-Engineering Approach', *Journal of Money, Credit and Banking*, vol. 50(8), pp. 1751–1783.

[32] Gete, P. and Reher, M. (2016). 'Two Extensive Margins of Credit and Loan-to-Value Policies', *Journal of Money, Credit and Banking*, vol. 48(7), pp. 1397–1438.

[33] Godoy de Araujo, D. K., Barroso, J. B. R. B. and Gonzalez, R. B. (2020). 'Loan-to-Value Policy and Housing Finance: Effects on Constrained Borrowers', *Journal of Financial Intermediation*, vol. 42, 100830.

[34] Green, R. K., Malpezzi, S. and Mayo, S. K. (2005). 'Metropolitan-Specific Estimates of the Price Elasticity of Supply of Housing, and Their Sources', *The American Economic Review*, vol. 95(2), pp. 334–339.

[35] Grodecka, A. (2020). 'On the Effectiveness of Loan-to-Value Regulation in a Multiconstraint Framework', *Journal of Money, Credit and Banking*, vol. 52(5), pp. 1231–1270.

[36] Guler, B., Jung, K. and Suh, H. (2016). 'Macroprudential Policy in a Heterogenous Agent Model', Working Paper.

[37] Halket, J. and Vasudev, S. (2014). 'Saving up or Settling down: Home Ownership over the Life Cycle', *Review of Economic Dynamics*, vol. 17(2), pp. 345–366.

[38] Himmelberg, C., Mayer, C. and Sinai, T. (2005). 'Assessing High House Prices: Bubbles,

Fundamentals and Misperceptions', *Journal of Economic Perspectives*, vol. 19(4), pp. 67–92.

[39] Ho, A. T. Y. and Zhou, J. (2016). 'The Impacts of Mortgage Regulations on Households' Life- cycle Housing Decisions', Working Paper.

[40] Hwang, S., Park, M. and Lee, H.-S. (2013). 'Dynamic Analysis of the Effects of Mortgage-lending Policies in A Real Estate Market', *Mathematical & Computer Modelling*, vol. 57, pp. 2106–2120.

[41] Hwang, M. and Quigley, J. M. (2006). 'Economic Fundamentals in Local Housing Markets: Evidence from U.S. Metropolitan Regions', *Journal of Regional Science*, vol. 46(3), pp. 425–453.

[42] Igan, D. and Kang, H. (2011). 'Do Loan-to-Value and Debt-to-Income Limits Work? Evidence from Korea', IMF Working Paper No. 11/297.

[43] International Monetary Fund (2003). World Economic Outlook, Chapter II, pp. 61–94.

[44] International Monetary Fund (2014). Staff Guidance Note on Macroprudential Policy.

[45] Jácome, L. I. and Mitra, S. (2015). 'LTV and DTI Limits—Going Granular', Working Paper No. 15/154.

[46] Johansen, A., Ledoit, O. and Sornette, D. (2000). 'Crashes as Critical Points', *International Journal of Theoretical and Applied Finance*, vol. 3(2), pp. 219–255.

[47] Jordà, O. (2005). 'Estimation and Inference of Impulse Responses by Local Projections', *The American Economic Review*, vol. 95 (1), pp. 161–182.

[48] Jung, Y., Kim, S. and Yang D. Y. (2017). 'Optimal Macroprudential Policies and House Prices in Korea', *Emerging Markets Finance and Trade*, vol. 53(11), pp. 2419–2439.

[49] Justiniano, A., Primiceri, G. E. and Tambalotti, A. (2019). 'Credit Supply and the Housing Boom', *Journal of Political Economy*, vol. 127(3), pp. 1317–1350.

[50] Kelly, R., McCann, F. and O'Toole, C. (2018). 'Credit Conditions, Macroprudential Policy and House Prices', *Journal of Housing Economics*, vol. 41, pp. 153–167.

[51] Krainer, J. and Wei, C. (2004). 'House Prices and Fundamental Value', FRBSF Economic Letter, Federal Reserve Bank of San Francisco, issue oct1.

[52] Kuttner, K. and Shim, I. (2012). 'Taming the Real Estate Beast: The Effects of Monetary and Macroprudential Policies on House Prices and Credit', Property Markets and Financial Stability, Reserve Bank of Australia.

[53] Kuttner, K. N. and Shim, I. (2016). 'Can Non-Interest Rate Policies Stabilize Housing Markets? Evidence from a Panel of 57 Economies', *Journal of Financial Stability*, vol. 26, pp. 31–44.

[54] Liu, X. (2014). 'Housing Supply Elasticity, Determinant Factors and Housing Price Performance of Urban China', *Finance & Trade Economics*, (4), pp. 125–137.

[55] Liu, R., Hui, E. C., Lv, J. and Chen, Y. (2017). 'What Drives Housing Markets: Fundamentals or Bubbles?', *Journal of Real Estate Finance and Economics*, vol. 55, pp. 395–415.

[56] Mayer, C. and Sinai, T. (2007). Housing and Behavioral Finance. Mimeo, Columbia University and University of Pennsylvania.

[57] McDonald, C. (2015). 'When Is Macroprudential Policy Effective?', BIS Working Papers No. 496.

[58] Mian, A. and Sufi, A. (2012). 'The Effects of Fiscal Stimulus: Evidence from the 2009 Cash for Clunkers Program', *The Quarterly Journal of Economics*, vol. 127(3), pp. 1107–1142.

[59] Neagu, F., Tatarici, L. and Mihai, I. (2015). 'Implementing Loan-to-Value and Debt Service-to-Income Measures: A Decade of Romanian Experience', MPRA Paper No. 65988.

[60] Nickell, S. (1981). ‘Biases in Dynamic Models with Fixed Effects’, *Econometrica*, vol. 49(6), pp. 1417–1426.

[61] Prasad, E. S. (2013). ‘Distributional Effects of Macroeconomic Policy Choices in Emerging Market Economies’, NBER Working Paper No. 19668.

[62] Qiang, J., Hou, X. and Fan, L. (2018). ‘Base Interest Rate, Expected Inflation and the Mechanism for Determining the Term Structure of Market Interest Rate in China’, *Economic Research Journal*, vol. 53, pp. 92–107.

[63] Ren, C., Wu, J. and Deng, Y. (2013). ‘The Effect of Market Expectation on the Change of Housing Rent to Price Ratio: An Analysis Based on User Cost Model’, *Journal of Zhejiang University (Humanities and Social Sciences)*, vol. (1), pp. 58–72.

[64] Richter, B., Schularick, M. and Shim, I. (2019). ‘The Costs of Macroprudential Policy’, *Journal of International Economics*, vol. 118, pp. 263–282.

[65] Rubio, M. (2016). ‘Short and Long-Term Interest Rates and the Effectiveness of Monetary and Macroprudential Policies’, *Journal of Macroeconomics*, vol. 47(Part A), pp. 103–115.

[66] Sá, F. (2016). ‘The Effect of Foreign Investors on Local Housing Markets: Evidence from the UK’, CEPR Discussion Paper DP11658.

[67] Shim, I., Bogdanova, B., Shek J. and Subelytė, A. (2013). ‘Database for Policy Actions on Housing Markets’, *BIS Quarterly Review*, pp. 83–95.

[68] Sornette, D. (2017). *Why Stock Markets Crash: Critical Events in Complex Financial Systems*, Princeton: Princeton University Press.

[69] Tressel, T. and Zhang, Y. S. (2016). ‘Effectiveness and Channels of Macroprudential Instruments Lessons from the Euro Area’, IMF Working Paper No. 16/4.

[70] Tzur-Ilan, N. (2020). ‘Unintended Consequences of LTV Limits on Credit and Housing Choices’, Working Paper.

[71] Van Bekkum, S., Gabarro, M., Irani, R. M. and Peydro, J.-L. (2019). ‘Take It to the Limit? The Effects of Household Leverage Caps’, Working Paper.

[72] Vandenbussche, J., Vogel, U. and Detragiache, E. (2015). ‘Macroprudential Policies and Housing Prices: A New Database and Empirical Evidence for Central, Eastern, and Southeastern Europe’, *Journal of Money, Credit and Banking*, vol. 47(S1), pp. 343–377.

[73] Vuolteenaho, T. (2002). ‘What Drives Firm-Level Stock Returns’, *The Journal of Finance*, vol. 57(1), pp. 233–264.

[74] Wang, S., Chan, S. H. and Xu, B. (2012). ‘The Estimation and Determinants of the Price Elasticity of Housing Supply: Evidence from China’, *Journal of Real Estate Research*, vol. 34(3), pp. 311–344.

[75] Wang, X. and Woo, W. T. (2011). ‘The Size and Distribution of Hidden Household Income in China’, *Asian Economic Papers*, vol. 10(1), pp. 1–26.

[76] Weeken, O. (2004). ‘Asset Pricing and the Housing Market’, Bank of England Quarterly Bulletin, Spring.

[77] Wong, T. C., Fong, T., Li, K. F. and Choi, H. (2011). ‘Loan-to-Value Ratio as a Macroprudential Tool - Hong Kong’s Experience and Cross-Country Evidence’, systemic Risk, Basel III, Financial Stability and Regulation.

[78] World Bank (1992). China: Implementation Options for Urban Housing Reform. Washington, D.C.

[79] Yang, J., Yu, Z. and Deng, Y. (2018). ‘Housing Price Spillovers in China: A High-Dimensional

Generalized VAR Approach', *Regional Science and Urban Economics*, vol. 68, pp. 98–114.

[80] Zhi, T., Li, Z., Jiang, Z., Wei, L. and Sornette, D. (2019). 'Is There a Housing Bubble in China?', *Emerging Markets Review*, vol. 39, pp. 120–132.

[81] Zhou, W. and Sornette, D. (2006). 'Is There a Real-Estate Bubble in the US?', *Physica A*, vol. 361, pp. 297–308.