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Essays on the Housing Market in China and Some Evidence on Inflation Targeting

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ESSAYS ON THE HOUSING MARKET IN CHINA AND SOME EVIDENCE ON
INFLATION TARGETING

A Dissertation
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy
In Economics

by
Yanchao Li
December 2021

Accepted by:
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ABSTRACT

The housing market in China enjoys great prosperity after a continuously rapid development for more than a decade. However, there are growing concerns about possible bubbles as the price continues to rise while ordinary workers cannot afford a house. The government of China has implemented different kinds of regulations to slow rapid price increases and stabilize the market since 2007. The first paper looks at the characteristics and determinants of housing prices in different tiers of cities in China over the period 2002–2017, and then the second paper examines the impact of different types of regulations on the real estate price and trading volume using monthly data from Jan 2008 to Dec 2017. Empirical results demonstrate that housing price increase cannot be well explained in terms of fundamental factors in all 3 city tiers. Heterogeneity is found in regulation effects in different city tiers and most of the government interventions are not effective on housing price or trading volumes. Fundamental factors and regulations work dramatically different in Tier 1 cities versus Tier 2 & 3 cities. The difference between Tier 2 and Tier 3 is smaller.

The third paper examines the treatment effects of inflation targeting (IT) on inflation and output growth over the period of 1980–2020, based on annual data of 20 Latin American countries. A variety of estimating methods are considered and regression results indicate no evidence that inflation targeting helps to lower inflation or stabilize the GDP growth rate in 10 Latin American emerging markets.

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CHAPTER ONE

Housing Price Fluctuation in Different Ties of Cities in China

1.1 Introduction

China's housing market enjoyed great development ever since the transformation from the socialist housing allocation system to market housing system in the late 1990s. Along with the market economy reform, the housing market has gradually become one of the major engines of economic growth. After a relatively stable development period lasting for 10 years, the market tends to be booming from 2002. Literature reported housing price has increased in a dramatical fashion. (See Wu, Gyourko, and Deng (2012), Fang, Gu, Xiong, and Zhou (2015) for example.) However, income growth is lagged behind housing prices in major urban cities. People see it as unsustainable but the price is still soaring with no sign of stop. Literatures regarding China's housing market show great research interest on the topic of housing market bubble. However, consensus has never been reached whether the bubble exist or not. Ahuja, Cheung, Han, Porter, and Zhang (2010), Ren, Xiong, and Yuan (2012), and Feng and Wu (2015) suggest the absence of a bubble, while Gabrieli, Pilbeam, and Wang (2017) Chen and Wen (2017) indicate evidence of a bubble. It is really hard to determine the existence of price bubble directly. However, the effects of fundamental factors can be used as a reference. Stiglitz (1990) provided this kind of a

definition of asset bubbles: “If the reason that the price is high today is only because investors believe that the selling price is high tomorrow -- when ‘fundamental’ factors do not seem to justify such a price -- then a bubble exists. At least in the short run, the high price of the asset is merited, because it yields a return (capital gain plus dividend) equal to that on alternative assets.” Inspired by this idea, this paper will focus on the effect of fundamental factors on the housing price and try to shed light on this topic based on the city level data.

Concerning that China is a very large country with huge income (and other things as well) gap between different tiers of cities and the existence of hukou regulation, which significantly restrain the liquidity of people across different regions, taking the market as a whole is not a good idea. In housing market, price also differs greatly in different tiers of cities. In this paper I use a supply and demand perspective to deal with the data of 35 major cities belonging to 4 tiers of cities from year 2002-2017, a panel data regression method is applied to find the effect of fundamental factors and finally, I use hypothesis testing to investigate the heterogeneity in different tiers of cities.

The remainder of the paper is organized as follows. Section 2 provides a history background of the reforms in the housing market. Section 3 reviews some existing literature. Section 4 presents a simple supply and demand theoretical framework of housing price and discuss the estimation techniques used. Section 5 discuss the data and preliminary analysis findings. Section 6 specify the empirical econometric modeling and Section 7 report the results of the panel data regressions. Finally, Section 8 concludes.

1.2 A History Review of Housing Market Reforms in China

As an old saying goes “Only when you know the past well enough, you can predict the future.” China’s housing market has many unique features than other countries along with the economic reform from socialism to partially capitalism (so-called Socialist Market Economy).

After the establishment of People’s Republic of China in 1949, socialism gradually transformed the nation. In the new socialist economy system, housing was a part of the socialist welfare system. The provision of housing was mainly relied on work units, i.e., firms or other organizations citizens belonging to. Land and 90% of the fund were provided through the central planning system and citizens only need to pay a very low amount of rent to maintain the house. Huang, Y. & Clark, W. A. (2002) argue that the allocation order of houses was based on one’s relationships with the work unit. Close relationship means priority in the waiting list and job rank and job seniority served as the indicators to evaluate this kind of relationship. According to a report of the State Real Estate Administration in 1965, the average rent per square meter was about 0.1 yuan, and rent to income ratio was about 1%-3%¹ Therefore, at that time period, the question was more about when would be my turn instead of whether can I afford a house. Excessive welfare resulted in low efficiency. The average living area was only $36m^2$ in 1978 and that number was $45m^2$ in

¹ Real Estate Magazine News Agency "Selection of National Real Estate Policy Documents (1948-1981)", p. 151

1949.² On one hand, 6890 thousand urban households were lack of housing, which was 35.8% of all households in 182 urban cities.³ On the other hand, government and firms bore high burden in the prevision and maintenance of housing due to the extremely low rent. The demand cap kept increasing in the process of urbanization.

Things began to change starting from the Reform and Opening in 1978. As a part of the Socialist Market Economy reform, commercial housing was first allowed in 1980 and private housing and home-ownership have been encouraged since 1988. This new commercial housing system coexisted with welfare housing system for approximately 20 years until the welfare housing system completely shut down in the end of 1990s. In response to the 1997 financial crisis, the central government decided to completely abandon the housing allocation system, announcing that new homes would only be built and sold in the market and construction land would only be supplied by the government through long-term leases. Work units were not allowed to build or buy residential units for their employees since then. As a consequence, modern Chinese housing market is finally established in 1998. Existing welfare housings were generally privatized in the transformation from allocation to market system. Current tenants of public housings could either pay an increased rent or buyout their living flats at a subsidized price under the condition that residents could not trade these buyout houses for at least 5 years. See TOLLEY, G. S. (1991) for detail.

² Cheng, S. "Reform of China's Urban Housing Distribution System-Target Model and Implementation Difficulties", Beijing: Democracy and Construction Press, 1999 Edition, p. 108

³ Zhou, S., Lin, S., "Talking about housing problems", People's Daily, August 5, 1980, 5th edition.

Since the allocation housing system was completely replaced by the market-oriented housing system, the restrained housing demand is gradually released. In 2000, 15% of the households acquire their houses through market, while 60% households lived in their bought allocated houses or self-constructed houses. In 2005, approximately 25% of the households got their houses via housing market and that number went up 45% in 2010.⁴

Good time always comes to an end. Along with the booming economy and rapidly urbanization process, most of the urban housing markets across China experienced a sustained price increase since 2002. A heated debate whether the pricing increase is fundamental or not started ever since. Despite of many short-position perspectives, housing price continued to go up to more than triple within 10 years. And it even gradually become a social problem as more and more citizens can't afford a house. In recent years, there are considerably concerns that the booming housing price may represents a real estate bubble similar to what happened in Japan in 1990s and US in 2007.

China's central government now face a dilemma. On one hand, government has to take actions against the rapidly rising price to appease the low-income residents. On the other hand, government can't afford the collapse of the real estate market as it has relied on real estate industry for not only local government funding but also much of its growth in recent years. According to World Bank statistics, real estate sector comprised 5.7% of China's output in 2010, while the construction sector contributed another 6.7%. That number increased to 7.0% and 7.2% respectively in 2019.⁵ To those who already own their houses,

⁴ Ren, R., Housing Tenure Choice in Urban China, JUL 2014.

⁵ Source: National Bureau of Statistics of China. The construction sector includes non-housing real estate and non-real estate activities such as infrastructure.

a sudden price drop will also be frustrated as report shows housing wealth is the main form of wealth for Chinese residents.⁶ Central government tried to find a balance between the social stability and the economic growth. Government control have taken place in order to flatten the housing price curve, however the effectiveness of these methods is remained to be seen.

1.3 Overview of the Literature

The literature on housing markets is enormous. Here I mainly focus on literature that analyses models to estimated equilibrium housing price and the efficiency of housing market. Generally speaking, there are three main-stream models about housing price:

1.3.1 Tenure choice model.

Owning verse renting is the very first question people need to answer when they need a place to live in. Economists believe household make choice of buying a house or renting an apartment through comparing the expected cost of owning a house against the rental cost. Equilibrium housing price can then be derived from a non-arbitrage condition between owing and renting in which $\text{Price} = \text{rent} = \text{user cost of owning}$. (Shelton (1968) Mills (1990) Poterba (1992) Holly et al. (2010)) Equilibrium housing price can be also solved in a utility maximization perspective where individuals maximize a multi-period utility function. (Henderson and Ioannides (1983))

1.3.2 Flow model

⁶ China urban household wealth health Report 2018 shows that more than 70% of household wealth is in housing wealth. China urban household wealth health Report is an annual report provided by Southwestern University of Finance and Economics, China.

Just like any other goods in the market, Housing also has an equilibrium price and supply will change gradually as demand shifts. Flow model, also known as stock adjustment models is one of the famous models trying to describe the mechanism of housing market in a supply and demand perspective. This stream can trace back to Chow (1957) and Muth (1960). A stock represents a quantity of existing durable goods at a specific time, which is rigid in the short run and a flow represents the changing amounts of quantities over a time interval, which reacts to short term shocks. Stock is the accumulation of flows over time and stock and flows are linked together through price. Hanushek and Quigley, (1979) extended the stock adjustment model to housing service and DiPasquale and Wheaton (1994) derive a reduced form equation from a stock adjustment model that incorporates a lagged adjustment from the annual percentage rate so that prices converge to an equilibrium price. Flow model can be extended to a DSGE model where household and firm both maximize their utility function under certain constraints. Households act as demander and firms serve as suppliers. (e.g., Iacoviello and Neri 2010, Eric C.Y. Ng 2015) Government can be introduced as a third sector to build a 3-sector DSGE model. Research showed that government policies are important determinants of the level of prices (Malpezzi, 1996; Malpezzi et al., 1998; Rose, 1989, among others). But as Abraham and Hendershott (1996) have pointed out, little explicit empirical work has been done on the effect of regulation on housing price dynamics.⁷

1.3.3 Efficiency of the housing market

⁷ A Simple Error Correction Model of House Prices

Commonly there are two most famous indicators to measure the efficiency of housing market, price-income ratio and price-rent ratio. First describes the functionality of demand and supply transmission and the second focus on the mechanism of return on investment. See (Malpezzi, 1990; Renaud, 1989; Malpezzi and Ball,1993) for the first indicator. Generally, these studies have suggested that in equilibrium, aggregate market housing price to income ratios range somewhere between 2 and 3. However, these two indicators should be inferred carefully in the context of China, taking into consideration of a large amount of existing welfare houses that is inferior to newly built residential houses. Since buyout welfare house can be sold at a considerably lower price than market ear houses, I only focus on price dynamics of newly built houses.

1.3.4 Literatures in China

Many literatures have investigated the determinants of residential housing prices in China (Ahuja et al., 2010; Chen et al.,2011; Liang and Cao,2007; Liu et al., 2002; Wu et al., 2012;). Both demand and supply factors has been tested. Common demand factors tested include real GDP growth, income growth, user costs, housing loan, migration and urbanization. Common supply factors tested include fiscal revenue and fiscal allocation system, land supply, land price and land auction.

1.4 Theoretical Framework and Empirical

Methodology

In this paper I will use a supply and demand framework, following the research stream of flow model. A standard demand function for housing can be described as

$$\frac{H}{pop} = F(Y, U, D)$$

Where H represents housing stock or trading volume. Pop denotes population. Y, U represents average real income and real user cost respectively and D represents other factors which shift the demand curve. User cost is commonly described as

$$U = p^h(r + \delta - \frac{p^{he}}{p^h})$$

Where p^h represents real price of houses. r is interest rate and δ denotes depreciation rate or rate of maintenance, last price ratio represents expected rate of appreciation, denoted as e in the following paper.

A standard flow model supply function can be described as

$$\dot{H} = F(p^h, pop, c, s) - \delta H$$

Where \dot{H} represents the changing amount between two periods. C is short for cost and S represents other factors which shift the supply curve.

Combine the demand and supply function above yields

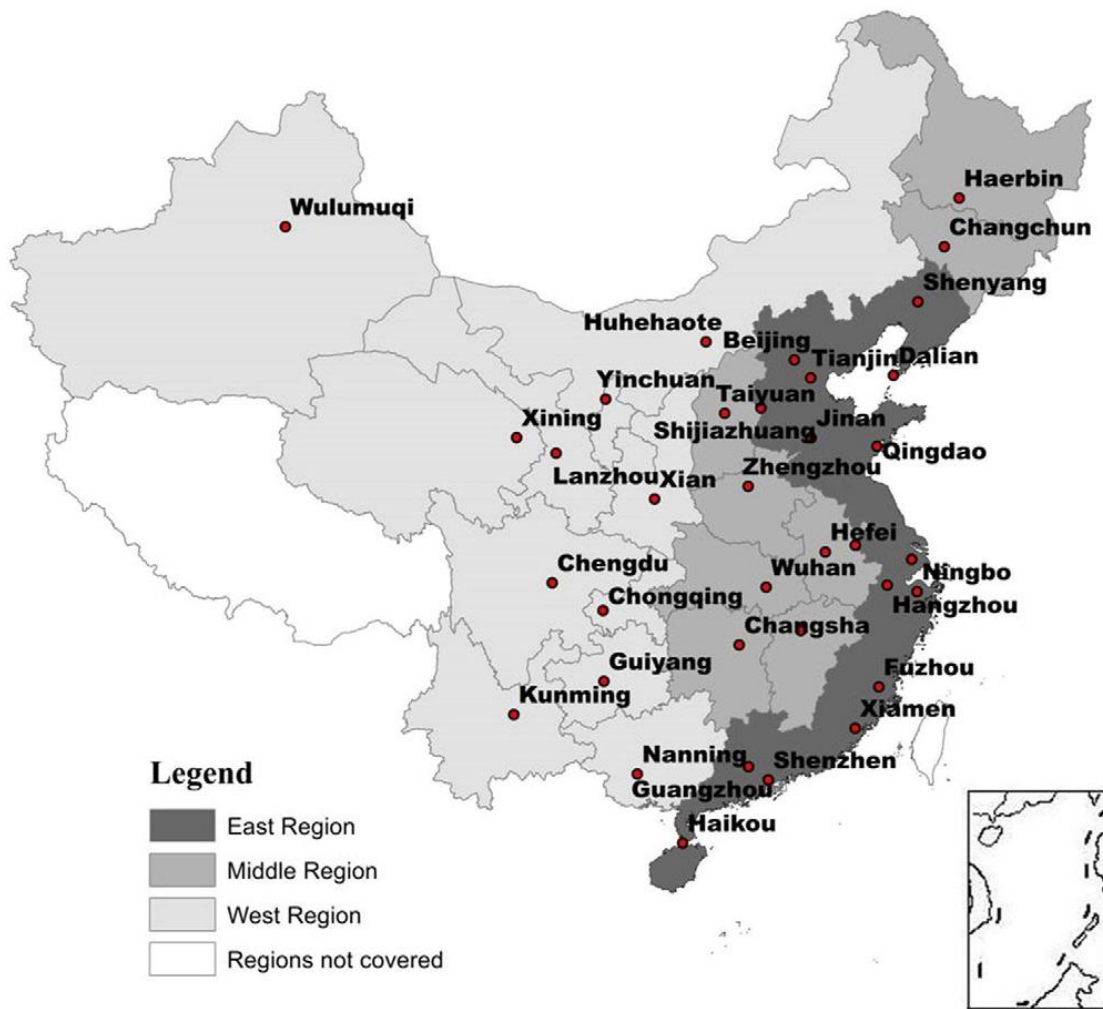
$$p^h = F(y, pop, c, r, e, \delta, x)$$

Where e is short for the expectation ration and x represent other influential factors.

1.5 Data and Preliminary Analysis

There are two main data sources about China's housing market from the National Bureau of Statistics of China, one is real estate situation in Major Cities Annual Data, which contains annual data of 35 major cities of China; the other one is Sales Price Indices of Residential Buildings in 70 Medium-Large Sized Cities, which contains monthly data of 70 medium-large sized cities. In order to match other variables like population, land price and wage, etc. price indices data is excluded. 35 major cities are chosen in common of these two data sources as the sample size of this paper, including Beijing, Tianjin, Shijiazhuang, Taiyuan, Hohhot, Shenyang, Dalian, Changchun, Harbin, Shanghai, Nanjing, Hangzhou, Ningbo, Hefei, Fuzhou, Xiamen, Nanchang, Jinan, Qingdao, Zhengzhou, Wuhan, Changsha, Guangzhou, Shenzhen, Nanning, Haikou, Chongqing, Chengdu, Guiyang, Kunming, Xi'an, Lanzhou, Xining, Yinchuan, Urumqi. City id 1-35 is assigned accordingly. See Figure 1.1 for the location of these cities.

Figure 1.1 The location of sample cities



As a big country like China, different part of China has different social and economic conditions. Unlike the US, China's development is highly unbalanced. Generally speaking, the east region is richer than the west. Big cities like Beijing and Shanghai have a GDP per capita over 20 thousand US dollars while some poor village in the west region seems no difference from the undeveloped countries. After some preliminary data analysis, it is

clearly that housing market in different cities also exhibit great heterogeneity. Figure 1.2 & 1.3 show the average price of the 35 cities from 2002-2017.

Figure 1.2 Annual average price in log of the 35 cities from 2002-2017 respectively

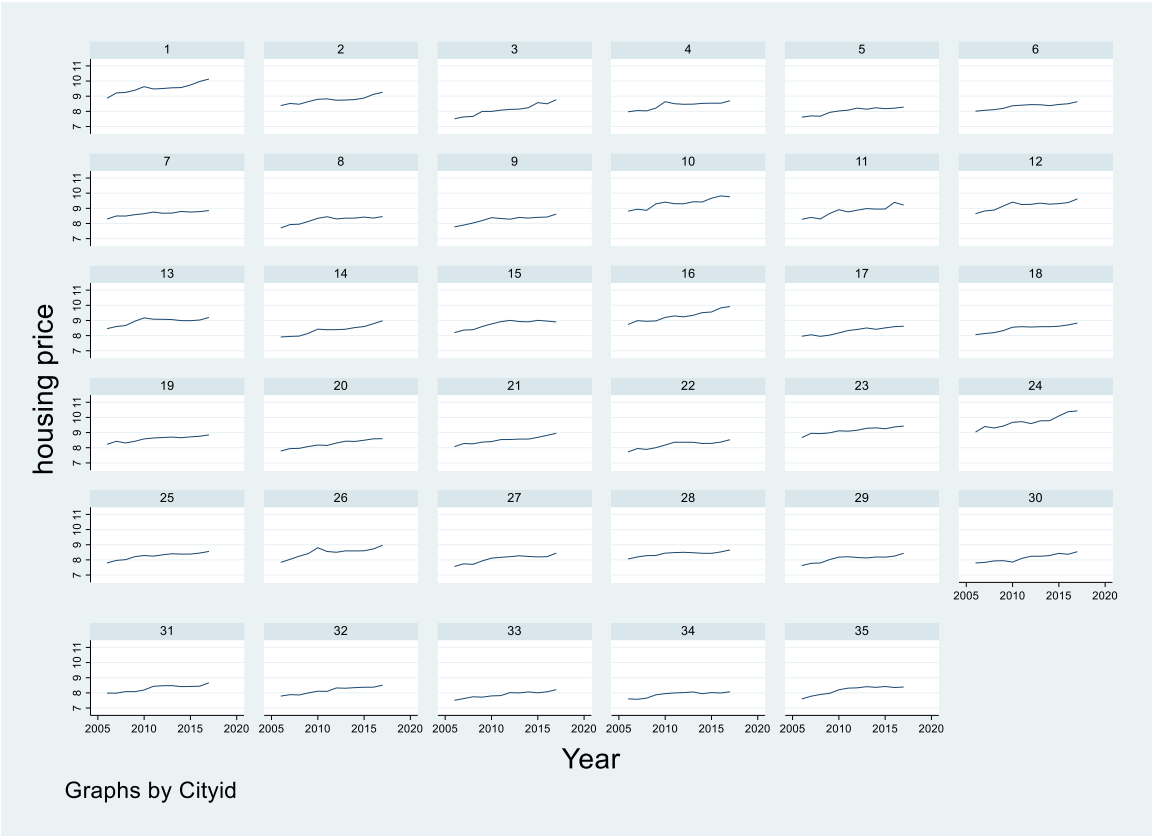
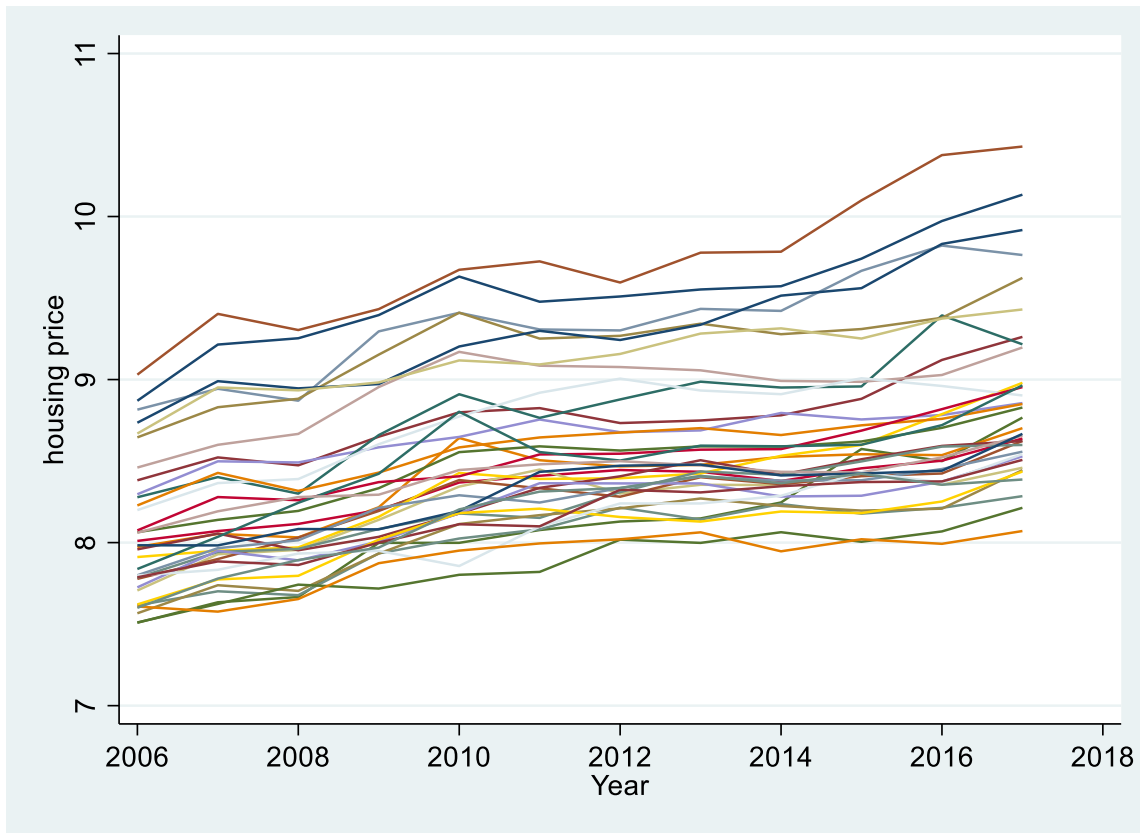


Figure 1.3 Annual average price in log of the 35 cities from 2002-2017 overlapped.



It is clear that housing price in all cities have a strong upward sloping trend. However, cross-cities and cross-time differences with respect to amount of increase, increase speed and price level is more noteworthy. Shenzhen appears the highest increasing rate of all cities, with price changing from 5267(yuan/sq.m) in 2002 to 48622(yuan/sq.m) in 2017. Almost 10 times the original price in 16 years. While most of the cities only have an average 4-5 times increase. In general, cities in the east of China have a much higher price and relatively higher increase rate than those in the west. Price increase leaders like Beijing, Shanghai, Guangzhou, Shenzhen, Hangzhou are all located in the eastern part of China, while western part cities like Xi'an, Lanzhou, Xining, Yinchuan, Urumqi has the lowest

average price and increase rate. In one word, taking China as a whole will dramatically biased the conclusion and cities in different social and economic conditions should be treated differently so that we may get the true scenario and some meaningful insight.

1.6 Econometric modeling

According to equation above. One can easily form an econometric model. However, several changes and clarification will be made to fit this specific research. First, the construction cost in real estate industry is usually limited to labor and material cost, while land price is always ignored in previous studies. The reason is that the relationship between housing price and land price is quite controversial. Therefore, land price is excluded from the most housing related studies. However, situation in China differs dramatically. Land price is a very important factor and plays unique role in China's housing market since land is a state-owned resource and can be only transferred to real estate firm through a public auction system called "Bidding, Auction and Quotation". Local government has the authority to decide the location and amount of land parcels to be offered in the auction and can even set an appraisal value called marked price to start the auction, both significantly affect the land price. To make it clear, local government is a monopoly player in the land market who can get a considerable amount of fiscal revenue through land transaction fee. It is highly likely that local government intervention may eventually lead to a higher housing price. In this paper land price will be specially examined to investigate its impact on the housing market.

Second, Housing stock and trading volume will be restricted to newly build houses since market era houses significantly differ from those built in the welfare era both in quality and area. In this paper two kinds of houses are treated as different commodities. In China, regulation of fixed assets depreciation declares that minimum depreciation period for normal house is 20 years. Assume 5% residual after 20 years, depreciation rate is thought to be 4.75% a year, which is the same across the country. As a result, depreciation will not be considered.

Third, population in a city will be limited to hukou holders. Two indicators regarding population exist in China, permanent resident population and household registered population, namely hukou holders. permanent resident population equals household registered population plus migrant population. Migrant population in general is less likely to buy a house compared with hukou holders and more important lots of cities in my sample size have restriction on the non- hukou holders to buy new houses as an effort to prevent speculation and cool down the market. Taking these into consideration, hukou population is a better choice for this study.

Finally, in order to deal with the heterogeneity problem, 35 cities are divided into 4 groups based on the city tiers system. According to the Wikipedia, the Chinese city tier system is a hierarchical classification of Chinese cities and different tiers reflect differences in consumer behavior, income level, population size, consumer sophistication, infrastructure, talent pool, and business opportunity. Though not officially recognized, it is widely used in media publications as a way of reference. 4 tiers are listed as follow:

Tier 1: Beijing, Shanghai, Guangzhou, Shenzhen

Tier 2: Chengdu, Hangzhou, Wuhan, Chongqing, Nanjing, Tianjin, Xi'an, Changsha, Shenyang, Qingdao, Zhengzhou, Dalian, Ningbo

Tier 3: Xiamen, Fuzhou, Hefei, Kunming, Harbin, Jinan, Changchun, Shijiazhuang, Nanning, Nanchang, Guiyang, Taiyuan, Haikou, Urumqi, Lanzhou

Tier 4 Hohhot, Xining, Yinchuan,

Thus, an econometric model is built as follows

$$\ln p_{jt}^h = \alpha_0 + \alpha_1 \ln Y_{jt} + \alpha_2 \ln Pop_{jt} + \alpha_3 \frac{p_{jt}^{he}}{p_{jt}^h} + \alpha_4 \ln Lp_{jt} + \alpha_5 \ln C_t + \alpha_6 \ln H_{jt} + \alpha_7 r_t + \varepsilon_{jt}$$

Where p_{jt}^h is the real housing price in year t for city in group j. Y_{jt} is the real income.

$\frac{p_{jt}^{he}}{p_{jt}^h}$ denotes the expected rate of appreciation. Lp_{jt} indicates real land price and H_{jt}

represents the housing stock or trading volume. ε_{jt} is error term. According to the data

availability, real income is replaced by real average wage of staff and workers. Population

is household registered population at year end. Expectation of price appreciation can be

fulfilled in several ways. Dipasquale, D., & Wheaton, W. C. (1996) addressed 3 most

common type of expectations: exogenous expectations, myopia price expectations

(adaptive expectation) and rational expectation. Adaptive expectation means people form

their expectations based on what has happened in the past. Here I use this definition as it

best reflects the reality. Then $\frac{p_{jt}^{he}}{p_{jt}^h}$ is calculated by the average price increase rate in the last

3 years. Land price is replaced with land value in terms of per unit floorage. Note that in

China, each land parcel has its own highest volume rate when it is sold by the government

so land value per unit floorage is a better indicator than land price per sq.m. Construction cost is not available directly, I use Value of Commercialized Residential Buildings completed divide by Floor Space of Commercialized Residential Buildings completed to get the construction cost per square meter. This indicator includes labor and material cost according the definition of Value of Commercialized Residential Buildings. The real interest rate is calculated using 5-year benchmark loan interest rate divided by the city CPIs. Housing trading volume use Floor Space of Residential Buildings Sold. All real term price variables are converted to comparable price based on the price level of 2002.

1.7 Regression Results

1.7.1 Unit root test and cointegration relationship

It is well known that non-stationarity may create spurious statistical results (Granger & Newbold, 1974)⁸. If data is not stationary then differenced data should be considered to prevent misleading conclusions. However, if there is a cointegrating relationship among the nonstationary variables, we can still have unbiased results running the original regression. Since the data has large panel and small time period, IPS test is employed. Result of unit root test is listed in appendix 1. As we can see, non-stationarity hypothesis of all variables cannot be rejected, but it can be rejected for the first differenced data. Therefore, all variables are stationary in I (1). Using the differenced data may be a solution but important information will be lost. So cointegration test is employed to test the long

⁸ Granger, C. W. J., & Newbold, P. (1974). Spurious regressions in econometrics. *Journal of Econometrics*, 2, 111–120.

run relationship between variables. Results are shown in appendix 2. Three different tests are used and all of them indicate the existent of cointegration relationship.

1.7.2 Panel regressions and results

According to the Hausman test (see appendix 3), fix effect model is used. 3 group of cities are regressed separately. Results are shown in Table 1.1

Table 1.1 Regression results

	(1) All P	(2) tier1 P	(3) tier2 P	(4) tier3 P	(5) tier4 P
Income	.763*** (.057)	1.04*** (.034)	.773*** (.088)	.748*** (.101)	.575** (.071)
population	.475*** (.15)	.46** (.086)	.039 (.21)	.55* (.278)	-.339 (.408)
expectation	1.077*** (.087)	1.081*** (.084)	1.112*** (.125)	1.149*** (.146)	.384 (.274)
Land price	.04** (.015)	.021 (.011)	.019 (.034)	.021 (.023)	.026 (.039)
cost	.127** (.051)	.112 (.104)	.128 (.106)	.091 (.064)	.282*** (.022)
Trading volume	-.058* (.029)	-.011 (.034)	-.014 (.064)	-.011 (.05)	.018 (.105)
Interest rate	.001 (.002)	-.007 (.01)	-.001 (.004)	0 (.004)	.016 (.008)
_cons	-4.564*** (.835)	-7.202*** (.404)	-2.084 (1.301)	-4.794*** (1.399)	.937 (2.568)
Observations	415	48	156	179	32
R-squared	.888	.953	.862	.903	.937

Standard errors are in parentheses

**** $p < .01$, ** $p < .05$, * $p < .1$*

1st column reports the result for all cities, 2nd-4th column reports the results for tier1 to tier3 cities respectively. From Table 1.1 we know that for tier 1 cities, 3 variables test significant in which average wage and people's expectation matter most, with coefficient both high than 1. While other factors including housing trading volume is insignificant, which is quite surprising. It is likely that the housing market in first tier cities has some extent of bubble since most fundamental factors does not contribute to the price change.

People's expectation rather than fundamental factors leads to the high rate of price increasing. However, another possible explanation should not be omitted that the regulation in housing purchase has dramatically distorted the market so that trading volume doesn't reflect the true equilibrium. For tier 2 cities income, construction cost, expectation and interest rate all test significant while population and housing trading volume didn't affect housing price change. For tier 3 cities, situation changes again, where income, construction cost, people's expectation and population help to explain the housing price change, while land price, interest rate and housing trading volume does not. Finally, for tier 4 cities, only income and construction cost matters and all other variables failed the test. However, expectation, the one matters most from tier1 to tier 3 cities is not even significant in tier 4 cities. If city tier system is not applied, the results is quite differently, as is shown in 1st column, which indicate that all variables except interest rate are all significant and the housing price can be well explained by the fundamental factors, which clearly bias the conclusion in group levels.

According to the result above, it is clear to see the heterogeneity between groups. On demand side, first tier cities have the highest income elasticity, then tier 2, tier 3 cities and tier 4 cities come last. This result indicates people are more like to buy houses in larger cities when their income increase. On supply side, construction cost shows somewhat impact on housing price in tier 3 cities while the first two tier cities dose not, indicating that supply side becomes less important to price change as cities level going up. People's expectation of appreciation can be seen as a measure of speculative demand. In this sense, tier 4 cities have the smallest speculative demand while other cities should be aware of

housing speculation. Taking all these into consideration, first tier cities are most likely to have a price bubble while 4 tier cities is the least. It is also worth noting that land price is insignificant in all groups which is on the contrary of the preliminary expectation. This result indicates that land auction system hasn't pushed up the housing price and government intervention on land failed to affect the housing market.

1.7.3 Joint hypothesis test

To further test if the heterogeneity is statistically significant. We first run a least square dummy variable regression with city tier dummies. Then test for joint significant for the dummy variables. Test results reject the null hypothesis that city tier dummies are the same. See Appendix 4 for detail. Then I test if the coefficients of fundamental factors are different in different city tiers. We test this hypothesis by run fixed effect model with interaction terms between city tier dummies and fundamental factors. Test results show that coefficients of all variables are statistically different across city tiers (Tier 1 city group is used as base group for comparison) See Appendix 5 for detail test results.

1.8 Conclusion

China is a big country with unbalanced social and economic development. In this paper, I use a panel data regression method to show the heterogeneity across city tiers. Housing market in different tiers of cities have different features on both demand and supply sides. Taking all the cities as a whole will significantly change the regression result. Housing price increase cannot be well explained in terms of fundamental factors in all the 3 city tiers and price bubble most likely exist in first tier cities.

APPENDICES

Appendix 1

Unit root test

Im-Pesaran-Shin unit-root test for p

Ho: All panels contain unit roots	Number of panels =	35
Ha: Some panels are stationary	Number of periods =	12
AR parameter: Panel-specific	Asymptotics: T,N ->	Infinity
Panel means: Included		sequentially
Time trend: Not included		

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-1.2917		-1.830	-1.740	-1.690
t-tilde-bar	-1.1624				
Z-t-tilde-bar	1.1415	0.8732			

Im-Pesaran-Shin unit-root test for D.p

Ho: All panels contain unit roots	Number of panels =	35
Ha: Some panels are stationary	Number of periods =	11
AR parameter: Panel-specific	Asymptotics: T,N ->	Infinity
Panel means: Included		sequentially
Time trend: Not included		

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-3.3691		-1.830	-1.740	-1.690
t-tilde-bar	-2.2024				
Z-t-tilde-bar	-7.4244	0.0000			

Im-Pesaran-Shin unit-root test for y

Ho: All panels contain unit roots
Ha: Some panels are stationary

Number of panels = 35
Number of periods = 12

AR parameter: Panel-specific
Panel means: Included
Time trend: Not included

Asymptotics: T,N -> Infinity
sequentially

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-1.4679		-1.830	-1.740	-1.690
t-tilde-bar	-1.1983				
Z-t-tilde-bar	0.8525	0.8030			

Im-Pesaran-Shin unit-root test for D.y

Ho: All panels contain unit roots
Ha: Some panels are stationary

Number of panels = 35
Number of periods = 11

AR parameter: Panel-specific
Panel means: Included
Time trend: Not included

Asymptotics: T,N -> Infinity
sequentially

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-3.4482		-1.830	-1.740	-1.690
t-tilde-bar	-2.2124				
Z-t-tilde-bar	-7.5054	0.0000			

Im-Pesaran-Shin unit-root test for c

Ho: All panels contain unit roots
Ha: Some panels are stationary

Number of panels = 35
Number of periods = 12

AR parameter: Panel-specific
Panel means: Included
Time trend: Not included

Asymptotics: T,N -> Infinity
sequentially

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-1.6856		-1.830	-1.740	-1.690
t-tilde-bar	-1.4777				
Z-t-tilde-bar	-1.4004	0.0807			

Im-Pesaran-Shin unit-root test for D.c

Ho: All panels contain unit roots
Ha: Some panels are stationary

Number of panels = 35
Number of periods = 11

AR parameter: Panel-specific
Panel means: Included
Time trend: Not included

Asymptotics: T,N -> Infinity
sequentially

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-3.7961		-1.830	-1.740	-1.690
t-tilde-bar	-2.3000				
Z-t-tilde-bar	-8.2174	0.0000			

Im-Pesaran-Shin unit-root test for lp

Ho: All panels contain unit roots
 Ha: Some panels are stationary

Number of panels = 35
 Avg. number of periods = 11.86

AR parameter: Panel-specific
 Panel means: Included
 Time trend: Not included

Asymptotics: T,N -> Infinity
 sequentially

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-1.3713		(Not available)		
t-tilde-bar	-1.1966				
Z-t-tilde-bar	0.8457	*			

* Normality of Z-t-tilde-bar requires at least 10 observations per panel with unbalanced data.

Im-Pesaran-Shin unit-root test for D.lp

Ho: All panels contain unit roots
 Ha: Some panels are stationary

Number of panels = 35
 Avg. number of periods = 10.86

AR parameter: Panel-specific
 Panel means: Included
 Time trend: Not included

Asymptotics: T,N -> Infinity
 sequentially

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-4.0621		(Not available)		
t-tilde-bar	-2.3905				
Z-t-tilde-bar	-8.9873	*			

* Normality of Z-t-tilde-bar requires at least 10 observations per panel with unbalanced data.

Im-Pesaran-Shin unit-root test for e

Ho: All panels contain unit roots
Ha: Some panels are stationary

Number of panels = 35
Number of periods = 12

AR parameter: Panel-specific
Panel means: Included
Time trend: Not included

Asymptotics: T,N -> Infinity
sequentially

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-1.6291		-1.830	-1.740	-1.690
t-tilde-bar	-1.4793				
Z-t-tilde-bar	-1.4134	0.0788			

Im-Pesaran-Shin unit-root test for D.e

Ho: All panels contain unit roots
Ha: Some panels are stationary

Number of panels = 35
Number of periods = 11

AR parameter: Panel-specific
Panel means: Included
Time trend: Not included

Asymptotics: T,N -> Infinity
sequentially

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-2.9917		-1.830	-1.740	-1.690
t-tilde-bar	-2.0730				
Z-t-tilde-bar	-6.3726	0.0000			

Im-Pesaran-Shin unit-root test for pop

Ho: All panels contain unit roots
Ha: Some panels are stationary

Number of panels = 35
Number of periods = 12

AR parameter: Panel-specific
Panel means: Included
Time trend: Not included

Asymptotics: T,N -> Infinity
sequentially

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-0.6951		-1.830	-1.740	-1.690
t-tilde-bar	-0.4637				
Z-t-tilde-bar	6.7741	1.0000			

Im-Pesaran-Shin unit-root test for D.pop

Ho: All panels contain unit roots
Ha: Some panels are stationary

Number of panels = 35
Number of periods = 11

AR parameter: Panel-specific
Panel means: Included
Time trend: Not included

Asymptotics: T,N -> Infinity
sequentially

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-2.1419		-1.830	-1.740	-1.690
t-tilde-bar	-1.4818				
Z-t-tilde-bar	-1.5673	0.0585			

Im-Pesaran-Shin unit-root test for r

Ho: All panels contain unit roots
Ha: Some panels are stationary

Number of panels = 35
Number of periods = 12

AR parameter: Panel-specific
Panel means: Included
Time trend: Not included

Asymptotics: T,N \rightarrow Infinity
sequentially

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-0.3996		-1.830	-1.740	-1.690
t-tilde-bar	-0.4175				
Z-t-tilde-bar	7.1462	1.0000			

Im-Pesaran-Shin unit-root test for D.r

Ho: All panels contain unit roots
Ha: Some panels are stationary

Number of panels = 35
Number of periods = 11

AR parameter: Panel-specific
Panel means: Included
Time trend: Not included

Asymptotics: T,N \rightarrow Infinity
sequentially

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-3.2838		-1.830	-1.740	-1.690
t-tilde-bar	-2.2731				
Z-t-tilde-bar	-7.9983	0.0000			

Im-Pesaran-Shin unit-root test for H

Ho: All panels contain unit roots

Number of panels = 35

Ha: Some panels are stationary

Number of periods = 12

AR parameter: Panel-specific

Asymptotics: T,N -> Infinity

Panel means: Included

sequentially

Time trend: Not included

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-1.7268		-1.830	-1.740	-1.690
t-tilde-bar	-1.4493				
Z-t-tilde-bar	-1.1716	0.1207			

Im-Pesaran-Shin unit-root test for D.H

Ho: All panels contain unit roots

Number of panels = 35

Ha: Some panels are stationary

Number of periods = 11

AR parameter: Panel-specific

Asymptotics: T,N -> Infinity

Panel means: Included

sequentially

Time trend: Not included

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-4.4360		-1.830	-1.740	-1.690
t-tilde-bar	-2.4351				
Z-t-tilde-bar	-9.3151	0.0000			

Appendix 2

Cointegration test

Kao test for cointegration

Ho: No cointegration
Ha: All panels are cointegrated

Number of panels = 35
Avg. number of periods = 9.8571

Cointegrating vector: Same

Panel means: Included
Time trend: Not included
AR parameter: Same

Kernel: Bartlett
Lags: 1.94 (Newey-West)
Augmented lags: 1

	Statistic	p-value
Modified Dickey-Fuller t	3.1759	0.0007
Dickey-Fuller t	1.7843	0.0372
Augmented Dickey-Fuller t	1.0710	0.1421
Unadjusted modified Dickey-Fuller t	-4.3743	0.0000
Unadjusted Dickey-Fuller t	-4.8610	0.0000

Pedroni test for cointegration

Ho: No cointegration
Ha: All panels are cointegrated

Number of panels = 35
Avg. number of periods = 10.857

Cointegrating vector: Panel specific

Panel means: Included
Time trend: Not included
AR parameter: Panel specific

Kernel: Bartlett
Lags: 2.00 (Newey-West)
Augmented lags: 1

	Statistic	p-value
Modified Phillips-Perron t	10.6636	0.0000
Phillips-Perron t	-11.6450	0.0000
Augmented Dickey-Fuller t	-7.5491	0.0000

Westerlund test for cointegration

Ho: No cointegration

Number of panels = 35

Ha: Some panels are cointegrated

Avg. number of periods = 11.857

Cointegrating vector: Panel specific

Panel means: Included

Time trend: Not included

AR parameter: Panel specific

	Statistic	p-value
Variance ratio	2.4850	0.0065

Appendix 3

Hausman test

Random-effects GLS regression
Group variable: Cityid

Number of obs = 415
Number of groups = 35

R-sq:

within = 0.8775
between = 0.8492
overall = 0.8172

Obs per group:

min = 9
avg = 11.9
max = 12

corr(u_i, X) = 0 (assumed)

Wald chi2(7) = 2506.64
Prob > chi2 = 0.0000

p	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
y	.8444245	.0392205	21.53	0.000	.7675536	.9212953
pop	.1137695	.0363893	3.13	0.002	.0424479	.1850911
e	1.160134	.0916059	12.66	0.000	.9805895	1.339678
lp	.0952222	.0134911	7.06	0.000	.06878	.1216643
c	.1872848	.0331172	5.66	0.000	.1223763	.2521933
H	-.0808819	.0189699	-4.26	0.000	-.1180621	-.0437016
r	.0371674	.0101332	3.67	0.000	.0173068	.057028
_cons	-4.102547	.4416032	-9.29	0.000	-4.968073	-3.237021
sigma_u	.12011046					
sigma_e	.08989819					
rho	.640945	(fraction of variance due to u_i)				

Fixed-effects (within) regression
Group variable: Cityid

Number of obs = 415
Number of groups = 35

R-sq:

within = 0.8884
between = 0.3687
overall = 0.4733

Obs per group:

min = 9
avg = 11.9
max = 12

corr(u_i, Xb) = -0.2364

F(7,373) = 424.15
Prob > F = 0.0000

p	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
y	.7854113	.0370803	21.18	0.000	.7124987	.8583238
pop	.4710734	.0779739	6.04	0.000	.3177498	.624397
e	1.079086	.080564	13.39	0.000	.92067	1.237503
lp	.0456187	.0125935	3.62	0.000	.0208555	.0703818
c	.1316705	.0303169	4.34	0.000	.0720571	.1912839
H	-.054703	.0177931	-3.07	0.002	-.0896904	-.0197157
r	.0137042	.0092259	1.49	0.138	-.0044372	.0318456
_cons	-4.941473	.5238237	-9.43	0.000	-5.971491	-3.911455
sigma_u	.38566937					
sigma_e	.08989819					
rho	.94846606	(fraction of variance due to u_i)				

F test that all u_i=0: F(34, 373) = 36.22

Prob > F = 0.0000

```
. hausman fe re,constant sigmamore
```

	—— Coefficients ——			
	(b) fe	(B) re	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
y	.7854113	.8444245	-.0590132	.0164208
pop	.4710734	.1137695	.3573039	.0816714
e	1.079086	1.160134	-.0810473	.0119448
lp	.0456187	.0952222	-.0496035	.0051502
c	.1316705	.1872848	-.0556143	.0105725
H	-.054703	-.0808819	.0261788	.0075119
r	.0137042	.0371674	-.0234632	.0030396
_cons	-4.941473	-4.102547	-.8389263	.4071596

b = consistent under Ho and Ha; obtained from xtreg
 B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

```
chi2(8) = (b-B)'[(V_b-V_B)^(-1)](b-B)
        =      102.78
Prob>chi2 =      0.0000
(V_b-V_B is not positive definite)
```

Appendix 4

LSDV joint significant test

```
. reg p y pop e lp c H r i.groupid,vce(cluster groupid)
```

```
Linear regression      Number of obs   =      415
                      F(2, 3)         =          .
                      Prob > F         =          .
                      R-squared        =     0.9157
                      Root MSE      =     .1545
```

(Std. err. adjusted for 4 clusters in groupid)

p	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
y	.6920597	.0188734	36.67	0.000	.6319962	.7521231
pop	-.0992312	.0271639	-3.65	0.035	-.1856787	-.0127837
e	1.155831	.1276181	9.06	0.003	.7496931	1.561969
lp	.2297132	.0190124	12.08	0.001	.1692072	.2902192
c	.1181064	.0874811	1.35	0.270	-.1602976	.3965104
H	-.1113925	.0443263	-2.51	0.087	-.2524586	.0296736
r	.0043654	.0037732	1.16	0.331	-.0076427	.0163734
groupid						
2	-.2484579	.0073963	-33.59	0.000	-.2719962	-.2249195
3	-.3984047	.0194616	-20.47	0.000	-.4603404	-.3364691
4	-.7817638	.0295333	-26.47	0.000	-.8757521	-.6877755
_cons	-.8952155	.2281582	-3.92	0.029	-1.621317	-.1691143

```
.
end of do-file
```

```
. testparm i.groupid
```

```
( 1) 2.groupid = 0
( 2) 3.groupid = 0
( 3) 4.groupid = 0
```

```
F( 3, 3) =33094.30
Prob > F = 0.0000
```

Appendix 5

Joint significant test (interaction term)

```

Fixed-effects (within) regression              Number of obs   =       415
Group variable: Cityid                       Number of groups =       35

R-squared:                                   Obs per group:
    Within = 0.9006                           min =          9
    Between = 0.3221                           avg =         11.9
    Overall = 0.2844                           max =         12

                                           F(19,34)
corr(u_i, Xb) = -0.9795                      =          .
                                           Prob > F
                                           =          .

```

(Std. err. adjusted for 35 clusters in Cityid)

	p	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]
groupid						
2		0 (omitted)				
3		0 (omitted)				
4		0 (omitted)				
y		1.040229	.028869	36.03	0.000	.9815601 1.098898
pop		.4597801	.072546	6.34	0.000	.3123489 .6072114
H		-.0111051	.0283837	-0.39	0.698	-.0687878 .0465776
r		-.0070455	.0085811	-0.82	0.417	-.0244845 .0103935
e		1.081434	.0702551	15.39	0.000	.9386586 1.22421
lp		.0205864	.0094137	2.19	0.036	.0014555 .0397173
c		.1123541	.0869369	1.29	0.205	-.0643229 .2890311
groupid#c.y						
2		-.2671466	.0913064	-2.93	0.006	-.4527036 -.0815896
3		-.2920426	.1047665	-2.79	0.009	-.5049537 -.0791316
4		-.4652414	.0607704	-7.66	0.000	-.5887417 -.3417411
groupid#c.pop						
2		-.4209667	.2190712	-1.92	0.063	-.8661729 .0242395
3		.0901593	.2862681	0.31	0.755	-.4916074 .671926
4		-.7986692	.3161549	-2.53	0.016	-1.441173 -.1561651
groupid#c.H						
2		-.0025109	.0688144	-0.04	0.971	-.1423586 .1373368
3		-.0002322	.0569269	-0.00	0.997	-.1159215 .1154571
4		.0288403	.0839745	0.34	0.733	-.1418164 .1994971
groupid#c.r						
2		.0060039	.0095148	0.63	0.532	-.0133324 .0253403
3		.0072199	.0092939	0.78	0.443	-.0116674 .0261073
4		.0230311	.0105822	2.18	0.037	.0015256 .0445366
groupid#c.e						
2		.0308906	.1420906	0.22	0.829	-.2578722 .3196535
3		.0679937	.1613382	0.42	0.676	-.2598851 .3958724
4		-.6970746	.2183224	-3.19	0.003	-1.140759 -.2533902
groupid#c.lp						
2		-.0015218	.0346007	-0.04	0.965	-.0718389 .0687954
3		.0003181	.0249568	0.01	0.990	-.0504003 .0510364
4		.0056261	.030835	0.18	0.856	-.0570382 .0682903
groupid#c.c						
2		.015771	.1359872	0.12	0.908	-.2605882 .2921302
3		-.0218043	.1079423	-0.20	0.841	-.2411695 .1975608
4		.1699966	.0885676	1.92	0.063	-.0099945 .3499877
_cons		-3.612049	.7854564	-4.60	0.000	-5.208289 -2.01581
sigma_u		2.2317029				
sigma_e		.08733272				
rho		.99847097	(fraction of variance due to u_i)			

```
. testparm 2.groupid#(c.y c.pop c.H c.r c.e c.lp c.c)
```

```
( 1) 2.groupid#c.y = 0  
( 2) 2.groupid#c.pop = 0  
( 3) 2.groupid#c.H = 0  
( 4) 2.groupid#c.r = 0  
( 5) 2.groupid#c.e = 0  
( 6) 2.groupid#c.lp = 0  
( 7) 2.groupid#c.c = 0
```

```
F( 7, 34) = 9.50  
Prob > F = 0.0000
```

```
. testparm 3.groupid#(c.y c.pop c.H c.r c.e c.lp c.c)
```

```
( 1) 3.groupid#c.y = 0  
( 2) 3.groupid#c.pop = 0  
( 3) 3.groupid#c.H = 0  
( 4) 3.groupid#c.r = 0  
( 5) 3.groupid#c.e = 0  
( 6) 3.groupid#c.lp = 0  
( 7) 3.groupid#c.c = 0
```

```
F( 7, 34) = 7.07  
Prob > F = 0.0000
```

```
. testparm 4.groupid#(c.y c.pop c.H c.r c.e c.lp c.c)
```

```
( 1) 4.groupid#c.y = 0  
( 2) 4.groupid#c.pop = 0  
( 3) 4.groupid#c.H = 0  
( 4) 4.groupid#c.r = 0  
( 5) 4.groupid#c.e = 0  
( 6) 4.groupid#c.lp = 0  
( 7) 4.groupid#c.c = 0  
Constraint 4 dropped  
Constraint 6 dropped
```

```
F( 5, 34) = 93.38  
Prob > F = 0.0000
```

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CHAPTER TWO

The Effects of Local Government Regulations in China's Housing Market

2.1 Introduction

China's housing market has experienced rapidly development since the market-oriented reform in the 1980s. After a relatively short period of stable development starting from 1998, the market seems to be overheated since 2002. Surging house prices have become a major concern as it may affect social stability. Literature reported housing price has increased in a dramatical fashion. (Wu, Gyourko, and Deng (2012), Fang, Gu, Xiong, and Zhou (2015)) However, income growth is lagged behind housing prices in major urban cities. Common indicators like price to income and price to rent ratio imply the market is overheated and homes become unaffordable to local middle-income families. (Yi Zhang (2013) Fang et al. (2015) Edward Glaeser et al (2016)). To maintain the sustainable growth of the housing market, China's government has introduced a series of regulations on both home buyers and developers. These includes, but not limited to, land action regulation, home purchase restriction, home loan restriction, home sale restriction. These policy tools are introduced in orders and may overlap with each other. Researchers usually focus on one regulation after it appeared and the effects of these regulations are still in heated debate.

Another key feature of China's housing market is unbalanced development (e.g., Tier-1 cities vs "ghost cities" (Shepard (2015), Woodworth and Wallace (2017))). Housing price in different cities shows great variation in term of price level and growth rate. Previous literatures usually don't distinguish cities from different city tiers, but in fact, China's policymakers at different levels can modify the regulation details considering its own geography and economic circumstances. As a consequence, most regulations in the housing market are on city level. Special attentions should be paid to heterogeneity among cities.

In this paper, I use panel data regressions to investigate the effect of different types of housing regulations on housing price and housing trading volume, based on the monthly data of several major urban cities of China from 2008-2017. The results show that the effects of different regulations are different across city tiers and overall analysis across all cities may give misleading results. heterogeneity do exist across city tiers. The remainder of the paper is organized as follows. Section 2 provides institutional background and Section 3 clarify different types of housing regulations. Section 4 talks about model specification and empirical methodology and then Section 5 describes data and variables. Section 6 presents the result of regressions. Finally, Section 7 concludes.

2.2 A Brief History Review of Government

Interventions in the Housing Market of China

It is very clear that the ultimate goal of China's government interventions in the economy is to ensure a consistent high GDP growth rate. Housing market seems to be no exception. On one hand, higher increasing rate of housing price may reduce the affordability of ordinary workers, thus may affect social stability. On the other hand, housing sector plays a vital role in China's economy as one of the major industries, which accounts for approximately 7.5% of GDP in 2021. A strong intervention will surely affect the economy. Finally, the government has no choice but trying to balance the homes affordability and the GDP growth rate. In practice, we see back-and -forth policy changes appear alternately. Interventions are usually taken place when the market is booming at a high speed and policies would be looser again if any sign of economic decline appears. This back-and-forth policy changing process is one of the key features in China's housing market history. (See Kaiji Chen (2020) for details).

If we describe the history of China's government interventions on housing market in a back-and -forth perspective, there are mainly 5 phases from 2005 to 2018.

Phase 1. From March 2005 to August 2008: tightening period.

In order to prevent housing speculation and slow the price increasing rate. The central bank of China started to raise the down payment ratio and benchmark interest rate. Down payment ratio for second home was raised to at least 30% in 2005, then raised to 40% in 2007. Down payment ratio for first home with a construction area higher than 90 was also raised to 30% in 2006. Benchmark interest rate was raised 8 times from 6.12% to 7.83%.

Phase 2. From September 2008 to March 2010: loosening period.

Global financial crisis in 2008 dramatically changes the economic climate in China. Expansionary monetary policies were taken place overwhelmingly in every place, in every industry. Real estate industry is no exception. In October 2008, the central government completely reversed the tightening policy enacted from 2005. The down payment ratio for first home was reduced to 20% and minimum mortgage interest rate was also reduced at the same time. Transaction taxes was also reduced in November 2008. In this period, the 5 year and above bank loan rate was reduced several times from 7.83% to 5.94%. Expansionary policies lead to rapid price increase in 2009. National home price growth index witnessed a dramatic rebound from -1.1% in early 2009, which is the lowest in ten years, to 5.8% in the fourth quarter of 2009. (See Xiaoqing Xu, Tao Chen (2012) for details)

Phase 3. From March 2010 to October 2014: tightening period.

As financial crisis finally came to an end, highly increased housing price was put under the spotlight. Tightening policies were back in the show. Down payment ratio for first home was put back to 30% in 2010, and for second home, the ratio went all the way from 40% to 50% and then 60% in 2011. The record was finally set as 70% for some most overheated cities in 2013. In this period, many cities implemented home purchase regulations. Citizens in the restricted areas can only buy 2 homes. Non-hukou holders (migrants from other cities without local citizenship) may only have one.

Phase 4. From November 2014 to September 2016: loosing period

In 2014, real estate industry was pretty cold. Price and trading volume were both going downward. On September 30, the rescue plan finally came out. Second home buyers without any mortgage loans were treated the same as first home buyer and enjoyed 30%

down payment ratio. Down payment ratio for second home buyers with loans was reduced to 40% in 2015, then 30% in 2016. Home purchase regulations were abandoned in most cities starting from August 2014.

Phase 5 From October 2016 to Dec 2018: tightening period

Real estate industry was totally overwhelmed in 2016. Housing price level and increasing rate, land price level, real estate investment and housing stocks were all skyrocketed. As a result, tightening regulations came back again. In this period, home purchase regulations were resumed in many cities along with a new policy tool, home sales regulation. New bought residential properties were prohibited from being resold within a certain period of years. (e.g., 1-3 years) Another feature in this period was the diversity of regulations in different cities. Local government had more freedom in decision-making. Down payment ratio, mortgage rate and policy details were all based on local realities.

From the above description, it is clear that government intervention on housing market is frequent and inconstant. Regulation appears, being released and then reintroduced time and time again. Different regulations can coexist at the same time but the details may change according to economy changes. With this background information in mind, the following sections carefully examined the effects of different regulations in the housing market.

2.3 Types of Regulations Used in the Housing Market of China

China is a unique country with a highly centralized government being an active player

and manager at the same time in the market system. In China, government has far more control over prices and construction than western countries. Housing market is no exception. To begin with, all land in China is state-owned and real estate developers only have the right to use certain land parcels (up to 70 years) through land auctions. Although Chinese Property Rights Law suggests that use rights will be automatically renewed, there is no guarantee this will be the case forever. Theoretically, Chinese government can stop the land supply to keep the housing price at a high level. Second, banking system, as one of the key sectors in China's economy, has been totally dominated by state-owned institutions. Starting from the People's bank of China, banks at all levels must follow the lead of the central government. Policies like interest rate, down payment ratio, mortgage benchmark rate and mortgage restrictions are largely influenced by the government. China's housing finance system has another source of funding besides commerce mortgage market, which is the Housing Provident Fund (HPF). HPF systems require employees to contribute a proportion of their income to the fund each month and employers contribute the same amount. The HPF works like a low-cost mortgage, but only limited to employees. It is not sufficient to afford a house, but may help to cover the down payment. (Deng and Fei (2008)) HPF is also government operated and HPF loan interest rate can be used as a policy tool in addition to bank interest rate. Notably, unlike its counterpart in U.S., China's real estate taxes are imposed only on transactions, property tax has been discussed for years but not yet fully implemented. Last but not least, as an authoritarian country with "Socialist Market Economy", the central government of China can impose direct regulations on both sides of the housing market. Sellers and buyers are not freely market entities, transactions

might only be allowed in certain circumstances. Some key regulations are listed as follows.

2.3.1 Home loan restriction (HLR)

Home loan restriction is a combination of down payment ratio and identification of home buyers. First time buyers face lower down payment ratio(ie,30%-40%) while second home down payment ratio will be much higher(ie,60%-70%). The distinguish between 1st and 2nd home buyers can date back to 2005 in selected cities with higher housing price. The mortgage rate for second home buyers can be higher than first home buyers as well. Government first required mortgage rate to be at least 10 percent higher than the benchmark interest rate in 2007, then released during the global financial crisis and reimposed in 2010. Third and more home buyers are usually prohibited from home loan.

2.3.2 Home purchase restriction (HPR)

Home purchase restriction is first introduced in 2010. The central government announced ‘New National Ten Articles’ in April, stating that local government can limit the number of houses purchased within a certain period of time. Home purchase restriction quickly spread to 46 cities till the end of 2011. (See Yi Wu & Yunong Li (2018), Kaiji Chen (2020) for details about HPR). Generally speaking, home purchase restriction limits households with a local Hukou (local household registration) to a maximum of two houses while non-hukou households can only buy one residential house with proof of local tax receipts or social security records for certain years. Details might be different according to circumstances in cities. (See Sun, et al. (2017) for the case in Beijing). HPR is generally viewed to be successful as researchers find it helps to curb the increase of price and speculative demands, at least in the short run. (Cao et al., (2015), Li, (2016), Sun et al.,

2017). The impacts of HPR may differ across regions. Some literatures argue that HPR is more effective in 1st and 2nd tier cities, (Wu and Li (2018), Jia et al. (2018)) On the contrary, Huang et al. (2018) found exactly the opposite. The only thing for sure is heterogeneity does exist across cities.

2.3.3 Home sale restriction (HSR)

Home sale restriction is a relatively new policy tool aiming at curb speculative demand. It was first introduced in Xiamen on March 25, 2017 and then quickly followed by 30 other cities by end of June 2017. Details of local house sale restrictions can be different and are usually decided on the city level but basic idea is that resales of newly purchased houses is prohibited for a period of time, the gap is usually 2-3 years. In some cities, HSR applies only to non-Hukou holders. But in many other cities, HPR applies to all residents regardless of their Hukou status. Yan et al. (2018) found “house-sale restriction could effectively reduce speculation in the market as well as decrease housing prices in the short term”. Not so much researches have been done on this topic and the long-term effect is still unclear.

2.3.4 Other policy tools

Government also use other policy tools to cooperate and supplement the above 4 main regulations. These tools include but not limited to:

1. Credit policy. Maximum loan accessible is based on loan-to-value ratio and payment-to-income ratio. Those ratios are defined by the central bank of China and will change according to the government regulations.

2. Tax policy. including transaction taxes, capital gains taxes and sales tax exemption.
3. Land-use policy. Additional requirements like price limit and floor area ratio of new built residential homes are imposed on potential real estate developers in Land auction.

As we all know, government interventions always lead to distortion and welfare loss. Housing market is no exception. Powerful impact of these kinds of regulations unintendedly changed the expectations of buyers and sellers in the market. Zheng et al. (2016) found that China's urban housing market dynamics can be predicted based on homebuyers' confidence, which mainly comes from beliefs on continuous economic growth and government macro control, rather than rational thinking of market conditions. This might be extremely harmful when market collapses, just like what happened in the stock market crash in 2015, fanatical belief paid the highest price.

Government intervention can be imposed through market system or through administrative regulations. In the housing market, the former is like mortgage and HPF interest rate. Falling interest rates on home loans are meant to encourage more borrowing and thus increase the demand of housing. Higher interest rates did the opposite. Notably, unlike its counterpart in U.S., Chinese real estate taxes are imposed only on transactions, property tax has been discussed for years but not yet implemented. Only some preliminary trails are going on in 2 or 3 selected cities. Thus, tax is excluded in this research. Market policies modify consumers' incentives while administrative regulations work on the transaction itself. This paper focuses on the administrative regulations that directly affect

the housing market, broader macro policies like monetary and fiscal policies are excluded. Please see Kehao Chen (2019) and António Afonso and Ricardo M. Sousa (2009) for reference of macro policies. In the sections below I will mainly investigate the effects of administrative regulations including home loan restriction, home purchase restriction and home sales restriction.

2.4 Model Specification and Empirical Methodology

Same type of regulations may have different details and interpretations in different cities. As previously stated, regulations details are usually defined in the local government level. For example, home purchase restriction can be partially implemented in several districts or the entire city, non-hukou holders may be excluded from the housing market for 1 to 5 years based on the details of local HPR. Duration of home sales restriction also differ greatly in different cities.

2.4.1 Empirical method

In order to measure the magnitude of different regulations in different cities, each regulation variable is further divided into 2 dummy variables as follows.

HLR1: down payment ratio for first home.

HLR2: down payment ratio for second home.

HPR1: low level home purchase restriction, dummy variable. HPR1=1 if one of the following requirements meets: 1. HPR is partially implemented 2. HPR has low requirement on non-local citizenship (gap \leq 2 years). HPR1=0 otherwise.

HPR2: high level HPR, dummy variable. HPR2=1 if HPR is all area implemented

and has high requirement on non-local citizenship ($\text{gap} \geq 3$ years). $\text{HPR2} = 0$ otherwise.

HSR1: low level home sale restriction, dummy variable. $\text{HSR1} = 1$ if one of the following requirements meets: 1. HSR is partially implemented 2. HSR has low requirement on banned time ($\text{gap} \leq 2$ years). $\text{HSR1} = 0$ otherwise.

HSR2: high level HSR, dummy variable. $\text{HSR2} = 1$ if HSR is all area implemented and has high requirement banned time ($\text{gap} \geq 3$ years). $\text{HSR2} = 0$ otherwise.

2.4.2 Panel data regression model

Many relating studies on the effects of housing regulations have employed the difference in difference approach (e.g., Yi Wu & Yunong Li (2018), Yan et al. (2018)). The DID method is widely used for testing the treatment effect of a policy or government intervention in empirical literatures. It estimates the effect of a treatment by comparing pre-treatment differences and post-treatment differences between the treatment group and the control group. An important assumption of DID is the parallel trend assumption which requires that the difference between control and treatment groups should be the same across time if the treatment never happens. Otherwise, the result is biased. In other words, DID requires similarities between treatment and control groups. However, in the context of China, it is very hard to satisfying this condition. Researchers either apply specific selection criteria (e.g., score matching) on control group or use a difference-in-difference-in-difference (DIDID) method to avoid heterogeneity issues. But heterogeneity is in fact one of the unique features of China's housing market that I'm interested in. What's more important is that in my research different types of regulations may be in effect at the same time, making it impossible to isolate the treatment effect of a certain regulation. So, in this

paper, a panel data regression method is implemented to examine the effects of different regulations.

First, to investigate the effects of regulations on housing price, consider the following regression:

$$\begin{aligned} \ln HP_{jt} = & \alpha_0 + \alpha_1 \ln AI_{jt} + \alpha_2 \ln Pop_{jt} + \alpha_3 \ln LS_{jt} + \alpha_4 MR_{jt} + \alpha_5 \ln HT_{jt} + \alpha_6 HLR1_{jt} \\ & + \alpha_7 HLR2_{jt} + \alpha_8 HPR1_{jt} + \alpha_9 HPR2_{jt} + \alpha_{10} HSR1_{jt} + \alpha_{11} HSR2_{jt} \\ & + \varepsilon_{jt} \quad (1) \end{aligned}$$

Where HP is housing price, AI is short for annual income, Pop is city population, LS is short for Land supply, MR is mortgage rate, HT is short for housing trading volume, HLR1&2, HPR1&2, HSR1&2 are regulation dummies defined as in Section 4.1, ε_{jt} is error term. The subscript $j=1, 2, \dots, N$ is the city index; $t=1, 2, \dots$, is the time period. Regulation variables are variables of interest and other variables are considered as control variables. Using a supply and demand perspective, higher AI, Pop will shift the demand curve upward while higher MR will do the opposite. Similarly, LS is the factor from supply side and HT should be negatively related with HP under standard price theory. So α_1, α_2 are expected to be positive while $\alpha_3, \alpha_4, \alpha_5$ are expected to be negative. Coefficients of regulations are all expected to be negative as they are intended to curb the housing price increase.

Second, regression (2) is implemented to investigate the effects of regulations on housing trading volume.

$$\begin{aligned}
\ln HT_{jt} = & \beta_0 + \beta_1 \ln AI_{jt} + \beta_2 \ln Pop_{jt} + \beta_3 \ln LS_{jt} + \beta_4 MR_{jt} + \beta_5 \ln HP_{jt} + \beta_6 HLR1_{jt} \\
& + \beta_7 HLR2_{jt} + \beta_8 HPR1_{jt} + \beta_9 HPR2_{jt} + \beta_{10} HSR1_{jt} + \beta_{11} HSR2_{jt} \\
& + e_{jt} \quad (2)
\end{aligned}$$

The notation is pretty much the same as in regression (1), the only difference is that housing price is treated as an explaining variable while housing trading volume is the dependent variable. β_6 to β_{11} are parameters of interest. Following the same analytical process, $\beta_1, \beta_2, \beta_3$ are expected to be positive while β_4, β_5 are expected to be negative. Coefficients of regulations are expected to be negative as well.

2.5 Data and Variables

The data sets employed in this study include monthly data of 22 cities from 2008-2017. These cities are Beijing, Tianjin, Shenyang, Dalian, Shanghai, Nanjing, Hangzhou, Fuzhou, Xiamen, Zhengzhou, Wuhan, Changsha, Guangzhou, Shenzhen, Xi'an, Chengdu, Haikou, Hefei, Ningbo, Qingdao, Xuzhou and Changchun. In order to deal with the heterogeneity problem, 22 cities are divided into 3 groups based on the city tiers system. According to the Wikipedia, “the Chinese city tier system is a hierarchical classification of Chinese cities and different tiers reflect differences in consumer behavior, income level, population size, consumer sophistication, infrastructure, talent pool, and business opportunity.” Though it is not officially recognized, it is frequently used by various media publications in recent years and has gained wide popularity in public as a way of reference. According to Yicai Global, a financial magazine (2017), 3 tiers are listed as follow:

Tier 1: Beijing, Shanghai, Guangzhou, Shenzhen

New tier 1: Chengdu, Hangzhou, Wuhan, Nanjing, Tianjin, Xi'an, Changsha, Shenyang, Qingdao, Zhengzhou, Dalian, Ningbo

Tier 2: Xiamen, Fuzhou, Hefei, Changchun, Haikou, Xuzhou

Note that Xiamen is sometime listed as tier 2 cities according to many other ranking systems. In this study, it is also treated as tier 2 city in consideration of its high housing price. For simplicity reasons, I use tier 1 tier 2 tier3 to refer to the 3 city tiers.

Data of housing price (HP), defined as average sold price (*yuan/m²*), housing trading volume (HT), defined as floor space sold (*m²*), land supply area (*m²*) (LS) are obtained from CREIS database⁹, which is the largest database of real estate industry data in China. Average income (AI), defined as Average Wage of Staff and Workers (*yuan*)¹⁰, mortgage rate (MR), defined as 5year above interest rate (%),¹¹ population (POP), defined as hukou population (10k person) are found in the Statistical Yearbook of each city. Regulation data is obtained from the government documents of regulations that published on their official website. HLR1&2, HPR1&2, HSR1&2 are defined in section 4.1. To make price comparable across time, I get the real price term by setting CPI2002=1. Log transformed descriptive statistics is reported in Table 2.1. Note that land supply area can be 0 in some observations. In order to avoid undefined number after log transformation,

⁹ <https://creis.fang.com/>

¹⁰ Average Wage of Staff and Workers refers to the amount of average wage of the on-the-job workers in the report period in one unit. The formula is: average wage of staff and workers = total wages of on-the-job workers /the average number of workers.

¹¹ Housing Provident fund interest rate is not included as it always moves in the same way as bank interest rate.

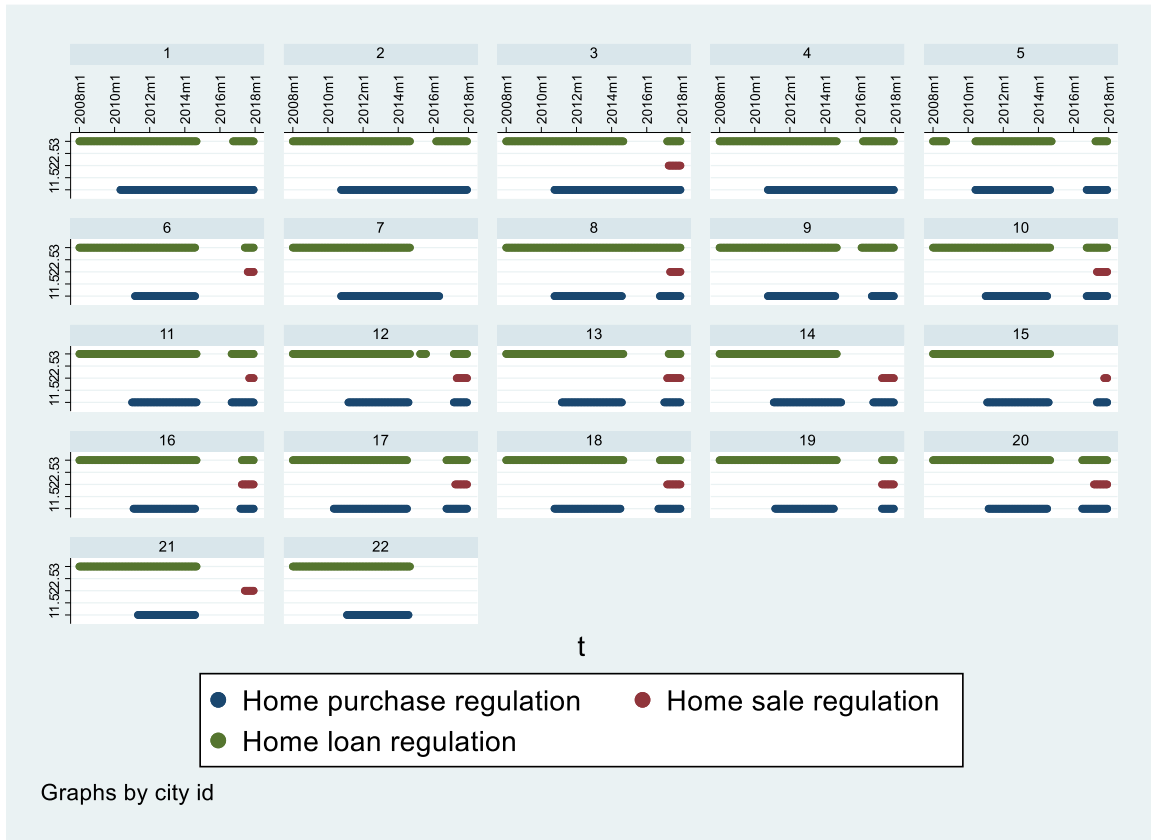
land supply value of 0 is replaced with 1, so the minimum log transformed value of land supply area is 0.

Table 2.1 Description of key variables. (Log transformed)

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Real housing price (yuan/m ²)	2,640	8.938	0.536	7.815	10.68
Real income (yuan)	2,640	8.171	0.308	7.473	9.025
Population (10K)	2,640	6.514	0.534	5.032	7.283
Interest rate (%)	2,640	6.144	0.867	4.900	7.830
Land supply area (m ²)	2,640	10.89	4.510	0	15.87
Trading volume (m ²)	2,640	13.19	0.841	10.22	15.06
HLR1 (home loan low)	2,640	26.99	4.225	20	35
HLR2 (home loan high)	2,640	46.08	14.29	20	70
HPR1 (home purchase low)	2,640	0.436	0.496	0	1
HPR2 (home purchase high)	2,640	0.113	0.316	0	1
HSR1 (home sale low)	2,640	0.0330	0.179	0	1
HSR2 (home sale high)	2,640	0.0117	0.108	0	1

According to Table 2.1 and the data, HLR is the first introduced regulation and also has the longest effective time in total. HLR1 can have a value of 20, 25, 30 or 35, HLR2 takes value from 20 to 70 with a min gap of 5 except 55. HLR1 can be equal or smaller than HLR2 and the former means that home loan regulation is not in effect. HPR is in effect if HPR1 or HPR2 is 1. Same definition applies to HSR as well. HLR, HPR and HSR are introduced in orders and they can be all in effect or not in effect at the same time. Observations of HSR is limited since it is only introduced after 2017. Time of regulation in effect is shown in Figure 2.1

Figure 2.1 Time of regulations in effect



2.6 Empirical Results

2.6.1 Unit root test and cointegration relationship

It is well known that non-stationarity may create spurious statistical results (Granger & Newbold, 1974). If data is not stationary then differenced data should be considered to prevent misleading conclusions, but it is helpful only if there is no cointegrating relationship among the nonstationary variables. So, we first do a unit root test. According to the data sets, we have $T=120$ and $N=22$, since the data has small panel

and large time period, LLC and ADF-fish test about unit root are applied.¹² Results of unit root test are listed in appendix A. As we can see, all variables are I (0) or I (1) except population. non-stationarity hypothesis cannot be rejected for differenced population variable. Population data is originally yearly data and has been transformed to monthly data assuming constant rate of net population growth. This might cause the non-stationary problem. Using the differenced data may be a solution but important information will be lost. So cointegration test is employed to test the long run relationship between variables. Results are shown in appendix B. Three different tests are made and two of them indicate the existent of cointegration relationship.

2.6.2 Panel regressions and results

According to the Hausman test (see appendix C), fix effect model is used. Robust standard error is applied to all regressions.

Table 2.2 Effects of regulations on housing price

	(1) all cities	(2) lagged	(3) %	(4) tier 1	(5) tier 2	(6) tier 3
	P	P	P	P	P	P
income	.246*** (.077)	.263*** (.081)	-.026*** (.008)	.162 (.307)	.281*** (.082)	.432** (.15)
population	.612** (.245)	.63** (.258)	.019 (.011)	1.017** (.196)	.437 (.452)	.216 (.129)
Land supply	.003** (.001)	.003*** (.001)	0 (0)	.002 (.001)	.003** (.001)	.005** (.001)
Trading volume	-.073*** (.016)	-.072*** (.016)	.004 (.003)	-.061 (.043)	-.058** (.021)	-.095** (.032)
Interest rate	-.122*** (.017)	-.118*** (.018)	-.006** (.002)	-.149** (.04)	-.11*** (.021)	-.089* (.04)
HLR1	.014*** (.002)		0 (0)	.021 (.009)	.014*** (.003)	.01** (.003)
HLR2	.002** (.001)		0 (0)	.001 (.001)	.002* (.001)	.003 (.003)

¹² According to Levin et al. (2002), LLC test is good for T range from 25 ~ 250 and N range from 10 ~ 250.

HPR1	.008 (.021)		-.003 (.004)	-.053 (.091)	-.01 (.027)	.027 (.045)
HPR2	.099 (.075)		-.003 (.004)	-.018 (.136)	.406*** (.094)	
HSR1	-.05 (.043)		.004 (.007)	-.281*** (.048)	-.063 (.051)	-.023 (.08)
HSR2	.002 (.088)		.011** (.005)		.051 (.082)	-.283*** (.058)
L.HLR1		.011*** (.002)				
L.HLR2		.002** (.001)				
L.HPR1		.018 (.022)				
L.HPR2		.108 (.073)				
L.HSR1		-.053 (.046)				
L.HSR2		.013 (.086)				
_cons	4.143*** (1.4)	3.91** (1.449)	.083 (.076)	2.457 (2.288)	4.668* (2.571)	5.114** (1.534)
Observations	2640	2618	2618	480	1560	600
R-squared	.653	.634	.006	.788	.603	.682

Standard errors are in parentheses
*** $p < .01$, ** $p < .05$, * $p < .1$

Table 2.2 reports various regressions results of equation (1).^{1st} column of Table 2.2 reports the average effects of the housing regulations on residential housing prices across all cities. The result is somewhat puzzled. On one hand, income, population, trading volume and interest rate are “well-behaved” as they are significant and have the right sign as expected. On the other hand, other factors don’t work well. Although Home loan restriction and Land supply are significant, the coefficients are both positive, indicating that higher down payment ratio and more land supply may lead to the increase of housing price. Positive land supply effect may imply that housing supply is not adequate to the

demand. Home purchase restriction and home sale restriction are both insignificant and most of the coefficients are positively associated with housing price as well. Only low-level home sale restriction has a negative effect as expected. Are the regulations really not effective at all? There might be 2 possible explanations. First is reverse causality. Previously we have talked about the react pattern of government interventions. Tightening regulations usually are a result of a booming housing market. So, in some cases, higher housing price do positively relate to tightening regulations. Second, note that we assume the regulations can affect the housing price the same month as they are enacted. This might not be the case. Often, consumers need some time to react to new regulations. To exam this possibility, we run regression with lagged regulations variables. 2nd column of Table 2.2 reports the result with one lag period, see appendix D for results of more lagged time periods. The coefficients of regulation variables do become smaller as lagged period goes up, but they are still positive. Lagged HPR and HSR are insignificant. Apparently, all the regulation variables failed to lower the housing price. Next, we'd like to know if government regulations can help slow down the increasing rate of housing price. So, I run a regression on the percentage change of housing price. According to 3rd column of Table 2.2, only interest rate has a significant coefficient with right sign. Other variables are either insignificant or with a wrong sign. This model doesn't fit well at all according to the R-square.

Column (4), (5), (6) reports the regression results with respect to different city tiers. It is clear that tier 1 cities have an entirely different scenario than tier 2 & 3 cities. The only significant term in common is interest rate, while all the others are different. Most of the

fundamental factors are insignificant in tier 1 cities, as we can see from column (4), income, land supply, trading volume are all insignificant, indicating that the housing market in tier1 cities cannot be explained by fundamental factors, which implies an abnormal market situation. Population is surprising significant with a coefficient higher than 1, and the only significant regulation variable is home sale restriction. Taking all these into consideration, the housing markets in tier 1 cities are likely to be inelastic and speculative. Comparing tier 2 and tier 3 cities, we see more similarities than differences. Though the coefficients are slightly different, the significance level and sign are pretty much the same. What's interesting is that the significant variables in tier 2 & 3 are totally different than that of tier 1 cities. Income, land supply, trading volume and interest rate are all significantly related with housing price, indicating the housing market of tier 2 & 3 cities are somewhat “healthier”.

Table 2.3 Effects of regulations on housing trading volume

	(1) all cities H	(2) lagged H	(3) % H	(4) tier1 H	(5) tier2 H	(6) tier3 H
price	-.809*** (.168)	-.771*** (.164)	-.125*** (.038)	-.427 (.282)	-.657** (.224)	-1.349** (.37)
income	.726*** (.218)	.834*** (.226)	.137 (.104)	-.319 (.878)	.785*** (.256)	1.014 (.493)
pop	.024 (.237)	.039 (.236)	.101 (.07)	.326 (.364)	-.002 (.534)	.42 (.37)
Land supply	.013*** (.004)	.013*** (.004)	.003 (.003)	.004 (.004)	.012** (.005)	.026** (.009)
Interest rate	-.269*** (.028)	-.243*** (.029)	.011 (.017)	-.167** (.029)	-.305*** (.03)	-.213** (.056)
HLR1	.006 (.006)		-.009* (.004)	-.058*** (.007)	.013** (.005)	-.005 (.014)
HLR2	-.002 (.003)		.002 (.002)	-.01* (.004)	.002 (.003)	.007 (.005)

HPR1	-.001 (.064)		-.038* (.021)	.657*** (.026)	-.123 (.073)	-.121 (.186)
HPR2	-.197 (.119)		.022 (.019)	.714** (.131)	-.99*** (.2)	
HSR1	-.356*** (.12)		.059 (.053)	-.077 (.104)	-.129 (.102)	-.317* (.134)
HSR2	-.214 (.134)		.075 (.059)		-.209 (.126)	-.857** (.207)
L. HLR1		-.007 (.007)				
L.HLR2		-.001 (.003)				
L.HPR1		.034 (.073)				
L.HPR2		-.161 (.127)				
L.HSR1		-.389*** (.114)				
L.HSR2		-.175 (.127)				
_cons	15.782*** (1.152)	14.586*** (1.287)	-.525 (1.18)	20.69** (4.796)	14.088*** (2.748)	14.617*** (2.156)
Observations	2640	2618	2618	480	1560	600
R-squared	.281	.279	.004	.281	.35	.296

Standard errors are in parentheses

*** $p < .01$, ** $p < .05$, * $p < .1$

Table 2.3 reports the average effects of regulations on housing trading volume. Column (1) to (6) represent same regression as in Table 2.3, but with housing trading volume as dependent variable. The analysis above holds pretty much the same here. Tier 1 cities are completely different, while tier 2 & 3 cities share some similarities. From column (4), we can see that home purchase regulations are positively significant, which once again implying a reverse causality possibility, especially in tier 1 cities. One interesting thing is that coefficients of population are insignificant across all regression models. Overall, different regulations are not effective on housing trading volume as well. In consideration

of the strong administrative power, it's hard to believe that the government of China failed to affect the market via regulations. It's more likely that they don't want to push it to the limit. Combined with the back-and-forth feature of the macro controls in housing market, it clear that regulations are only responses to economics shocks and their effects on housing price and trading volume is limited.

2.6.3 Heterogeneous effects and hypothesis tests

As previously stated, another key feature of China's housing market is heterogeneity between different tiers of cities. This statement is proved according to the analysis above. However, the differences in coefficients are not sufficient enough to say that they are indeed statistically different, especially when the difference is relatively small, as the case between tier 2 & 3 cities in Table 2.2 & 2.3. In this subsection, we investigate the heterogeneous effects by testing hypothesis.

To further examine if the heterogeneous effects are statistically significant in different city tiers, I construct hypothesis tests using the following procedures. Consider regression models (1) and (2) with city tier dummy variables as follows:

$$\begin{aligned}
 \ln HP_{jt} = & \alpha_0 + \alpha_1 \ln AI_{jt} + \alpha_2 \ln Pop_{jt} + \alpha_3 \ln LS_{jt} + \alpha_4 MR_{jt} + \alpha_5 \ln HT_{jt} \\
 & + \alpha_6 HLR1_{jt} + \alpha_7 HLR2_{jt} + \alpha_8 HPR1_{jt} + \alpha_9 HPR2_{jt} + \alpha_{10} HSR1_{jt} \\
 & + \alpha_{11} HSR2_{jt} + \alpha_{12} G_2 + \alpha_{13} G_3 \\
 & + \varepsilon_{jt}
 \end{aligned} \tag{3}$$

$$\begin{aligned}
\ln HT_{jt} = & \beta_0 + \beta_1 \ln AI_{jt} + \beta_2 \ln Pop_{jt} + \beta_3 \ln LS_{jt} + \beta_4 MR_{jt} + \beta_5 \ln HP_{jt} + \beta_6 HLR1_{jt} \\
& + \beta_7 HLR2_{jt} + \beta_8 HPR1_{jt} + \beta_9 HPR2_{jt} + \beta_{10} HSR1_{jt} + \beta_{11} HSR2_{jt} \\
& + \beta_{12} G_2 + \beta_{13} G_3 \\
& + e_{jt}
\end{aligned} \tag{4}$$

Where G_2 and G_3 are dummies for tier 2 and tier 3 cities, tier1 is the base group for comparison. Coefficients α_9 and α_9 measure the effect of city tier difference, i.e.,

tier3-tier1, tier2-tier1. Run least square dummy variable regressions with equation (3) and (4), then test the joint hypothesis that $\alpha_{12}=\alpha_{13}=0$. Alternatively, dummies for all 3 groups can be included in regression (3) & (4) without constant term. Results are in column (2) and (4) in Table 2.4. Regression result are reported in first and third column of Table 2.4, test results are reported in Table 2.5. From Table 2.4, coefficients of all 3 tiers are significant, implying that the classification of citer tiers helps to predict housing price and trading volumes. Results of joint F-test of hypothesis that $\alpha_{12}=\alpha_{13}=0$ rejects the null hypothesis, indicating that the heterogeneity between city tiers is significant. Results of F-test of hypothesis that $\alpha_{12}=\alpha_{13}$ rejects the null hypothesis as well, indicating that the heterogeneity between tier2 and tier3 is also significant. Hypothesis testing on trading volume have similar results, once again prove the heterogeneity do exist.

Table 2.4 Least square dummy variable regression

	(1) LSDV	(2) No constant	(3) LSDV	(4) No constant
	p	p	H	H
income	.992*** (.083)	.992*** (.083)	.932** (.134)	.932** (.134)
population	-.093 (.06)	-.093 (.06)	.432** (.066)	.432** (.066)
Land supply	.001 (.002)	.001 (.002)	.011 (.005)	.011 (.005)

Trading volume	-.286*** (.024)	-.286*** (.024)		
Interest rate	-.087** (.012)	-.087** (.012)	-.303* (.081)	-.303* (.081)
HLR1	.003 (.002)	.003 (.002)	.013 (.015)	.013 (.015)
HLR2	.005 (.002)	.005 (.002)	.003 (.006)	.003 (.006)
HPR1	-.047 (.089)	-.047 (.089)	-.111 (.145)	-.111 (.145)
HPR2	-.008 (.029)	-.008 (.029)	-.303 (.205)	-.303 (.205)
HSR1	-.159 (.082)	-.159 (.082)	-.334 (.125)	-.334 (.125)
HSR2	-.096 (.108)	-.096 (.108)	-.145 (.065)	-.145 (.065)
2.tier	-.368*** (.031)		-.675*** (.063)	
3.tier	-.611*** (.034)		-1.17*** (.083)	
Tier1		5.837*** (.578)		15.048*** (.67)
Tier2		5.469*** (.547)		14.373*** (.611)
Tier3		5.226** (.544)		13.877*** (.593)
price			-1.151*** (.087)	-1.151*** (.087)
_cons	5.837*** (.578)		15.048*** (.67)	
Observations	2640	2640	2640	2640
R-squared	.769	.999	.623	.998

Standard errors are in parentheses

*** $p < .01$, ** $p < .05$, * $p < .1$

Table 2.5 LSDV model hypothesis testing results

test	F value	Prob > F
$\alpha_{12} = \alpha_{13} = 0$	F (2, 2) = 38523.17	0.0000

$\alpha_{12} = \alpha_{13}$	F (1, 2) = 4776.36	0.0002
$\beta_{12} = \beta_{13} = 0$	F (2, 2) = 10485.65	0.0001
$\beta_{12} = \beta_{13}$	F (1, 2) = 610.83	0.0016

Then, to further examine if the effects of regulations are statistically different across city tiers, consider regression models (3) and (4) with interaction terms between city tier dummy variables and regulation dummy variables as follows:

$$\begin{aligned}
\ln HP_{jt} = & \alpha_0 + \alpha_1 \ln AI_{jt} + \alpha_2 \ln Pop_{jt} + \alpha_3 \ln LS_{jt} + \alpha_4 MR + \alpha_5 HLR1_{jt} \\
& + \alpha_6 HLR1_{jt} + \alpha_7 HLR2_{jt} + \alpha_8 HPR1_{jt} + \alpha_9 HPR2_{jt} \\
& + \alpha_{10} HSR1_{jt} + \alpha_{11} HSR2_{jt} + \alpha_{12} G_2 HLR1_{jt} + \alpha_{13} G_2 HLR2_{jt} \\
& + \alpha_{14} G_2 HPR1_{jt} + \alpha_{15} G_2 HPR2_{jt} + \alpha_{16} G_2 HSR1_{jt} \\
& + \alpha_{17} G_2 HSR2_{jt} + \alpha_{18} G_3 HLR1_{jt} + \alpha_{19} G_3 HLR2_{jt} \\
& + \alpha_{20} G_3 HPR1_{jt} + \alpha_{21} G_3 HPR2_{jt} + \alpha_{22} G_3 HSR1_{jt} + \alpha_{23} G_3 HSR2_{jt} \\
& + \alpha_{24} G_2 + \alpha_{25} G_3 + \mu_{jt} \quad (5)
\end{aligned}$$

$$\begin{aligned}
\ln HT_{jt} = & \beta_0 + \beta_1 \ln AI_{jt} + \beta_2 \ln Pop_{jt} + \beta_3 \ln LS_{jt} + \beta_4 MR_{jt} + \beta_5 \ln HP_{jt} \\
& + \beta_6 HLR1_{jt} + \beta_7 HLR2_{jt} + \beta_8 HPR1_{jt} + \beta_9 HPR2_{jt} + \beta_{10} HSR1_{jt} \\
& + \beta_{11} HSR2_{jt} + \beta_{12} G_2 HLR1_{jt} + \beta_{13} G_2 HLR2_{jt} \\
& + \beta_{14} G_2 HPR1_{jt} + \beta_{15} G_2 HPR2_{jt} + \beta_{16} G_2 HSR1_{jt} \\
& + \beta_{17} G_2 HSR2_{jt} + \beta_{18} G_3 HLR1_{jt} + \beta_{19} G_3 HLR2_{jt} + \beta_{20} G_3 HPR1_{jt} \\
& + \beta_{21} G_3 HPR2_{jt} + \beta_{22} G_3 HSR1_{jt} + \beta_{23} G_3 HSR2_{jt} + \beta_{24} G_2 + \beta_{25} G_3 \\
& + e_{jt} \quad (6)
\end{aligned}$$

Note that equation (5) and (6) assume city tier dummies only affect regulations. If we assume that city tier dummies can affect all the other variables, more interaction terms will be needed. Regression results are shown in Table 2.6 After running regression (5) and (6), we can run several hypothesis tests according to specific heterogeneity effect of interest. First, we can test if the effects of all regulations are the same across city tiers, e.g., $\alpha_{12} = \alpha_{13} = \alpha_{14} = \alpha_{15} = \dots = \alpha_{23} = 0$. Joint F-test results reject this null hypothesis, indicating that the effects of regulations are statistically different in different city tiers. Then we can test the heterogeneity between any two city tiers. Since tier1 is used as comparison, the parameters of interaction terms actually capture the differences between tier1 and other city tiers. The significance of a certain parameter of interaction term means that particular regulation's effect is statistically different compared with tier1 cities. To see if the effect of a certain regulation is different between tier2 and tier3 cities, we can test the equivalency between parameters of interaction terms, e.g., For HLR, test $\alpha_{12} = \alpha_{18}$ & $\alpha_{13} = \alpha_{19}$. Test results between tier2 and tier3 cities are shown in Table 2.7. Based on the test results of Table 2.7, the heterogeneous effects between tier2 and tier3 cities are mixed. The effects

of HSR are statistically different on both housing price and trading volume, while the effects of HLR are both not. Test result of HPR on trading is significant while insignificant on price. Alternatively, we can use tier 2 cities as base group then test the parameters of interest directly. e.g., For total difference of all 3 regulations, test $\alpha_{18} = \alpha_{19} = \dots = \alpha_{23} = 0$. Joint F-test gives a value of 0.0429, barely reject the null, implying that the differences of effects of regulations between tier 2 and tier 3 are not that far away compared with tier 1 cities. To see if the effect of a certain regulation is the same around all 3 tiers, we can run joint F-tests, e.g., $\alpha_{12} = \alpha_{18} = 0$, $\alpha_{13} = \alpha_{19} = 0$, $\alpha_{14} = \alpha_{20} = 0$. See appendix E for detail testing results of regressions on housing price. See appendix F for detail testing results of regressions on housing trading volumes.

Table 2.6 Fixed effect with interactions

	(1) Price	(2) Trading volume
HLR1	.016* (.009)	-.064*** (.012)
HLR2	.001 (.001)	-.007 (.004)
HPR1	0 (.085)	.525*** (.028)
HPR2	.067 (.13)	.382*** (.055)
HSR1	-.264*** (.052)	-.317*** (.053)
HSR2	-.283*** (.022)	-.802*** (.171)
2.tier#c.HLR1	-.003 (.009)	.077*** (.013)
3.tier #c.HLR1	-.004 (.009)	.055*** (.018)
2.tier#c.HLR2	.002 (.002)	.007 (.006)
3.tier #c.HLR2	.003 (.002)	.016* (.009)
2.tier #1.HPR1	-.02 (.087)	-.62*** (.077)
3.tier #1.HPR1	.018 (.081)	-.719*** (.186)
2.tier #1.HPR2	.288* (.125)	-1.259*** (.259)

3.tier #1.HPR2	(.144) (empty)	(.148) (empty)
2.tier #1.HSR1	.197** (.071)	.221* (.107)
3.tier #1.HSR1	.223*** (.076)	-.088 (.182)
1bn.tier #1.HSR2	(empty)	(empty)
2.tier #1.HSR2	.319*** (.089)	.651*** (.205)
3.tier #1.HSR2	(omitted)	(omitted)
income	.282*** (.072)	.851*** (.192)
pop	.585** (.261)	.138 (.226)
Trading volume	-.071*** (.016)	
Interest rate	-.12*** (.017)	-.253*** (.027)
Land supply	.003*** (.001)	.013*** (.003)
price		-.788*** (.163)
_cons	3.985** (1.506)	13.943*** (1.104)
Observations	2640	2640
R-squared	.665	.309

Standard errors are in parentheses

*** $p < .01$, ** $p < .05$, * $p < .1$

Table 2.7 Tier2 vs Tier3 heterogeneity hypothesis testing results

Test tier2 vs tier3	F value	Prob > F
HLR on price	F (2, 21) = 0.09	0.9106
HPR on price	F (2, 21) = 2.69	0.0911
HSR on price	F (2, 21) = 6.52	0.0063
HLR on trading	F (2, 21) = 1.31	0.2898

HPR on trading	$F(2, 21) = 37.21$	0.0000
HSR on trading	$F(2, 21) = 12.01$	0.0003

2.7 Conclusion

In this paper, a panel data regression approach is applied to investigate the effects of local government regulations in different tiers of cities in China. Contrast to many existing literatures on housing regulations, this paper indicates that most of the local government regulations are not effective in terms of housing price or trading volume. Additionally, the impacts of regulations are far less than fundamental variables. Based on the regression results of different tiers of cities and various hypothesis tests, this paper finds that heterogeneities do exist across different city tiers. All housing regulations in Tier 1 cities work dramatically different than tier 2 & 3 cities. However, the situation between tier 2 & tier 3 cities is mixed. We should specify the regulation and its affecting object before making any conclusions.

APPENDICES

Appendix A

Unit root test

```
. xtunitroot llc y
```

Levin-Lin-Chu unit-root test for y

H0: Panels contain unit roots	Number of panels =	22
Ha: Panels are stationary	Number of periods =	120
AR parameter: Common	Asymptotics: N/T ->	0
Panel means: Included		
Time trend: Not included		

ADF regressions: 1 lag

LR variance: Bartlett kernel, 15.00 lags average (chosen by LLC)

	Statistic	p-value
Unadjusted t	-3.9391	
Adjusted t*	-3.0750	0.0011

```
. xtunitroot fisher p, dfuller lags(0)
(17 missing values generated)
```

Fisher-type unit-root test for p
Based on augmented Dickey-Fuller tests

H0: All panels contain unit roots	Number of panels =	22
Ha: At least one panel is stationary	Avg. number of periods =	119.23
AR parameter: Panel-specific	Asymptotics: T ->	Infinity
Panel means: Included		
Time trend: Not included		
Drift term: Not included	ADF regressions: 0 lags	

		Statistic	p-value
Inverse chi-squared(44)	P	118.5447	0.0000
Inverse normal	Z	-5.1110	0.0000
Inverse logit t(114)	L*	-5.9850	0.0000
Modified inv. chi-squared	Pm	7.9465	0.0000

P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.

```
. xtunitroot llc pop
```

```
Levin-Lin-Chu unit-root test for pop
```

```
H0: Panels contain unit roots      Number of panels =    22
Ha: Panels are stationary          Number of periods =   120

AR parameter: Common              Asymptotics: N/T -> 0
Panel means: Included
Time trend: Not included
```

```
ADF regressions: 1 lag
```

```
LR variance: Bartlett kernel, 15.00 lags average (chosen by LLC)
```

	Statistic	p-value
Unadjusted t	2.9865	
Adjusted t*	6.0742	1.0000

```
. xtunitroot llc d.pop
```

```
Levin-Lin-Chu unit-root test for D.pop
```

```
H0: Panels contain unit roots      Number of panels =    22
Ha: Panels are stationary          Number of periods =   119

AR parameter: Common              Asymptotics: N/T -> 0
Panel means: Included
Time trend: Not included
```

```
ADF regressions: 1 lag
```

```
LR variance: Bartlett kernel, 15.00 lags average (chosen by LLC)
```

	Statistic	p-value
Unadjusted t	-5.5727	
Adjusted t*	2.0198	0.9783

```
. xtunitroot fisher pop, dfuller lags(0)
```

Fisher-type unit-root test for pop
Based on augmented Dickey-Fuller tests

H0: All panels contain unit roots	Number of panels =	22
Ha: At least one panel is stationary	Number of periods =	120

AR parameter: Panel-specific	Asymptotics: T -> Infinity
Panel means: Included	
Time trend: Not included	
Drift term: Not included	ADF regressions: 0 lags

		Statistic	p-value
Inverse chi-squared(44)	P	185.1472	0.0000
Inverse normal	Z	-5.4324	0.0000
Inverse logit t(59)	L*	-12.7230	0.0000
Modified inv. chi-squared	Pm	15.0463	0.0000

P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.

```
. xtunitroot llc r
```

Levin-Lin-Chu unit-root test for r

H0: Panels contain unit roots	Number of panels =	22
Ha: Panels are stationary	Number of periods =	120

AR parameter: Common	Asymptotics: N/T -> 0
Panel means: Included	
Time trend: Not included	

ADF regressions: 1 lag
LR variance: Bartlett kernel, 15.00 lags average (chosen by LLC)

	Statistic	p-value
Unadjusted t	-7.6643	
Adjusted t*	-1.4087	0.0795

```
. xtunitroot llc d.r
```

Levin-Lin-Chu unit-root test for D.r

H0: Panels contain unit roots	Number of panels =	22
Ha: Panels are stationary	Number of periods =	119

AR parameter: Common	Asymptotics: N/T -> 0
Panel means: Included	
Time trend: Not included	

ADF regressions: 1 lag

LR variance: Bartlett kernel, 15.00 lags average (chosen by LLC)

	Statistic	p-value
Unadjusted t	-24.5291	
Adjusted t*	-16.6431	0.0000

```
. xtunitroot llc ls
```

Levin-Lin-Chu unit-root test for ls

H0: Panels contain unit roots	Number of panels =	22
Ha: Panels are stationary	Number of periods =	120

AR parameter: Common	Asymptotics: N/T -> 0
Panel means: Included	
Time trend: Not included	

ADF regressions: 1 lag

LR variance: Bartlett kernel, 15.00 lags average (chosen by LLC)

	Statistic	p-value
Unadjusted t	-29.4241	
Adjusted t*	-22.5856	0.0000

```
. xtunitroot llc L1
```

Levin-Lin-Chu unit-root test for L1

H0: Panels contain unit roots	Number of panels =	22
Ha: Panels are stationary	Number of periods =	120

AR parameter: Common	Asymptotics: N/T -> 0
Panel means: Included	
Time trend: Not included	

ADF regressions: 1 lag

LR variance: Bartlett kernel, 15.00 lags average (chosen by LLC)

	Statistic	p-value
Unadjusted t	-6.6335	
Adjusted t*	1.5353	0.9376

```
. xtunitroot llc d.L1
```

Levin-Lin-Chu unit-root test for D.L1

H0: Panels contain unit roots	Number of panels =	22
Ha: Panels are stationary	Number of periods =	119

AR parameter: Common	Asymptotics: N/T -> 0
Panel means: Included	
Time trend: Not included	

ADF regressions: 1 lag

LR variance: Bartlett kernel, 15.00 lags average (chosen by LLC)

	Statistic	p-value
Unadjusted t	-35.9826	
Adjusted t*	-29.6548	0.0000

Appendix B

Cointegration test

```
. xtointtest kao p y ls pop r H
```

Kao test for cointegration

H0: No cointegration	Number of panels	=	22
Ha: All panels are cointegrated	Avg. number of periods	=	117.14
Cointegrating vector: Same			
Panel means:	Included	Kernel:	Bartlett
Time trend:	Not included	Lags:	3.82 (Newey-West)
AR parameter:	Same	Augmented lags:	1

	Statistic	p-value
Modified Dickey-Fuller t	-4.1832	0.0000
Dickey-Fuller t	-4.2902	0.0000
Augmented Dickey-Fuller t	-1.4936	0.0676
Unadjusted modified Dickey-Fuller t	-31.8323	0.0000
Unadjusted Dickey-Fuller t	-13.1129	0.0000

```
. xtointtest pedroni p y ls pop r H
```

Pedroni test for cointegration

H0: No cointegration	Number of panels	=	22
Ha: All panels are cointegrated	Avg. number of periods	=	118.18
Cointegrating vector: Panel specific			
Panel means:	Included	Kernel:	Bartlett
Time trend:	Not included	Lags:	3.00 (Newey-West)
AR parameter:	Panel specific	Augmented lags:	1

	Statistic	p-value
Modified Phillips-Perron t	-9.5247	0.0000
Phillips-Perron t	-11.2363	0.0000
Augmented Dickey-Fuller t	-12.2109	0.0000

```
. xtointtest westerlund p y ls pop r H
```

Westerlund test for cointegration

H0: No cointegration	Number of panels	=	22
Ha: Some panels are cointegrated	Avg. number of periods	=	119.23
Cointegrating vector: Panel specific			
Panel means:	Included		
Time trend:	Not included		
AR parameter:	Panel specific		

	Statistic	p-value
Variance ratio	-1.3141	0.0944

Appendix C

Hausman test

```
. hausman fe re,constant sigmamore
```

Note: the rank of the differenced variance matrix (9) does not equal the number of coefficients being tested (12); be sure this is what you expect, or there may be problems computing the test. Examine the output of your estimators for anything unexpected and possibly consider scaling your variables so that the coefficients are on a similar scale.

	— Coefficients —		(b-B) Difference	sqrt(diag(V_b-V_B)) Std. err.
	(b) fe	(B) re		
y	.2481709	.3259606	-.0777897	.0054612
pop	.6308675	.2887897	.3420778	.0331352
ls	.0025288	.0019069	.0006219	.0000561
H	-.0739648	-.0836132	.0096484	.000843
r	-.1231348	-.1229204	-.0002143	.0009921
L1	.0143789	.0143064	.0000726	.0001402
L2	.0023735	.0025253	-.0001518	.0000221
P1	-.0034546	-.0042079	.0007533	.0007905
P2	.067837	.0778115	-.0099744	.001602
S1	-.0542889	-.0554096	.0011207	.0004446
S2	.0236812	.021166	.0025152	.0006031
_cons	3.996421	5.723968	-1.727547	.2015178

b = Consistent under H0 and Ha; obtained from xtreg.

B = Inconsistent under Ha, efficient under H0; obtained from xtreg.

Test of H0: Difference in coefficients not systematic

$$\begin{aligned}\text{chi2}(9) &= (b-B)'[(V_b-V_B)^{-1}](b-B) \\ &= 243.06\end{aligned}$$

Prob > chi2 = 0.0000

(V_b-V_B is not positive definite)

Appendix D

Regressions with more lagged time period

Fixed-effects (within) regression	Number of obs	=	2,579
Group variable: cityid	Number of groups	=	22
R-squared:			
Within = 0.6193	Obs per group:	min =	101
Between = 0.0036		avg =	117.2
Overall = 0.0469		max =	118
	F(11,2546)	=	376.54
corr(u_i, Xb) = -0.4802	Prob > F	=	0.0000

p	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
y	.2981577	.027877	10.70	0.000	.2434939	.3528216
pop	.6620662	.050803	13.03	0.000	.5624468	.7616855
ls	.0028639	.0007764	3.69	0.000	.0013415	.0043864
H	-.0792732	.0060586	-13.08	0.000	-.0911535	-.0673929
r	-.1151407	.0069395	-16.59	0.000	-.1287483	-.1015331
L1						
L2.	.0090167	.0011764	7.66	0.000	.00671	.0113234
L2						
L2.	.0027799	.0003513	7.91	0.000	.002091	.0034687
P1						
L2.	.0049921	.0100201	0.50	0.618	-.0146563	.0246405
P2						
L2.	.0746496	.0151252	4.94	0.000	.0449905	.1043086
S1						
L2.	-.0602282	.0189683	-3.18	0.002	-.0974231	-.0230333
S2						
L2.	.0480698	.0325119	1.48	0.139	-.0156826	.1118223
_cons	3.5245	.384311	9.17	0.000	2.770906	4.278094
sigma_u	.59473969					
sigma_e	.14201741					
rho	.94605564	(fraction of variance due to u_i)				

F test that all u_i=0: F(21, 2546) = 381.85 Prob > F = 0.0000

```
. xtreg p y pop ls H r l3.L1 l3.L2 l3.P1 l3.P2 l3.S1 l3.S2, fe
```

```
Fixed-effects (within) regression      Number of obs   =      2,557
Group variable: cityid                 Number of groups =       22
```

```
R-squared:                             Obs per group:
  Within = 0.6081                      min =      100
  Between = 0.0051                     avg =     116.2
  Overall = 0.0477                     max =     117
```

```
corr(u_i, Xb) = -0.4900                F(11,2524)      =     356.08
                                      Prob > F         =     0.0000
```

p	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
y	.3397196	.0281772	12.06	0.000	.2844669	.3949724
pop	.6773803	.0515914	13.13	0.000	.5762145	.7785462
ls	.0032262	.0007894	4.09	0.000	.0016783	.0047741
H	-.0836343	.0060816	-13.75	0.000	-.0955596	-.0717089
r	-.1090179	.0072119	-15.12	0.000	-.1231597	-.094876
L1						
L3.	.0058298	.0011717	4.98	0.000	.0035321	.0081275
L2						
L3.	.0031184	.0003591	8.68	0.000	.0024142	.0038227
P1						
L3.	.0065496	.0101999	0.64	0.521	-.0134513	.0265506
P2						
L3.	.0773637	.0152912	5.06	0.000	.0473792	.1073483
S1						
L3.	-.0593347	.0205109	-2.89	0.004	-.0995546	-.0191149
S2						
L3.	.0765027	.0372101	2.06	0.040	.0035373	.1494682
_cons	3.169956	.391518	8.10	0.000	2.402227	3.937685
sigma_u	.59768474					
sigma_e	.14288464					
rho	.94593832	(fraction of variance due to u_i)				

```
F test that all u_i=0: F(21, 2524) = 368.86                Prob > F = 0.0000
```

Fixed-effects (within) regression
Group variable: cityid

Number of obs = 2,535
Number of groups = 22

R-squared:
Within = 0.5909
Between = 0.0061
Overall = 0.0466

Obs per group:
min = 99
avg = 115.2
max = 116

F(11,2502) = 328.52
Prob > F = 0.0000

corr(u_i, Xb) = -0.5055

p	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
y	.3806568	.0284094	13.40	0.000	.3249484	.4363652
pop	.6988607	.0528487	13.22	0.000	.5952291	.8024923
ls	.003471	.0008083	4.29	0.000	.001886	.005056
H	-.0878683	.0061878	-14.20	0.000	-.100002	-.0757345
r	-.0995348	.0075967	-13.10	0.000	-.1144314	-.0846383
L1						
L4.	.0022638	.0011737	1.93	0.054	-.0000377	.0045653
L2						
L4.	.0030286	.0003726	8.13	0.000	.0022979	.0037593
P1						
L4.	.0162979	.0104501	1.56	0.119	-.0041939	.0367896
P2						
L4.	.0842523	.0155942	5.40	0.000	.0536733	.1148312
S1						
L3.	-.0515005	.0208724	-2.47	0.014	-.0924295	-.0105715
S2						
L3.	.0766231	.0378432	2.02	0.043	.0024158	.1508303
_cons	2.785399	.4004057	6.96	0.000	2.000238	3.57056
sigma_u	.60341001					
sigma_e	.14512397					
rho	.94531957	(fraction of variance due to u_i)				

F test that all u_i=0: F(21, 2502) = 354.17 Prob > F = 0.0000

Appendix E

Hypothesis testing results (housing price)

Fixed-effects (within) regression
 Group variable: cityid

Number of obs = 2,640
 Number of groups = 22

R-squared:
 Within = 0.6655
 Between = 0.0057
 Overall = 0.0590

Obs per group:
 min = 120
 avg = 120.0
 max = 120

corr(u_i, Xb) = -0.4194

F(17,21) = .
 Prob > F = .

(Std. err. adjusted for 22 clusters in cityid)

p	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
groupid						
2	0 (omitted)					
3	0 (omitted)					
L1	.0163781	.008745	1.87	0.075	-.0018082	.0345643
L2	.000683	.001084	0.63	0.535	-.0015713	.0029374
1.P1	.0003318	.085185	0.00	0.997	-.1768202	.1774838
1.P2	.0667128	.1295211	0.52	0.612	-.2026411	.3360667
1.S1	-.2644592	.0520244	-5.08	0.000	-.3726499	-.1562686
1.S2	-.2825003	.0222163	-12.72	0.000	-.3287016	-.2362989
groupid#c.L1						
2	-.0031111	.0092512	-0.34	0.740	-.0223501	.0161278
3	-.0040466	.0090823	-0.45	0.660	-.0229344	.0148411
groupid#c.L2						
2	.0020765	.0018314	1.13	0.270	-.001732	.005885
3	.0029507	.0018987	1.55	0.135	-.0009978	.0068992
groupid#P1						
2 1	-.0199752	.0870882	-0.23	0.821	-.2010851	.1611347
3 1	.0182507	.0806116	0.23	0.823	-.1493902	.1858917
groupid#P2						
2 1	.2877118	.1441617	2.00	0.059	-.0120888	.5875125
3 1	0 (empty)					
groupid#S1						
2 1	.1967908	.0709445	2.77	0.011	.0492536	.3443279
3 1	.2232008	.0757564	2.95	0.008	.0656567	.380745
groupid#S2						
1 1	0 (empty)					
2 1	.3190949	.0889673	3.59	0.002	.1340773	.5041124
3 1	0 (omitted)					
y	.2818823	.0722723	3.90	0.001	.1315839	.4321806
pop	.5851914	.2607727	2.24	0.036	.0428849	1.127498
H	-.071288	.0155876	-4.57	0.000	-.1037043	-.0388718
r	-.1196214	.0174428	-6.86	0.000	-.1558957	-.0833471
ls	.0025147	.0007729	3.25	0.004	.0009073	.0041221
_cons	3.985159	1.506426	2.65	0.015	.8523734	7.117944
sigma_u	.56595879					
sigma_e	.13532221					
rho	.94592162	(fraction of variance due to u_i)				


```

. testparm 2.groupid#(c.L1 c.L2 P1 P2 S1 S2)

( 1) 2.groupid#c.L1 = 0
( 2) 2.groupid#c.L2 = 0
( 3) 2.groupid#1.P1 = 0
( 4) 2.groupid#1.P2 = 0
( 5) 2.groupid#1.S1 = 0
( 6) 2.groupid#1.S2 = 0

      F( 6, 21) = 106.58
      Prob > F = 0.0000
. testparm 3.groupid#(c.L1 c.L2 P1 P2 S1 S2)

( 1) 3.groupid#c.L1 = 0
( 2) 3.groupid#c.L2 = 0
( 3) 3.groupid#1.P1 = 0
( 4) 3.groupid#1.S1 = 0

      F( 4, 21) = 6.09
      Prob > F = 0.0020

. testparm i.groupid#(c.L1 c.L2 P1 P2 S1 S2)

( 1) 2.groupid#c.L1 = 0
( 2) 3.groupid#c.L1 = 0
( 3) 2.groupid#c.L2 = 0
( 4) 3.groupid#c.L2 = 0
( 5) 2.groupid#1.P1 = 0
( 6) 3.groupid#1.P1 = 0
( 7) 2.groupid#1.P2 = 0
( 8) 2.groupid#1.S1 = 0
( 9) 3.groupid#1.S1 = 0
(10) 2.groupid#1.S2 = 0

      F(10, 21) = 96.78
      Prob > F = 0.0000

. testparm 3.groupid#(c.L1 c.L2 P1 P2 S1 S2)

( 1) 3.groupid#c.L1 = 0
( 2) 3.groupid#c.L2 = 0
( 3) 3.groupid#1.P1 = 0
( 4) 3.groupid#1.S1 = 0
( 5) 3.groupid#1.S2 = 0

      F( 5, 21) = 2.81
      Prob > F = 0.0429

```

Appendix F

Hypothesis testing results (trading volume)

Fixed-effects (within) regression	Number of obs	=	2,640
Group variable: cityid	Number of groups	=	22
R-squared:			
Within	=	0.3087	
Between	=	0.0187	
Overall	=	0.0428	
Obs per group:			
	min	=	120
	avg	=	120.0
	max	=	120
F(17,21) = .			
corr(u_i, Xb) = -0.7635 Prob > F = .			

(Std. err. adjusted for 22 clusters in cityid)

H	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
groupid						
2	0 (omitted)					
3	0 (omitted)					
L1	-.0640577	.0120153	-5.33	0.000	-.0890448	-.0390706
L2	-.0067832	.0043846	-1.55	0.137	-.0159015	.0023352
1.P1	.5254496	.0280514	18.73	0.000	.4671134	.5837858
1.P2	.3821476	.0548964	6.96	0.000	.2679844	.4963108
1.S1	-.3167504	.0528364	-5.99	0.000	-.4266297	-.2068711
1.S2	-.8020621	.1706471	-4.70	0.000	-1.156942	-.4471821
groupid#c.L1						
2	.0769669	.0131648	5.85	0.000	.0495892	.1043446
3	.0549911	.0183205	3.00	0.007	.0168915	.0930906
groupid#c.L2						
2	.006627	.0059009	1.12	0.274	-.0056447	.0188986
3	.0163782	.0087367	1.87	0.075	-.0017908	.0345473
groupid#P1						
2 1	-.6195576	.0773004	-8.01	0.000	-.7803126	-.4588025
3 1	-.7185052	.1864611	-3.85	0.001	-1.106272	-.330738
groupid#P2						
2 1	-1.259018	.1483864	-8.48	0.000	-1.567605	-.9504318
3 1	0 (empty)					
groupid#S1						
2 1	.2207932	.1068361	2.07	0.051	-.0013847	.4429711
3 1	-.0875195	.1818688	-0.48	0.635	-.4657364	.2906974
groupid#S2						
1 1	0 (empty)					
2 1	.6505112	.204749	3.18	0.005	.2247124	1.07631
3 1	0 (omitted)					
y	.8509095	.1917322	4.44	0.000	.4521806	1.249638
pop	.1382332	.2256609	0.61	0.547	-.3310543	.6075207
p	-.7882515	.1632588	-4.83	0.000	-1.127767	-.4487362
r	-.2531843	.0265579	-9.53	0.000	-.3084145	-.1979541
ls	.0131392	.0034151	3.85	0.001	.0060371	.0202413
_cons	13.94333	1.103908	12.63	0.000	11.64763	16.23903
sigma_u	1.0959632					
sigma_e	.44997994					
rho	.85574277	(fraction of variance due to u_i)				

```
. testparm 2.groupid#(c.L1 c.L2 P1 P2 S1 S2)
```

```
( 1) 2.groupid#c.L1 = 0  
( 2) 2.groupid#c.L2 = 0  
( 3) 2.groupid#1.P1 = 0  
( 4) 2.groupid#1.P2 = 0  
( 5) 2.groupid#1.S1 = 0  
( 6) 2.groupid#1.S2 = 0
```

```
      F( 6,    21) =   25.03  
      Prob > F =    0.0000
```

```
. testparm 3.groupid#(c.L1 c.L2 P1 P2 S1 S2)
```

```
( 1) 3.groupid#c.L1 = 0  
( 2) 3.groupid#c.L2 = 0  
( 3) 3.groupid#1.P1 = 0  
( 4) 3.groupid#1.S1 = 0
```

```
      F( 4,    21) =   16.23  
      Prob > F =    0.0000
```

```
. testparm i.groupid#(c.L1 c.L2 P1 P2 S1 S2)
```

```
( 1) 2.groupid#c.L1 = 0  
( 2) 3.groupid#c.L1 = 0  
( 3) 2.groupid#c.L2 = 0  
( 4) 3.groupid#c.L2 = 0  
( 5) 2.groupid#1.P1 = 0  
( 6) 3.groupid#1.P1 = 0  
( 7) 2.groupid#1.P2 = 0  
( 8) 2.groupid#1.S1 = 0  
( 9) 3.groupid#1.S1 = 0  
(10) 2.groupid#1.S2 = 0
```

```
      F(10,    21) =   38.07  
      Prob > F =    0.0000
```

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CHAPTER THREE

Does Inflation Targeting Matters for Emerging Markets? — Evidence from Latin American Countries

3.1 Introduction

Inflation targeting (IT) is one of the main monetary policy regimes in the world today. It is first appeared in the early 1990s then quickly spread to other countries—industrial countries at first then followed by many developing countries—New Zealand in 1990, Canada in 1991, Israel in 1991, the United Kingdom in 1992, Sweden and Finland in 1993 and Australia in 1994, Brazil and Chile in 1999 and so on. Based on the classification of the International Monetary Fund (IMF), 43 countries have joined the family of IT by year 2020, about half of which are emerging markets.¹³ Table 3.1 lists countries within the IT family by the year 2020. The empirical practice of IT has led to many empirical studies of this monetary framework. See Bernanke et al. (1999), Sterne (2002), Mishkin and Schmidt- Hebbel (2002), and Truman (2003), for example. However,

¹³ Source: IMF's Annual report on exchange arrangements and exchange restrictions 2020

the effectiveness of IT framework on inflation and other macroeconomic performance (i.e., GDP growth rate, real interest rate) still remains controversial among researchers and policymakers.

This paper attempts to measure the treatment effects of inflation targeting on inflation and GDP performance. To make countries more comparable, I focus on the IT practice in the Latin American area. Twenty emerging Latin American countries are examined based on the annual data from 1980-2020. Half of the countries adopted inflation targeting and the other half did not. Considering that recent studies show that two-way fixed effects treatment analysis could be problematic when having variation in treatment timing, this study also uses the propensity score matching method and the newly built semi-parametric DID estimators by Callaway and Sant'Anna (2020) to estimate the treatment effect of IT, in comparison to the two-way fixed effects results. Surprisingly, almost all the regressions yield non-significant IT treatment coefficients, indicating that IT is not effective in Latin American countries. This study has two major contributions. Firstly, it employs a very comprehensive data set to examine this issue, lasting from 1980 to 2020. It helps to update inflation targeting researches to modern scenarios. Secondly, I use the newly developed two-way fixed effect estimators to avoid issues like variation in treatment timing and heterogeneity in treatment effect and provide an example to compare the new estimator with the traditional DID estimator and the propensity score matching estimator.

The rest of the paper is organized as follows. Section 2 provides background information of inflation targeting and reviews of relating empirical studies. Section 3 describes the data and methodology used. Section 4 presents the results of various

regressions using different estimation methods. Finally, Section 5 concludes.

Table 3.1 IT countries and adoption time

Country	Inflation targeting adoption time	Country	Inflation targeting adoption time
New Zealand	1990	Romania	2005
Canada	1991	Armenia	2006
United Kingdom	1992	Serbia	2006
Sweden	1993	Turkey	2006
Australia	1993	Ghana	2007
Czech Republic	1997	Albania	2008
Israel	1997	Uruguay	2008
Poland	1998	Georgia	2009
Brazil	1999	Moldova	2010
Chile	1999	Dominican Republic	2012
Colombia	1999	Japan	2012
South Africa	2000	Paraguay	2012
Thailand	2000	Uganda	2014
Korea	2001	India	2015
Mexico	2001	Russia	2015
Iceland	2001	Kazakhstan	2016
Norway	2001	Ukraine	2017
Hungary	2001	Costa Rica	2018
Peru	2002	Jamaica ¹⁴	2018
Philippines	2002	Seychelles	2020
Guatemala	2005	Sri Lanka	2020
Indonesia	2005		

Sauce: Roger, Scott (2010) and IMF's Annual report on exchange arrangements and exchange restrictions (2000-2020).

¹⁴ The authorities reported that their monetary policy framework is referred to as inflation targeting "lite".

3.2 Inflation Targeting and Empirical Studies

According to IMF, inflation targeting is a monetary framework, where “a central bank estimates and makes public a projected, or “target,” inflation rate and then attempts to steer actual inflation toward that target, using such tools as interest rate changes.”¹⁵ The primary goal of inflation targeting is maintaining price stability. Based on the IMF classification, other monetary frameworks that can be contrasted to IT includes Exchange rate anchor (monetary authority maintains the exchange rate at its predetermined level or within a range), Monetary aggregate target (monetary authority targets growth rate for a monetary aggregate, such as reserve money, M1, or M2) and Others (country has no explicitly stated nominal anchor).¹⁶

3.2.1 Inflation Targeting in Practice

The detail of IT can be considerably different across countries, in terms of targeting point (range) of inflation, accountability of monetary authority, if there are other macro targeting variables, and so on. But there are some underlying elements in common to inflation targeters. These include (Milshkin, 2004; and Heenan, Peter, and Roger, 2006):

- A central bank commitment to price stability as the primary goal of monetary policy
- An explicit target for inflation;
- High-accountability of central bank to achieve its inflation objectives

¹⁵ Source: Sarwat Jahan, Inflation Targeting: Holding the Line.
<https://www.imf.org/external/pubs/ft/fandd/basics/target.htm>

¹⁶ Source: IMF Annual Report on Exchange Arrangements and Exchange Restrictions 2020

- High-transparency of central bank's policy strategy and implementation; and
- An information inclusive approach to determine policy instruments.

Most of the inflation targeters share these four broad features, but there are considerable variations in details of empirical implementation. For example, the price index that a central bank refers to can be overall or “core” inflation and the inflation target itself can be a point or within a range. At a more basic level, some central banks implement a target set by the government, while others set their own targets. Heterogeneity also exists in the ways that central banks communicate with the public. (See Fracasso, Genberg, and Wyplosz (2003) for detail)

3.2.2 Has inflation targeting been a success?

The question of whether IT is effective or not is hotly debated ever since it is first emerged in 1990. At the early stage of the research of IT, most of the monetary economists seemed to be positive. Many studies showed that IT could be beneficial. For example, Frederic S. Mishkin (2000) concludes that Inflation targeting has been successful in controlling Inflation, weakening the effects of inflationary shocks, promoting Growth while not leading to increased output fluctuations. Mishkin and Schmidt-Hebbel (2007) conclude that inflation targeting in advanced industrial countries can effectively lower inflation in the long run. Similar arguments include Svensson 1997, Mishkin 1999, Bernanke et al. 1999, King 2002, and others. But in recent years, researchers have claimed different opinions about IT using some new methodologies. For example, Ball and Sheridan (2005) argue that “there is no evidence that inflation targeting improves performance as measured by the behavior of inflation, output, or interest rates” in a cross-

section investigation between advanced industrial inflation targeters and non-targeters. Lin and Ye (2007) investigate the self-selectivity issue when adopting IT and find that IT has no significant effects on either inflation or inflation variability in some industrialized countries.

The experience of emerging markets with inflation targeting is also controversial. The International Monetary Fund (2005), report inflation targeting is significant in reducing average inflation and its standard deviation. Similar arguments include Goncalves and Salles (2008) and Lin and Ye (2009), De Mendonça and Guimaraes e Souza (2012) and others. By contrast, John Thornton (2015) argues that the results of Goncalves and Salles (2008) can be problematic under a more rational and larger sample of developing countries that control for other alternative monetary regimes. Ricardo and Brianne (2010) show “there is no evidence that inflation targeting regime improves economic performance” in terms of inflation and output growth in developing countries.

3.3 Data and methodology

3.3.1 Targeters and Nontargeters

From Table 3.1, we know that there are 33 developing countries¹⁷ including:

- Europe: Czech Republic, Poland, Hungary, Serbia, Turkey and Romania, Albania, Georgia, Moldova, Russia, Ukraine, 11 in total.
- Asia: Thailand, Philippines, Indonesia, Armenia, India, Kazakhstan, Sri Lanka, 7 in total.

¹⁷ Korea and Israel are not included according to their high level of GDP per capita.

- Latin America: Brazil, Chile, Colombia, Mexico, Peru, Guatemala, Uruguay, Dominican Republic, Paraguay, Costa Rica, Jamaica, 11 in total.
- Africa: South Africa, Ghana, Uganda, Seychelles, 4 in total.

We might be willing to focus on Europe and Latin America categories since they both contain 11 countries. But we should also think about comparison. Since it is not possible to directly detect the effect of IT by comparing one country's performance under two different policy regimes over the same period, we need to compare similar countries with different monetary regimes. The control group should be similar in all aspects besides IT treatment. This similarity requirement is called parallel assumption in standard Difference in Difference (DID) setup. Since Europe contains most of the developed countries, it is not wise to make a comparison where the membership of the EU could easily make a difference. On the contrary, all the Latin American countries are emerging market economies and they also have similar cultural and language backgrounds, which are perfect for comparison.

In this paper, I will refer to Brazil, Chile, Colombia, Mexico, Peru, Guatemala, Uruguay, Dominican Republic, Paraguay, Costa Rica, as targeters. Note that Jamaica is excluded since it is not a full-fledged IT country. Jamaica's monetary policy framework is referred to as inflation targeting "lite" since 2018. Inflation targeting lite (ITL) countries announce an inflation target but are not able to maintain the inflation target as their primary policy goal. To make sure that the targeter group and the control group are similar and comparable, the nontargeter group only includes countries with a population size of at least as large as 3 million. 13 countries are excluded from the sample. Argentina, Bolivia,

Ecuador, El Salvador, Haiti, Honduras, Jamaica, Nicaragua, Panama, Venezuela are non-targeters.¹⁸

At last, my dataset consists of 20 emerging countries in Latin America for the years from 1980 to 2020. Half of them are IT targeters and the other half are not. Most of the data are drawn from the World Bank's World Development Indicator and the IMF's World Economic Outlook Database. Information about inflation targeting starting time is obtained from the Annual Report on Exchange Arrangements and Exchange Restrictions from the IMF's AREAER database.

3.3.2 Difference in differences

When it comes to the topic of treatment effect, the difference in differences (DID) estimation is always the first idea to jump into researchers' minds. DID is a very common quasi-experimental research design to estimate the average effect of a treatment (e.g., a new policy, a new patent, a natural disaster) on those who receive the treatment. Standard DID setup usually has two groups, control group and treatment group, and two time periods, pre and post-treatment period. There are two differences in this setup, difference between the changes in outcome before and after a treatment happened in the control group and in the treatment group. By comparing two differences, one can estimate the treatment effect without concerning the unobserved factors that may affect the outcome other than the treatment itself. This result can also be obtained from the coefficient (β) of the interaction term in the following regression

$$y_{it} = \gamma + \gamma_i Treat_i + \gamma_t Post_t + \beta Treat_i \times Post_t + \varepsilon_{it} \quad (t = 1, 2) \quad (1)$$

¹⁸ Data of Cuba is not available through IMF or the World Bank database.

DID is widely used in a variety of economic topics, see, e.g., Hanushek and Ludger (2006), Bonhomme and Sauder (2011), Dimick and Ryan (2014). In IT relating literature, Ball and Sheridan (2005) use this setup to run a cross-section regression to estimate the IT treatment effect on emerging countries. However, it is highly likely to have more than two time periods in empirical studies, treatments can occur at different times as well. As the case in this study, each country can have its' own time of accepting IT. In situations like this, researchers usually estimate a more generalized DID model as follows. (See Wing, Simon, and Bello-Gomez (2018) for example.) It can be also referred to as two-way fixed effects (TWFE) difference in differences, as it contains a time fixed dummy and a group fixed dummy:

$$Y_{it} = a_i + b_t + D_{it}\beta + \varepsilon_{it} \quad (2)$$

Where a_i represents the effects of the time-invariant characteristics of group i , and b_t represents the effects of the group-invariant factors. The treatment is denoted by D_{it} , where $D_{it} = 1$ for all observations that are subject to the treatment in group i at time t . All units at a given time are either treated or untreated. Note that covariates (i.e., individual-level characteristics) can be added in the specification above as well.

In the context of inflation targeting, the empirical model can be defined as:

$$y_{i,t} = \alpha \cdot y_{i,t-1} + \beta \cdot IT_{i,t} + \delta_t + \eta_i + \varepsilon_{i,t} \quad (3)$$

Where $y_{i,t}$ is the outcome of interest (i.e., inflation rate, GDP growth rate, inflation volatility or GDP growth volatility; The lagged value of $y_{i,t-1}$ is included to capture the persistence and mean-reversion as Ball and Sheridan (2005) indicate that the effect of IT could be overestimated simply because of regression to the mean since targeters usually

had a higher inflation in the pretargeting period. $IT_{i,t}$ is a dummy variable equal to 1 if country i is an inflation targeter at time t and zero otherwise. The term δ_t captures time varying fixed effect, η_i captures country specific fixed effect, and $\varepsilon_{i,t}$ is the disturbance. β is the parameter of interest which measures the average treatment effect of the IT across all targeting countries. The subscript i is the country and t is the time period.

In contrast to the standard 2x2 setup, we don't know much about the two-way fixed effects setup with variation in treatment timing and heterogeneous treatment effects. In fact, recent literature indicate that two-way fixed effects estimators could be problematic or even provide a wrong sign of the treatment effect when treatment timing or treatment effects varies (see Goodman-Bacon (2021) for a decomposition analysis of TWFE estimator). To make a long story short, the core of these problems with TWFE specifications is that OLS attempts to compare all possible cohorts with each other, as long as there is "variation in treatment status" in a given time. Actually, TWFE estimator gives a weighted average of all possible simple 2x2 DID terms, regardless "treatment" and "comparison" status. Ideally, one would only want to compare treatment group with untreated group, but in fact, already-treated units can act as the control group to late-treated units in some 2x2 DID terms. Thus, TWFE estimator is biased when there is variation in treatment effects. Fortunately, Callaway and Sant'Anna (2020) has developed flexible estimators to deal with this issue by enforcing the estimation and inference procedure only use desired variations.

Consider a random sample

$$\{(Y_{i,1}, Y_{i,2}, \dots, Y_{i,T}, D_{i,1}, D_{i,2}, \dots, D_{i,T})\}_{i=1}^n$$

where $D_{i,t} = 1$ if unit i is treated in period t , and 0 otherwise

- $G_{i,g} = 1$ if unit i is first treated at time g , and zero otherwise (Treatment starting-time)
- $C = 1$ is a “never-treated” comparison group

Then the parameter of interest would be

$$ATT(g, t) = E[Y_t - Y_{g-1} | Gg = 1] - E[Y_t - Y_{g-1} | C = 1] \quad (4)$$

Which is the average treatment effect for the group of units first treated at time period g , in calendar time t . After taking weighted averages for all $ATT(g, t)$'s, we will have a sample average treatment effect.¹⁹

3.3.3 Propensity score matching (PSM)

Propensity score matching is another useful method to estimate the treatment effect especially when there is self-selection concern. The difference in the outcome between treated and untreated groups may be caused by covariates that predict treatment rather than the treatment itself. A propensity score is the probability of a unit adopting a treatment given some control covariates. The central idea of PSM is to match the treated units to the control units with similar values of covariates that predict receiving the treatment, thus reducing the selection bias. Under the assumption that the outcome is independent of the treatment dummy, conditioning on the covariates, the treatment effect on the treated can be given by:

$$ATT(i) = E[Y_{i,1} - Y_{i,0} | D_i = 1, p(X_i)] - E[Y_{j,1} - Y_{j,0} | D_j = 0, p(X_j)] \quad (5)$$

¹⁹ This estimation can be implemented using Stata command `csdid`

Where $p(X_j)$ is the probability of unit i adopts the treatment and unit i and j have similar propensity score. See Rosenbaum and Rubin (1983) for detailed explanation. Commonly used propensity score matching methods includes nearest-neighbor matching, radius matching, kernel matching and local linear matching. In this paper, all above matching methods are tested as a robustness check. Note that all the 20 countries in my sample share similar economic and cultural features, the selection bias is automatically reduced, but PSM is still implemented in comparison to other methods.

3.4 Estimating the Effect of Inflation Targeting

First, we use two-way fixed effects model to estimate the average treatment effects of inflation targeting on inflation and output. Inflation is defined as the annual percentage change of GDP deflator. Inflation volatility is defined as the standard deviation of a three-year moving average of inflation. Output is defined as the annual growth rate of GDP and GDP volatility is defined as the standard deviation of a three-year moving average of GDP growth. Considering that extremely high inflation numbers could bias the regression results, I use a natural logarithm transformation formula as follows, $y_{i,t} = 100 * \ln(1 + \frac{y_{i,t}}{100})$. GDP growth rate is also log-transformed to make results consistent.

3.4.1 Two-way fixed effects estimation

Table 3.2 IT treatment effect on inflation

	(1) Level-OLS	(2) Volatil~S	(3) Level-T~E	(4) Volatil~E
IT	-4.018*** (-3.52)	-2.710** (-2.43)	-3.749 (-0.93)	4.247 (1.61)
L.INF	0.795*** (31.61)	0.354*** (10.20)	0.738*** (36.41)	0.337*** (7.60)
_cons	4.958*** (4.14)	2.591** (2.29)	2.693 (1.06)	3.343* (1.97)
N	800	780	800	780

t statistics in parentheses

* p<0.1, ** p<0.05, *** p<0.01

Table 3.3 IT treatment effect on output growth

	(1) Level-OLS	(2) Volatil~S	(3) Level-T~E	(4) Volatil~E
IT	0.083 (0.45)	-0.674** (-2.79)	0.867 (1.42)	-0.404 (-1.02)
L.GDPGR	0.589*** (4.48)	-0.145*** (-11.36)	0.490*** (3.67)	-0.111*** (-5.34)
_cons	0.743 (1.59)	3.065*** (12.45)	-0.095 (-0.11)	4.461*** (7.34)
N	800	780	800	780

t statistics in parentheses

* p<0.1, ** p<0.05, *** p<0.01

Tables 3.2 and Table 3.3 presents various estimates of Eq. (3). The first two columns of Tables 3.2 present estimates of IT treatment effect on the treated (ATT) on both level and volatility of inflation, using a pooled OLS method that ignores the time and country

fixed effects. The third and fourth columns present estimates from TWFE models. Table 3.3 presents estimates of ATT on output growth and volatility. Robust standard errors clustered by countries is applied to all regressions. The result of pooled OLS on inflation is negative and significant, with a coefficient of -4.018, indicating a strongly ATT on inflation and volatility, which is in agreement with the findings of Ball and Sheridan (2005). OLS also find positive result regarding output growth volatility, showing that IT can help to stabilize GDP growth. However, results from TWFE models considerably modifies this inference. None of the four regressions have significant coefficients of IT, indicating that inflation targeting framework works no better than other monetary frameworks in terms of stabilizing inflation and output growth. Note that IT coefficient of the fourth column at Table 3.2 is even positive, implying that IT could be harmful to inflation stabilization. But this result could be still problematic if there is heterogeneity in treatment effect. This may be a biased result comes from “undesired” comparisons between early and late targeters, as discussed above in section 3. To exam this probability, I re-evaluate the TWFE model using the estimators developed by Callaway and Sant’Anna (2020). Results are reported in Table 3.4.

Table 3.4 Group and average IT treatment effects on inflation

	(1) drimp-g~p	(2) drimp-s~e	(3) dripw-g~p	(4) dripw-s~e
G1999	-3.029 (-0.80)		-3.034 (-0.81)	
G2001	-3.930 (-0.99)		-6.135 (-1.41)	
G2002	2.160 (0.52)		2.335 (0.56)	
G2005	-1.342** (-2.37)		-1.407*** (-2.66)	
G2008	0.235 (0.23)		0.103 (0.11)	
G2012	0.365 (0.28)		0.286 (0.24)	
G2018	1.074* (1.65)		1.120* (1.69)	
ATT		-1.588 (-0.71)		-1.879 (-0.83)
N				

t statistics in parentheses

* p<0.1, ** p<0.05, *** p<0.01

Unlike traditional DID estimators, this new semi-parametric DID estimators specify a group status using first-treated time. That is to say, when a country gets treated is more important than whether it is now in the treatment group or not. The first column of Table 3.4 reports the estimates of ATT for each group in all periods. The second column reports the estimates of ATT for all groups across all periods. First two models are estimated using improved doubly robust DID estimator and the last two columns reproduce the former results using an alternative doubly robust DID estimator based on stabilized inverse probability weighting and ordinary least squares. The latter one is served as a comparison. Both methods give similar coefficients. Among all group, only group 2005, i.e., Guatemala, who adopted IT in 2005, has a significant negative coefficient of inflation targeting, while

all the other countries do not. The simple average ATTs for all groups across all periods are insignificant as well. In comparison with the TWFE method, the average ATT here is significantly lower than traditional TWFE estimator. Coefficient in column 2 is -1.588, in column 4 is -1.87, which are both more than half smaller than -3.749 in the TWFE case. This proves that traditional TWFE estimator can be biased. More surprisingly, 3 of 7 coefficients are, in fact, positive numbers, implying an opposite effect on lowering inflation. This once again proves the ineffectiveness of IT in terms of lowering inflation. Since this new semi-parametric DID estimator is a consistent and unbiased estimator under parallel assumptions, this result is more convincing than the traditional TWFE estimator. However, it is also possible that parallel assumption is not satisfied and we have heterogeneity in treatment effect. To further address this problem, I consider the propensity score matching method to estimate treatment effects.

3.4.2 Propensity Score Matching

A propensity score matching method is applied to address the self-selection issue and also serves as a robust test to the previous findings. Firstly, I estimate the propensity scores using a probit model. The dependent variable is the IT dummy. According to Truman (2003) and Minella et al, (2003), inflation targeting should be adopted only after some preconditions are met. For example, a country should maintain its' inflation at a reasonably low level before accepting IT, otherwise it may harm the economy growth. Taking this into consideration, the control variables include lagged inflation rate (LINF), broad money growth rate (BMG), GDP per capita growth rate (GDPPG). Trade to GDP ratio (Trade) is also included as a measure of openness to trade, since a trade relying country is more likely

to have an exchange rate anchor as its monetary framework. The regression results are shown in Table 3.5. Note that, in order to make observations more comparable, treatment observations whose propensity score is higher than the maximum or less than the minimum propensity score of the controls are dropped. In addition to the standard nearest neighbor estimation, other alternative matching techniques are also checked to see if the results are sensitive to different specifications. These specifications include three-nearest neighbor matching, radius matching, kernel matching and local linear regression matching.

Table 3.5 Propensity Score Matching

	(1)	(2)	(3)	(4)	(5)
	Nearest	three-nearest	radius	kernel	llr
	neighbor	neighbor			
ATT	-1.990	-1.628	-2.010	-1.946	-1.880
	(-1.75)	(-1.89)	(-2.23)	(-6.71)	(-1.65)
_cons	13.03***	13.03***	13.03***	13.03***	13.03***
	(23.96)	(23.96)	(23.96)	(23.96)	(23.96)
N	739	739	739	739	739

t statistics in parentheses
 * p<0.05, ** p<0.01, *** p<0.001

As we can see in Table 3.5, all the matching methods yield similar results --all negative but insignificant treatment effect. Once again reinforce the previous findings that there is no evidence indicating that IT helps to lower the inflation rate.

3.5 Conclusion

In this paper, I pick emerging countries from a single location –Latin America— to study the treatment effect of inflation targeting on both inflation and output growth. I find no evidence that inflation targeting helps to lower the inflation or stabilize the GDP growth rate. I compare the regression results of TWFEDID models using newly developed estimators with the results of the propensity score matching model. Quite surprisingly, almost all the coefficients of IT in all kinds of regressions are insignificant. That is to say, IT doesn't work better than other monetary frameworks in the Latin American area. The result is also robust to different scenarios and models.

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