Determinants of Housing Prices: Evidence from thirty-five cities in China

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ABSTRACT

By comparing housing prices for major cities since 1998 housing reform in China, the study finds enormous housing prices appreciation. The research aims to investigate the major determinants affecting housing prices in the 35 large cities in China from 2003 to 2018. Based on panel data set of 560 observations on four variables, the research compared three regression models, including regular ordinary least square, fixed-effects with least squares dummy variable, and random-effects. The main determinants are land price from the supply sector, and GDP per capita, disposable income per capita, population density from the demand sector. The regional difference is studied by adding regional dummy variables, including the eastern, western, northeast, and middle area in the model. The results have further policy recommendations regarding homeownership, fiscal revenue, and income support.

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CHAPTER 1. INTRODUCTION

HOUSING MARKET GROWTH

Since 1998, with the end of the welfare allocating house policy and the implementation of the "housing system reform" policy, China entered a period of rapid growth in housing prices, which have maintained an annual growth of 7% (Shih et al., 2014; Lin, Tsai, 2016). From the year 2003 to 2015, housing prices in Chinese cities increased almost five-fold (Wu et al., 2015). Pessimistic view argues that house price has been overvalued and will face downward corrections soon, like the bursting of housing bubbles in some developed countries (Barth et al., 2012). Given macro-economic control on housing prices, the housing market is still rising and appears elusive.

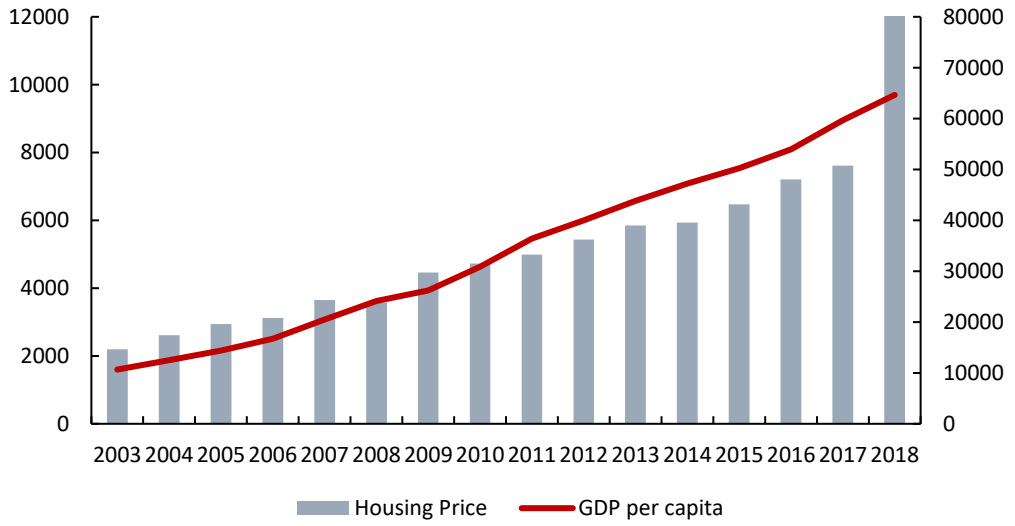

Figure 1. Housing prices and GDP change over years

The table of compound annual growth rate (CAGR) of housing prices and GDP shows how economic development and housing market change over the five periods.

Table 1. Housing prices and GDP CAGR

	2003-2006	2006-2009	2009-2012	2012-2015	2015-2018
Housing prices CAGR	12.39%	12.65%	6.79%	6.03%	24.62%
GDP CAGR	16.21%	16.14%	15.12%	7.90%	8.76%

After joined the WTO in December 2001, the Chinese economy reached a stage of rapid growth in 2003-2006. Housing prices is in a reasonable rising period after the housing commoditization reform, and the government has not issued a regulatory policy on the housing market. From 2006 to 2009, the government adopted the easy monetary and fiscal policy, which led to an average annual economic growth rate of more than 15%. At the same time, the role of housing as an investment product has gradually emerged. Policies have been made to restrict the second house ownership, tighten mortgages, and limit land acquisition. The growth rate of residential prices in the same period still lower than the GDP. From 2009 to 2012, due to the impact of the financial crisis, the economic and housing prices growth rate fell back. The central government adopted the 4 trillion investment plan to stabilize the economy, which also led to a rapid increase in land costs and housing prices. From 2012 to 2015, the Chinese economy ended "double-digit growth" and enter the period of shifting growth rates, structural adjustment, and digestion of stimulus policies. The housing prices growth rate has also decreased because of multiple restriction policies. From 2015 to 2018, housing prices rose faster than expected, with 24.2% CAGR. However, the land acquisition and development has decreased because of the restriction policy.

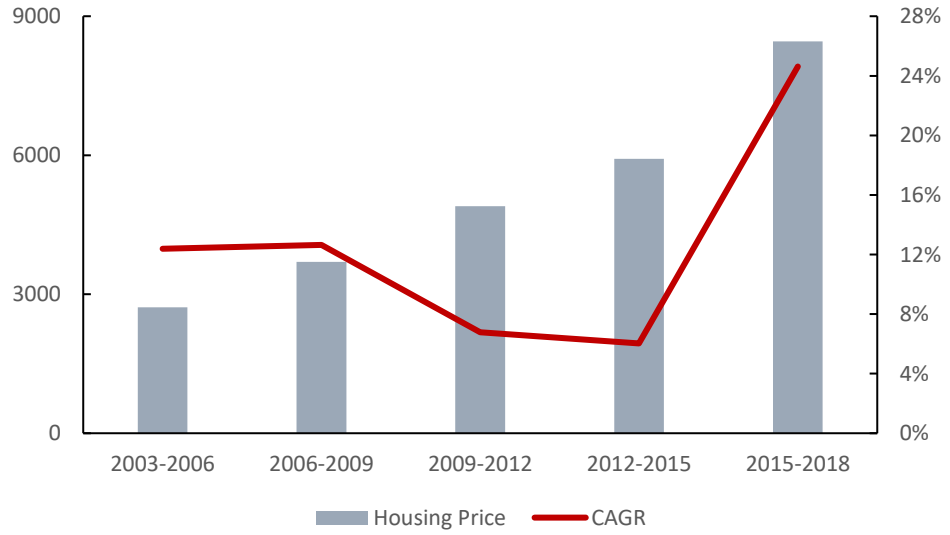

Figure 2. Housing prices change over time

REGIONAL DIFFERENCE

In addition to the changes in housing prices among time series, the country also faces a severe challenge in the emergence of regional imbalance in housing prices (Li, Gibson, 2013). Regional differences in housing prices in China also become a burning issue with the highest average price in Beijing, reaching a level of 67.7 times that of the lowest in Yinchuan in 2014. Changes among time and area attract attention from both policymakers and scholars.

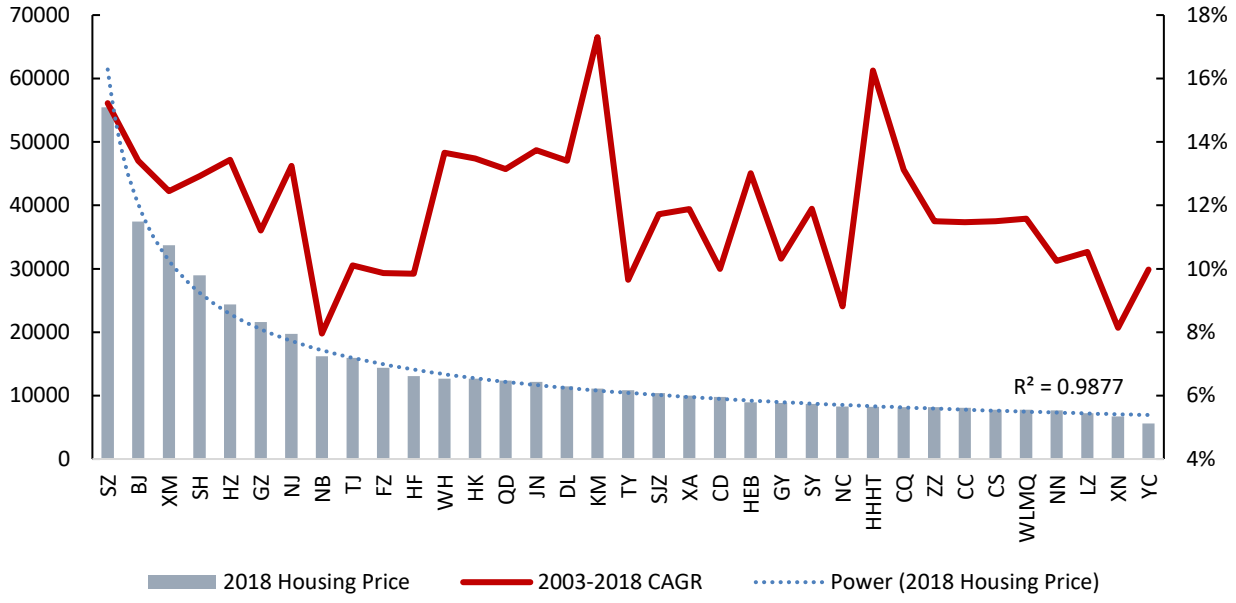

Figure 3. Housing prices growth in regions

In terms of the regional difference of housing prices, the research established a matrix from 35 large cities as representatives. Cities in the first quadrant have higher housing prices and growth rates; cities in the second quadrant have lower prices and faster growth; cities in the third quadrant have lower prices and growth rates; cities located in the fourth quadrant has high prices and slow growth. As shown in the figure with housing prices growth from 2003 to 2018, about half of the cities' housing prices have a CAGR below 12%. Hefei, Nanjing, Shijiazhuang are the top fastest-growing cities with lower housing prices. Xiamen, Beijing, Shenzhen are the fast-growing cities

with higher housing prices. Shanghai, Guangzhou are the cities with high housing price and growth rate. Cities under housing price control include Beijing, Shanghai, and Guangzhou.

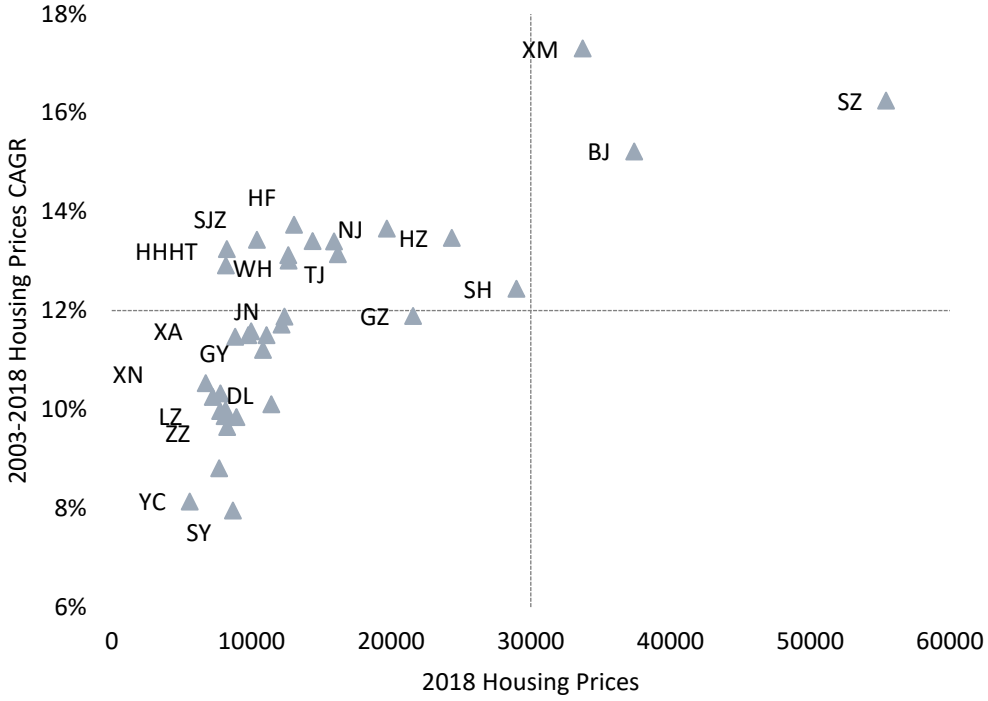

Figure 4. Housing prices difference in regions

CHAPTER 2. LITERATURE REVIEW

What is the crucial impact of housing price fluctuation? Extensive studies have been placed on the factors of housing prices in the field of urban economics. The existing literature addressing the determinants of housing prices fall into two main categories. The first category of research explained changes in housing prices basing on the national and regional macroeconomic factors (Glindro et al., 2008; Amiraslanova et al., 2018; Nistor and Reianu, 2017; Guo et al., 2017; Wang et al., 2011; Liu, 2012; Dong et al., 2010). The second category of research investigated regional housing prices determinants basing on spatial heterogeneity of real estate submarkets (Wang et al., 2017; Qiu and Ma, 2015; Ju et al., 2019; Diewert et al., 2015; McCord et al., 2012; Zhou et al., 2019).

Despite contributions to study the determinants in housing prices, limitations in previous research include the indicator selection and spatial patterns. Firstly, existing research on housing prices determinants lacks a systematic way of variable selection. Some of the researches focused on key indicators in macroeconomics, which have a potential impact on housing prices, for example, urban economic openness (Wang et al., 2011), economic development (Lu et al., 2004), interest rate (Mohammad, 2009). Other researchers studied the relationship between social factors and housing prices, for example, population size (Yu and Yang, 2005), net migration (Beiler, 2015), household income (Wu, 2019), and urban infrastructure (Zhang Lin, 2011). As a result, the systematic impact of housing prices fluctuation remains unanswered.

On the other hand, there is a lack of research on housing prices change over both time and space. Hedonic pricing model (Breedon and Joyce,1993), ordinary least squares regression model (Lei, 2016), vector autoregression (Luo et al., 2012), and Bayes model averaging (Lu and Zhang, 2016) concentrate on time series analysis on housing market change. Besides, the geographically

weighted regression model (McCord, 2012) focuses on the regional heterogeneity on housing prices.

This research categorized determinants based on supply and demand perspective since market mechanisms have priced residential houses since the reform of housing commoditization in 1998. Due to the imbalance in regional development in China, the real estate prices between cities and rural areas differ significantly. In order to analyze the change between time and space, the research adopted panel data, which has four dimensions of time, location, determinants, and value. Panel data is more informative than a simple time series of aggregates, as they allow tracking individual histories. The research adds four regional dummy variables in the fixed-effects model with least squares dummy variable including eastern, western, and middle area to analyze the regional difference in the housing market.

CHAPTER 3. METHODOLOGY

HYPOTHESIS

When we examine the changes in the house price indexes of the 35 large and medium cities in China (such as Beijing, Shanghai, Tianjin, Shenyang, Yinchuan, Shenzhen, and Urumqi), it shows a gradual and stable increase. Like other commodity prices, house price is also mainly determined by demand and supply factors. According to standard economic theory, when demand exceeds supply, price rises. Besides, Real estate industry is top-down and is greatly affected by government policies.

Supply-side is measured by land price in the research. The land acquisition price is one of the main components of real estate development costs. According to the cost-plus pricing method, price is based on the unit cost of the product plus a certain percentage of profit (Edward and Joseph, 2018). The formula is price = cost * (1 + Profit Rate of Cost), where the cost of land acquisition profoundly influences the housing prices. Increasing land costs will cause the supply curve to move upward, thereby increasing the housing prices. The cost of land acquisition in Beijing has increased from 1538 RMB/m^2 in 2003 to 108475 RMB/m^2 in 2018, an increase of about seven times. Therefore, the research hypothesis is that increase in the supply-side factor, land price, will cause an increase in housing price.

Demand-side is measured by GDP per capita, population density, and disposable income per capita in the research. The GDP per capita implies the level of economic development, also the level of purchasing power. Population density measures the absolute demand for housing since the increase in population density will lead to insufficient housing supply. Besides, The disposable income per capita respectively measures the effective demand for housing. For low-income homeless population, an increase in income level will make the willingness to live in a house to

become real demand. For the median- and high-income population, income level increase will lead to a demand for housing improvement. Therefore, the research hypothesis is that the increase in demand-side factors - GDP per capita, population density, and disposable income per capita, will cause an increase in housing prices.

DATA COLLECTION

The data used in this paper is collected from the National Bureau of Statistics of China Website, China Statistical Yearbook, and China Real Estate Yearbook. The research aims to identify the relationship between cost, market factors, demand sectors, and housing prices by using the annual data of 35 large cities from 2003 to 2018, which include 560 data sample in total.

Figure 5. Four region dummy variables

Dependent Variable

Average housing prices: Housing prices refers to the average sales price of market residential housing per square meter. The description of Average housing prices is Price, and the unit is RMB per square meter.

Table 2. Housing prices summary

	Mean	Std Dev	Max	Min	Coefficient of Variance	Max/Min
2003	2428.33	1019.02	5793.00	1277.00	0.42	4.54
2004	2705.20	1139.12	6385.00	1430.00	0.42	4.47
2005	3200.26	1435.17	6996.00	1541.00	0.45	4.54
2006	3690.87	1760.13	8848.00	1940.32	0.48	4.56
2007	4596.73	2605.05	13370.00	2230.00	0.57	6.00
2008	4878.18	2565.32	12823.00	2512.00	0.53	5.10
2009	5705.97	3055.17	14389.00	2811.00	0.54	5.12
2010	7059.77	4047.16	18953.00	3196.00	0.57	5.93
2011	7439.37	3903.46	21037.00	3439.00	0.52	6.12
2012	7718.51	3709.07	18996.00	4187.00	0.48	4.54
2013	8372.69	4424.66	23427.00	4380.00	0.53	5.35
2014	8598.60	4651.27	24040.00	4111.00	0.54	5.85
2015	9519.97	6151.71	33661.00	4498.00	0.65	7.48
2016	11027.13	8548.37	45498.00	4448.00	0.78	10.23
2017	12537.92	9240.32	48622.00	4892.00	0.74	9.94
2018	14411.09	10428.09	55441.00	5589.00	0.72	9.92

Independent Variables

Table 3. Data source

Type		Variable	Ticker	Unit	Resource
Dependent Variable		Average Housing prices	Price	RMB/m²	China Real Estate Yearbook
Independent Variable	Supply	Average Land Price	LandPrice	RMB/m²	China Real Estate Yearbook
	Demand	GDP per cap	GDPCapita	RMB	China Statistical Yearbook
		Population Density	PopDensity	num/km²	China Statistical Yearbook
		Disposable income per cap	Income	RMB	China Statistical Yearbook

Land price: The average land price is total land acquisition price divided by land purchase area. The description of land price is LandPrice, and the unit is RMB per square meter.

GDP per capita: GDP per capita measure of a level of economic development that accounts for its number of people. It divides the city's gross domestic product by its total population. The description of GDP per capita is GDPCapita, and the unit is RMB per cap.

Population density: Population density refers to the number of people per unit of area. The area with higher population density has higher absolute demand for housing and thus contributes to increasing the housing prices. The description of population density is PopDensity.

Disposable income per capita: Disposable income includes salaries, income via running a business, property income, and interest income. Usually, the disposal income measures the effective demand for housing, which will have an impact on housing prices. The description of disposable income per cap is Income, and its unit is RMB per cap.

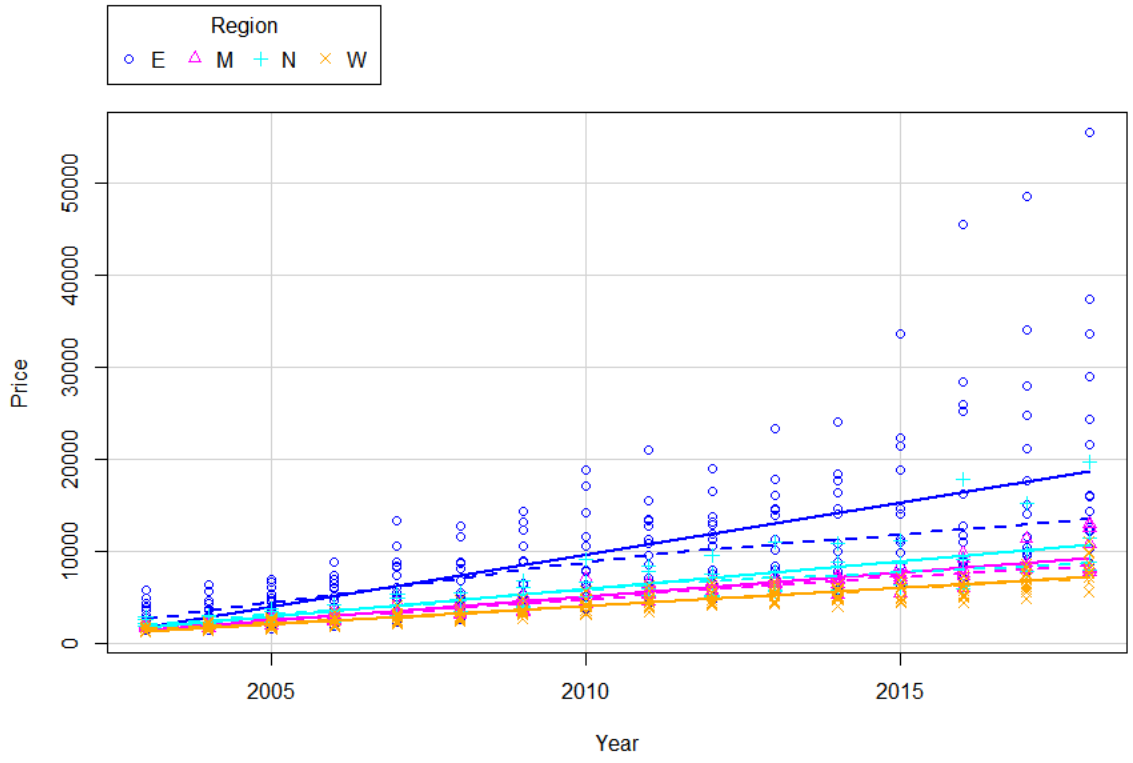

Figure 6. Housing prices in eastern, western, northeast, and middle regions

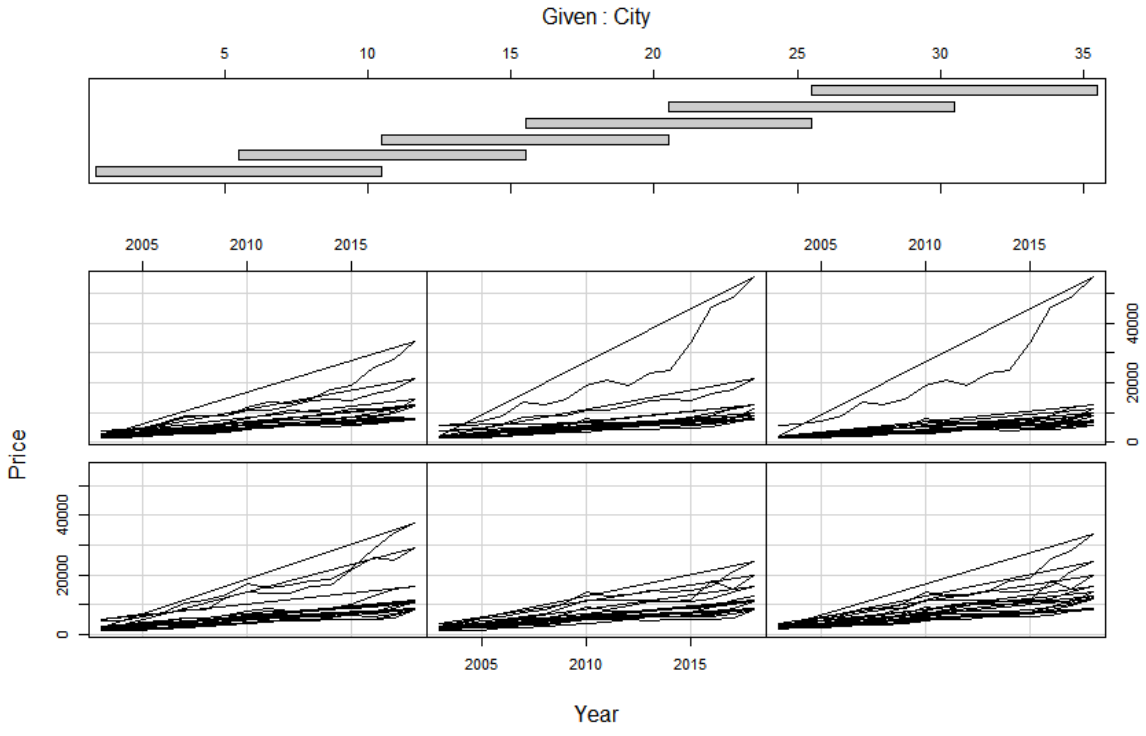

Figure 7. Data corresponding graph

PANEL DATA REGRESSION

The panel data has observations on n entities at two-dimensional, the variable has two subscripts. One dimension is the cities (n), and the other dimension is time (t). Since the number of cities is larger than the number of times, it is called a cross-section panel, which is common in microeconomics.

$$\begin{bmatrix} X_{11} & \cdots & X_{1T} \\ \vdots & \ddots & \vdots \\ X_{NT} & \cdots & X_{NT} \end{bmatrix}$$

The research dataset consists of 560 observations on six variables. Notice that the variable city is a factor variable with 35 levels (one for each of the 35 large cities in China). The variable year is also a factor variable that has 16 levels identifying the time. The observations are 16×35=560 in total. Since all variables are observed for all entities, and overall periods, the panel is balanced. If there were missing data for at least one entity in at least one time period, the panel is unbalanced.

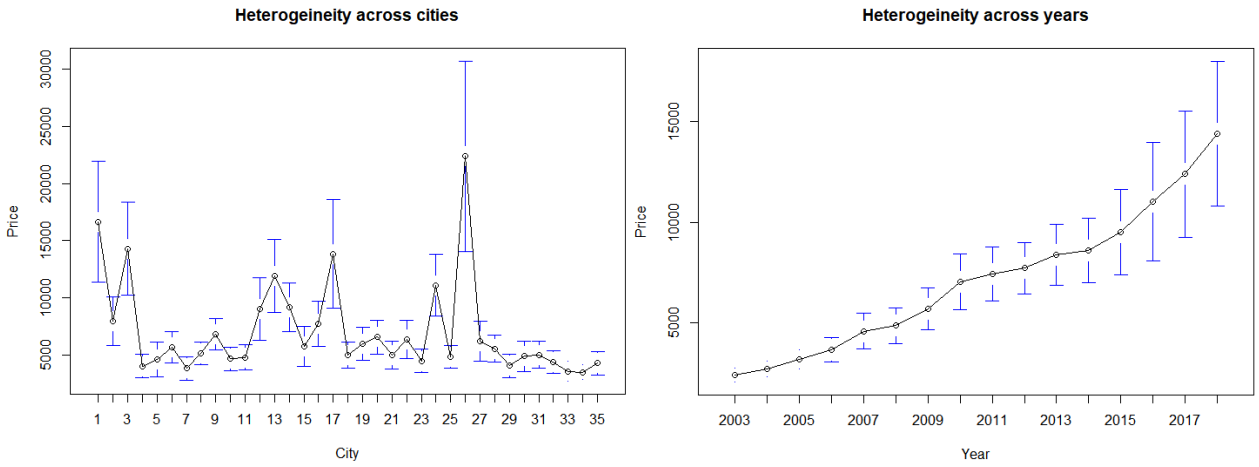

Figure 8. Heterogeneity across cities and years

In the housing prices model, other factors may have a random impact on the result. The error term thus represents other random factors that affect the dependent variable but are not included in our regression equation. With the application of the log transformation regression model, the data is closer to the linear, and the errors are normally distributed. The purpose of the log transformation is to obtain residuals that are approximately symmetrically distributed. With the reduction of the variability of data, the data is more conform to normality. And the regression coefficient has a clear economic meaning with the log transformation, which means the change of the housing prices for every 1% change of the independent variable.

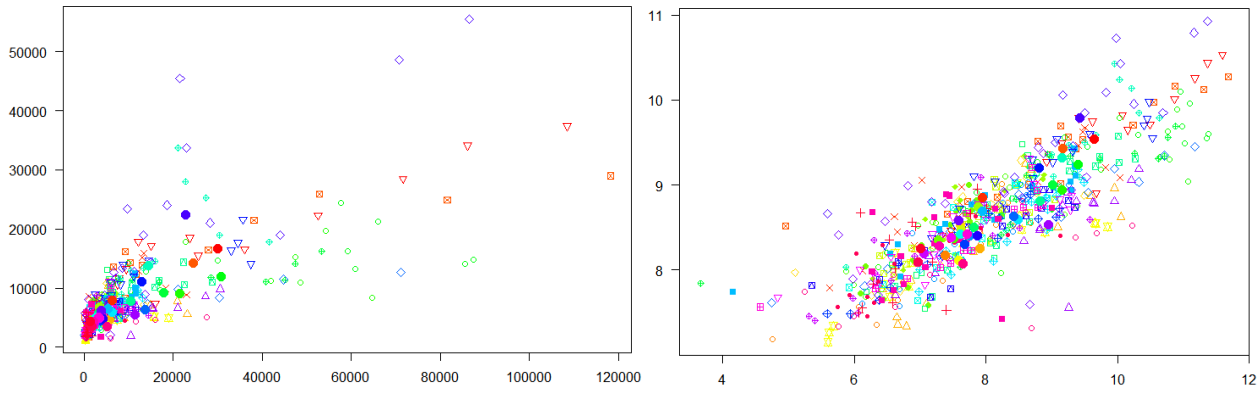

Figure 9. Data log transformation (Left: raw data; Right: logarithm data)

Table 4. Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Dev	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Price	560	1277.0	55441	7109	6110	3.284	0.103	16.133	0.206
LandSupply	560	0.1	118157	8419	15095	3.686	0.103	16.069	0.206
GDPCapita	560	8167.0	189568	59263	34216	0.815	0.103	0.355	0.206
PopDensity	560	124.0	6522	837	948	3.472	0.103	13.278	0.206
Income	560	7040.2	68034	25111	12798	0.691	0.103	-0.056	0.206
LPrice	560	3.106	4.744	3.746	0.291	0.358	0.103	0.094	0.206
LLandSupply	560	-0.925	5.072	3.473	0.710	-1.271	0.103	6.643	0.206
LGDPCapita	560	3.912	5.278	4.693	0.277	-0.416	0.103	-0.482	0.206
LPopDensity	560	2.093	3.814	2.774	0.336	0.454	0.103	0.737	0.206
LIncome	560	3.848	4.833	4.340	0.234	-0.195	0.103	-0.945	0.206

Simple Ordinary Least Squares Panel Regression Model (OLS)

The basic one-way panel regression is using plain OLS on the pooled data. The research generalized linear regression on all 560 observations of log-linear models. The research reached the regression model as equations.

Simple OLS regression model equation:

$$LPrice_{it} = \beta_0 + \beta_1 LLandPrice_{it} + \beta_2 LGDPCapita_{it} + \beta_3 LPopDensity_{it} + \beta_4 LIncome_{it} + v_{it}$$

β_0 is the estimate of intercept, which is the base predictor of y when all x variables are fixed at zero. The equation contains v_{it}, which denoted the individual-specific effects. The coefficient of independent variables indicates how much housing prices change over time, controlled by differences in cities. The results are shown in the table:

Table 5. Pooled OLS Regression Result

	Estimate	Std. Error	t-value	Pr(>|t|)	Signif. Codes
(Intercept)	-2.09504	0.22006	-9.5204	0.0000	***
LLandPrice	0.05154	0.00865	5.9556	0.0000	***
LGDPCapita	0.19090	0.04496	4.2457	0.0000	***
LPopDensity	0.19687	0.01389	14.1700	0.0000	***
LIncome	0.69932	0.05627	12.4284	0.0000	***
Total Sum of Square:		251.13	R-Squared:		0.88289
Residual Sum of Square:		29.409	Adj. R-Squared:		0.88205
P-value:		<2.22E-16	F-statistic:		1046.05

Note： Signif. Codes 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Fixed-effects Model with Least Square Dummy Variable (FEM LSDV)

In order to capture the difference in regions, The LSDV model has 4 different intercepts including eastern region, western region, northeast region, and middle east region factors. One intercept capture heterogeneity across entities and represents each region.

Fixed-effects LSDV model equation:

$$LPrice_{it} = \beta_1 LLandPrice_{it} + \beta_2 LGDPCapita_{it} + \beta_3 LPopDensity_{it} + \beta_4 LIncome_{it} + \beta_5 LFiscal_{it} + \gamma_1 D_{1i} + \gamma_2 D_{2i} + \gamma_3 D_{3i} + \gamma_4 D_{4i} + v_{it}$$

In the equation, D_{1i}, D_{2i}, D_{3i}, D_{4i} are dummy variables represent each region. γ_1, γ_2, γ_3, $\gamma_4$estimates the common difference to all years in the independent variables in each region.

Table 6. Fixed effects least square dummy variable model result

	Estimate	Std. Error	z-value	Pr(>|z|)	Signif. Codes
LLandPrice	0.040278	0.008454	4.764	0.0000	***
LGDPCapita	0.15998	0.045722	3.499	0.0000	***
LPopDensity	0.171859	0.01592	10.795	0.0000	***
LIncome	0.734861	0.056013	13.119	0.0000	***
Factor (Eastern Region)	-1.78702	0.224246	-7.969	0.0000	***
Factor (Middle Region)	-1.97384	0.223163	-8.845	0.0000	***
Factor (Northeast Region)	-1.82024	0.219788	-8.282	0.0000	***
Factor (Western Region)	-1.92537	0.216253	-8.903	0.0000	***
Residual Standard Error		0.22	R-Squared:		0.9994
P-value:		2.22E-16	Adj. R-Squared:		0.9994
F-statistic:		108200			

Note： Signif. Codes 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Random-effects Panel Regression Model (REM)

There are four methods of random-effects, Swamy-Arora, Amemiya, Wallace-Hussain, and Nerlove (Baltagi 2005). The research adopts the Swamy-Arora method for the best estimate result. Random-effects regression model equation:

$$LPrice_{it} = \beta_0 + \beta_1 LLandPrice_{it} + \beta_2 LGDPCapita_{it} + \beta_3 LPopDensity_{it} + \beta_4 LIncome_{it} + \mu_{it} + v_{it}$$

μ_{it} is the random effects intercepts that capture heterogeneities across cities and times. The equation also contains v_{it}, which denoted the individual-specific effects. The coefficient of independent variables indicates how much housing prices change over time with random fixed effects. The results are shown in the table:

Table 7. Random-effects Regression Result

	Estimate	Std. Error	z-value	Pr(>|z|)	Signif. Codes
(Intercept)	-2.35643	0.225535	-10.4482	0.0000	***
LLandPrice	0.026637	0.006717	3.9658	0.0000	***
LGDPCapita	0.20036	0.048981	4.0906	0.0000	***
LPopDensity	0.243277	0.033015	7.3686	0.0000	***
LIncome	0.705512	0.054263	13.0017	0.0000	***
Total Sum of Square:		150.91	R-Squared:		0.91529
Residual Sum of Square:		12.783	Adj. R-Squared:		0.91468
P-value:		<2.22E-16	F-statistic:		5996.89

Note： Signif. Codes 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Model Selection and Diagnosis

	OLS	FEM	REM
OLS			
FEM	**F-test** => FEM		
REM	**Lagrange Multiplier test** => REM	**Hausman test** => FEM	

Figure 10. Model Comparation

The research uses F-test to compare the fixed-effects and the pooled OLS. The null hypothesis is OLS better than the fixed-effects model. From the test result, the p-value is < 0.05. Then the null hypothesis is rejected, and the fixed effects model is a better choice.

Table 8. F test Result

Test Summary	F-value	df1	df2	P-value
FEM	22.425	34	521	0.0000

The research uses Lagrange Multiplier test (Breusch-Pagan) for balanced panels (Honda, 1985) to compare the random-effects regression and the pooled OLS regression model. The null hypothesis in the Lagrange Multiplier test is that variances across entities are zero, which means that no significant difference across units (i.e., no panel effect). Here we can reject the null and conclude that the random-effects model is better than the simple OLS regression model.

Table 9. Lagrange Multiplier Test Result

Test Summary	Chisq	df	P-value
Panel Effect	1258.5	1	0.0000

The research uses the Hausman test to compare the random-effects model and fixed-effects model (Hausman and Taylor 1981). It tests whether the unique errors are correlated with the

regressors. The null hypothesis is that the preferred model is random-effects; The alternate hypothesis is that the model is fixed-effects (Green, 2008). From the test result, the p-value is significant enough to use fixed effects.

Table 10. Hausman Test Result

Test Summary	Chisq	df	P-value
REM	305.48	4	0.0000

Then the research adopts the Augmented Dickey-Fuller Test to check for stochastic trends. The null hypothesis is that the series has a unit root (i.e., non-stationary). From the test result, p-value < 0.05, then there is no unit roots present, which means that the model is effective.

Table 11. Augmented Dickey-Fuller Test

Test Summary	Dickey-Fuller	P-value
Stationary	-8.5165	0.01

RESULT AND ANALYSIS

Based on the Lagrange Multiplier test, Hausman test, F-test, and ADF test, the fixed-effects regression model with least square dummy variable is selected for housing prices determinant analysis. The model generate result with 99.94% R-square, 0.22 Residual Standard Error, F-statistics is 108200 on 4 DF, p-value < 2.22e-16. The constant for eastern region is -1.787, for middle region is -1.974, for northeast region is -1.820, and for western region is -1.925. The partial slope of land price, disposable income, GDP per capita, and population density is statistically significant at more than 99% confidence level. There is a significant relationship between housing prices and the set of 4 predictors and four dummy variables.

The estimated regression equation is as below:

$$LPrice_{it} = 0.040LLandPrice_{it} + 0.160LGDPCapita_{it} + 0.172LPopDensity_{it} + 0.734LIncome_{it} - 1.787D_{east} - 1.974D_{middle} - 1.820D_{north} - 1.925D_{west}$$

First, in the supply-side, every 1% increase in land price will lead to a 0.040% rise in housing prices. The influence of land prices on housing prices generates a significant level of 99.99%. The null hypothesis is rejected, and the relationship between land price and housing prices is positive.

Second, in the demand-side, every 1% increase in GDP per capita will lead to 0.160% rise in housing prices; every 1% increase in population density will lead to a 0.172% rise in housing prices; every 1% increase in disposable income per capita will lead to a 0.734% rise in housing prices. The influence of population density, GDP and disposable income per capita on housing prices generate a higher significant level of more than 99.99%. An increase in demand-side factors - GDP per capita, population density, and disposable income per capita will cause an increase in housing prices.

VALIDITY THREATS

Several limitations are worth mentioning. First, the research chose variables based on supply and demand perspectives on the city scale. When it comes to the same level of dependent variables, one city may have other incentives, which will potentially cause a change in housing prices.

Second, real estate development cost contains land acquisition, construction cost, tax fee, and maintenance fee. The research analyzed the relationship with land acquisition fees and housing prices because of the land price available on the city scale. The research divided the land acquisition fee in total with land acquisition total area. Other development costs, for example, construction cost, varies with different development projects.

Third, it should be noted that China's demographic statistics are currently based on the location of household registration, which indicates a lack of statistics on the immigration population. Housing demand driven by immigrant labor cannot be identified through population density.

Furthermore, there are also differences in each city. Housing prices of downtown is significantly higher than that in suburban. On a smaller scale, public transportation accessibility and infrastructure will become other determinants. Therefore, future research is being recommended with the possibility of inclusion of these variables and with a smaller scale, if possible, to obtain better research outcomes.

CHAPTER 4. CONCLUSION

RESEARCH CONCLUSION

As can be seen from the above analysis on regression results, a 1% increase in land price leads to housing prices rose by 0.040%. Although the impact of supply-side cost factor on housing prices can pass the significance test at a statistical level, the impact is small from the standardized coefficient. The result indicates that the real estate industry in 35 large cities is not only based on cost pricing, which means that changes in housing prices are not primarily due to the changes in the cost sector. The reason can be as follows. First, China's real estate industry can still generate high-profit margins in new development, compared to the real estate industry in developed countries, where the real estate industry is more market-oriented. Second, central and local government intervention cause distortions in the real estate industry.

From the perspective of demand-side, the impact of disposable income per capita on housing prices is the most significant on both statistical and economic levels, which aligned with empirical studies. The income level directly influences the actual housing demand, and the income growth will significantly bring up the housing prices in China. In terms of regions, the research divided 35 cities into the eastern region, the middle region, western region, and northeast region. Cities in the eastern region have the highest average disposable income per capita, which is 24417 RMB per person, compared to 20844 RMB in the western region. Moreover, the eastern region has the lowest standardized coefficient of income on housing prices in the eastern region, compared to the highest in the western region.

Another significant determinant on the statistical and economic level is population density, which indicates the absolute demand for housing. Cities in the eastern region have the highest population density among the four regions, which is 1303 people per square kilometer. The

standardized coefficient of the eastern region on population influence on housing prices is also the highest. The result implied that population density plays a more critical role in housing prices in eastern China. The standardized coefficient of the middle region on population influence on housing prices is the lowest, which implied that the increase in population density is not likely to cause a significant increase in housing prices.

Third, GDP per capita impact on housing demand is not as significant as the other two indicators. Real estate and infrastructure are the primary means of macro-economic control by the local and central government. The linkage between real economic growth and housing prices are weakening due to government intervention and macro-economic control.

POLICY RECOMMENDATION

The result can have further implications on policy suggestions. Firstly, the government should focus on land system reform to provide more affordable housing programs rather than merely income support. Affordable housing programs can fulfill the housing demand for the low-income population, at the same time, maintain the same level of housing prices. Currently, there are three primary types of affordable housing programs in China, which are Cheap Rental Housing (CRH), Economic and Comfortable Housing (ECH), and Public Rental Housing (PRH). The CRH focus on rent subsidies to facilitate marketization, while the ECH mainly targeted middle and low-income households. Rent subsidies differ in each affordable housing program, and the government restricts the way of spending subsidies. Due to land restriction, the local government has limited the amount of urban land for housing and commercial development, which increased the housing price. Although the government decided to increase land supply in 2011, especially for low-income housing, there was only 13% of planned land supply is for CRH, ECH, and PRH. The government should pay more attention to the land acquisition and application process monitoring to ensure the affordable housing is provided to those who need houses.

Secondly, policymakers should weaken the connection between the local government and the housing market. Chinese local governments are highly engaged in the housing market through land supply and fiscal revenue. Compared to the US, where the local zoning restrictions determine the land supply for housing, local governments determine the land supply in China. As land is legally owned by the State and controlled by the local government, the revenue from land sales has become an essential source of local government's fiscal revenue (Guofeng and Wei, 2018). Besides, governments provide subsidies through the urban investment platform to finance land development, infrastructure, and other activities undertaken by the local government. As a result, local

governments' fiscal revenue is a proxy for infrastructure investment and land supply to the local real estate market. China undertook fiscal decentralization reforms in 1979 and 1994, which enhance the relationship between local government and land sales. The tax-sharing reform managed to extract a large portion of fiscal revenue from the local governments so that the governments shifted from industrial growth to real estate development and construction (Zhang et al., 2015). The Budget Law in 1995 prohibited local government from running budgetary deficits or obtaining external financing, which incentivized the government to rely on non-budgetary funding sources such as land sale (Guofeng and Wei, 2018). Weaken the relationship between local government and the housing market can not only ease the market overheats but also contribute to central government policy implementation.

Thirdly, central government macroeconomic control should focus on structural adjustment rather than total adjustment. The structural shift includes the restriction on second homeownership. The homeownership rate in China is 89.68% in 2018, compared to a 64.3% national homeownership rate according to the data from the US Census Bureau. Both culture and contextual factors determine high homeownership in China. The growth of owner-occupied society gradually developed since the housing reform. Besides, cultural tradition also contributes to the high homeownership of Chinese households. One long-standing tradition is that adults own property to accumulate wealth for the next generation (Mak et al., 2007), and ownership of a house could be an essential component of a catalyst for marriage. As a result, Chinese people prefer to collect properties once they have the money. House is not only used for a living but also used for investment. Housing will become less affordable as a result of the housing prices increase. In September 2007, the central bank introduced a 40% down-payment for the second-house mortgage, with the effect of suppressed demand for the second house. The central government then decreased the lower bound of the mortgage rate because of the weak performance of the housing market in

2008. In 2010, the down-payment for a second house was set at 50% in order to cool down the real estate market (Huang et al., 2018). Those fundamental policy changes regarding the second house ownership are the performance of structural adjustment. The increase in income and economic development lead to an increase in housing prices and speculative demand. This requires the government to curb speculative demand to a certain extent through structural adjustment.

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