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A Tale of Two Policies: Examining Treatment Effects on Housing Prices in Shenzhen, China*

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The city of Shenzhen has seen a surge in housing prices. In response, the Shenzhen government implemented policies to make housing more affordable. Two notable policies were implemented between 2016-2018. The first policy increases the supply of land for housing and raises down payment rates. The second policy restricts the sale of houses for a certain period of time. We use the Hsiao et al. (2012) method and factor model method to assess the effectiveness of these policies. Our empirical results suggest that the first policy had significant effects on housing prices while the second policy had no significant effect.

Key Words: Housing prices; Program evaluation; Panel data.
JEL Classification Numbers: C23, R31, R38.

1. INTRODUCTION

Over the past 20 years, the Chinese housing market has experienced significant growth, with prices rising rapidly in major cities. The government's policies to promote urbanization and stimulate economic growth have contributed to this expansion. However, the market has also been subject to speculation, leading to concerns about a potential housing bubble. The government has implemented various measures to regulate the market, including restricting home purchases and increasing down payment requirements. Despite these efforts, the housing market remains a crucial factor in the Chinese economy and a subject of ongoing debate and scrutiny.

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There is a large literature studying the Chinese housing market. For example, Fan et al. (2019) use wavelet analysis to examine housing price changes in five major Chinese cities, finding that the average cycle for all cities is 3.25 years and that there are changing lead-lag relationships between the cities over time. Duan et al. (2021) investigate the macroeconomic and hedonic determinants of housing prices in Beijing using the vector autoregression and geographically weighted regression models. They find that both monetary policies and mortgage rates can regulate the dynamics of housing prices.

As one of the largest cities in China, Shenzhen has experienced an unprecedented housing price boom, driven by rapid urbanization, population growth, and speculation. The impact of high housing prices in Shenzhen extends beyond just the financial realm. The high cost of living in the city has also had social and psychological consequences for its residents, as they struggle to afford basic necessities and experience increased stress and anxiety. In response to this trend, the Shenzhen government has implemented a series of policies aimed at making housing more affordable for its citizens. Two major policies implemented during the period of 2016-2018 are particularly noteworthy. The first policy was implemented in March 2016. We label it as the "2016-policy". The government increased the supply of land for housing to improve the supply of housing while simultaneously raising the down payment rate for individuals purchasing houses to limit the demand for housing. The second policy was implemented in July 2018. We label it as the "2018-policy". It places restrictions on the transaction of houses. Specifically, new purchases of new houses and second-hand houses by individuals are restricted from sale for three years.

To assess the effectiveness of these two policies, we employ two approaches to estimate the counterfactual: the Hsiao, Ching and Wan (HCW) method (Hsiao et al., 2012) and factor model (FM) method (Bai, 2004). The HCW method has been widely used in estimating treatment effects. For example, Bai et al. (2014) use the HCW method to study how the implementation of property taxes in Shanghai and Chongqing affects housing prices in these two cities. Du and Zhang (2015) examine the impact of home-purchase restrictions and trial property taxes on housing prices in China. The results indicate that the purchase restrictions led to a 7.69% decrease in the annual growth rate of housing prices in Beijing, while the trial property tax in Chongqing reduced the annual growth rate by 2.52%. However, the trial property tax in Shanghai did not have a significant effect on housing prices. Ouyang and Peng (2015) analyze the macroeconomic impact of the 2008 Chinese Economic Stimulus Program. Their findings suggest that the fiscal stimulus plan temporarily increased real GDP growth by approximately 3.2%. Ke et al. (2017) employ the HCW method to investigate the impact of High-Speed-Rail projects on the economic growth of specific cities in China between 1990 and 2013.

The Factor Model method is also popular in treatment effect analysis. Under a factor model framework, Gobillon and Magnac (2016) provide a practical example of evaluating the impact of an enterprise zone policy on local unemployment in France in the 1990s. Chan et al. (2016) find that the factor-model-based estimator delivers strong economics interpretation in both microeconomic and macroeconomic empirical studies. Xu (2017) uses a factor model approach to estimate the effect of Election Day Registration on voter turnout in the United States. Li and Sonnier (2023) adopt the factor model method to study the effect of legalizing marijuana on the beer market and the effect of a digital online firm opening a physical showroom on sales.

Our empirical results based on the Chinese housing price data from 2009 to 2019 suggest that the 2016-policy had significant effects on reducing housing prices, while the 2018-policy had no significant effects. Increasing land supply and raising down payment requirements in the 2016-policy are effective measures to control rising housing prices. The 2018-policy only imposes a delay restriction on selling newly purchased houses, which may not be as effective in reducing housing prices. The potential reason is that people are willing to wait until the restriction is lifted to sell their properties, and thus have no incentive to reduce prices. Therefore, the 2018-policy is not an effective measure to slow down the increase in housing prices in Shenzhen.

The rest of the paper is structured as follows: Section 2 presents the data, Section 3 discusses the econometric approaches, Section 4 reports the empirical results, and finally, Section 5 concludes the paper.

2. DATA DESCRIPTION

We obtain monthly housing price indices data for 68 of China's major cities from March 2009 to November 2019 from the Chinese National Bureau of Statistics. Each city's housing price index is standardized to 100 for the year 2015. Shenzhen is the treatment unit. We did not include Beijing, Shanghai, and Guangzhou in the control group since they have undergone distinct policy changes during the sample period. As a result, the control group consists of 64 cities. Table 1 presents all cities in the dataset.

Denote the total time periods in the dataset as T. The 2016-policy was introduced in March 2016, denoted as T_1. The 2018-policy went into effect in July 2018, denoted as T_2. When we study the treatment effects of the 2016-policy, we set the pre-treatment periods as $t = 1, 2, \cdots, T_1 - 1$ and the post-treatment periods as $t = T_1, T_1 + 1, \cdots, T_2 - 1$. When we study the treatment effects of the 2018-policy, we set the pre-treatment

TABLE 1.

City List

Beijing (excluded)	Xiamen	Mudanjiang	Changde
Shanghai (excluded)	Nanchang	Wuxi	Shaoguan
Guangzhou (excluded)	Jinan	Xuzhou	Zhanjiang
Shenzhen (treatment unit)	Qingdao	Yangzhou	Huizhou
Tianjin	Zhengzhou	Wenzhou	Nanning
Shijiazhuang	Wuhan	Jinhua	Guilin
Taiyuan	Changsha	Bengbu	Beihai
Hohhot	Chongqing	Quanzhou	Haikou
Shenyang	Chengdu	Jiujiang	Sanya
Dalian	Xi'an	Ganzhou	Luzhou
Changchun	Lanzhou	Yantai	Nanchong
Harbin	Tangshan	Jining	Guiyang
Nanjing	Qinhuangdao	Luoyang	Zunyi
Hangzhou	Baotou	Pingdingshan	Kunming
Ningbo	Dandong	Yichang	Xining
Hefei	Jinzhou	Xiangyang	Yinchuan
Fuzhou	Jilin	Yueyang	Urumqi

periods as $t = T_1, T_1 + 1, \cdots, T_2 - 1$ and the post-treatment periods as $t = T_2, T_2 + 1, \cdots, T$. Figure 1 shows the housing price indices of all 68 cities from March 2009 to November 2019 and marks the two treatment time periods.

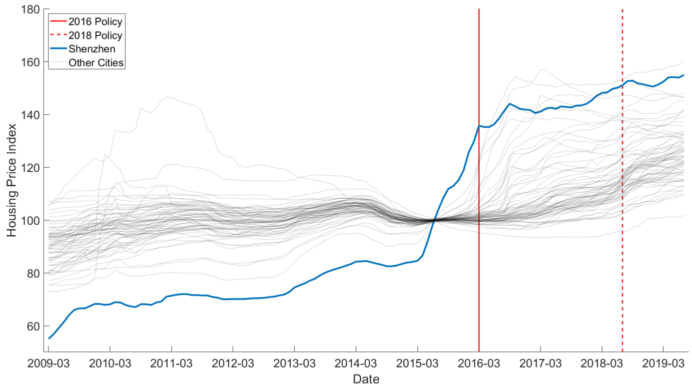
3. ECONOMETRIC MODELS

In this section, we discuss the HCW and FM methods to estimate the average treatment effects on the treated (ATT). Then we report empirical estimation results using these two methods in Section 4. As in Hsiao et al. (2012), we focus on the case that there is one treatment unit and there are N potential control units.

3.1. The HCW method

Let y_{0t} denote the outcome of the treatment unit at time t. In our application, y_{0t} is Shenzhen's housing price index at time t. We use y_{0t}^1 and y_{0t}^0 denote the treatment unit's outcome with treatment and without treatment, respectively. We do not observe both y_{0t}^1 and y_{0t}^0, instead, we observe $y_{0t} = y_{0t}^1 d_t + y_{0t}^0 (1 - d_t)$, where $d_t = 1$ if unit 0 is under treatment at time t, $d_t = 0$ otherwise. The treatment effects at time t is defined by

FIG. 1. Housing Price Indices of 68 Cities



$\Delta_{0t} = y_{0t}^1 - y_{0t}^0$ and the ATT is defined by

$$ATT = \frac{1}{T_2 - T_1} \sum_{t=T_1}^{T_2-1} \Delta_{0t}, \tag{1}$$

which is the average of treatment effects over the posttreatment periods $t \in \{T_1, T_1 + 1, \ldots, T_2 - 1\}$.

For $j = 1, \ldots, N$, let y_{jt} denote the outcome for the j-th control unit at time t. To estimate the 2016-policy effects on Shenzhen's housing price, following HCW, we choose a subset of control cities from the pool of 64 cities using the Forward HCW method as suggested by Shi and Huang (2021). Let N_1 denote the number of control cities selected by the Forward HCW method. We then estimate counterfactual outcome based on the following linear regression model (using pre-treatment data $t < T_1$)

$$y_{0t}^0 = x_t'\beta + u_t, \qquad t = 1, \ldots, T_1 - 1, \tag{2}$$

where $x_t = (1, y_{1t}, \ldots, y_{N_1 t})'$ is an $(N_1 + 1) \times 1$ vector consists of a constant one and N_1 control units' outcomes. Let $\hat{\beta}$ denote the least squares estimator of β based on (2). We estimate the counterfactual outcome y_{0t}^0 by $\hat{y}_{0t}^0 = x_t'\hat{\beta}$ and the treatment effects at time $t \geq T_1$ is estimated by

$$\hat{\Delta}_{0t} = y_{0t} - \hat{y}_{0t}^0 \qquad t = T_1, T_1 + 1, \ldots, T_2 - 1. \tag{3}$$

We can estimate the ATT by

$$\widehat{ATT} = \frac{1}{T_2 - T_1} \sum_{t=T_1}^{T_2-1} \hat{\Delta}_{0t}. \quad (4)$$

We can estimate the 2018-policy effects similarly by noting that the pre-treatment periods are $\{T_1, \ldots, T_2 - 1\}$ and the post-treatment periods are $\{T_2, T_2 + 1, \ldots, T\}$.

For selecting control units using the Forward HCW method, we use the forecasting mean squared error (MSE) as the criterion function. To obtain the forecasting MSE, we first estimate the model with the first k time periods in the pre-treatment data and then forecast the next h time periods (within the pre-treatment data). Denote the resulting forecasting MSE as $MSE(k, h)$. The 2016-policy has 84 pre-treatment time periods (from March 2009 to February 2016). We use the average of three forecasting MSEs

$$\frac{1}{3}[MSE(48, 12) + MSE(60, 12) + MSE(72, 12)]$$

as the criterion function, which evaluates the overall one-year-ahead forecasting performance at different time periods. The 2018-policy has 27 pre-treatment time periods (from March 2016 to June 2018). We use $MSE(15, 12)$ as the criterion function. The number of control units associated with the smallest criterion function value will be selected.

3.2. The Factor Model method

The factor model method replaces the N control units with r common factors. Let $\mathbf{X} = \mathbf{X}_{T\times N}$ denote the control data matrix. First, we assume that the number of factor, r, is known. We will discuss how to estimate r when it is unknown at the end of this subsection. We estimate factor matrix $(F)_{T\times r}$ by the first r eigenvectors of $(\mathbf{XX}')_{T\times T}$ which correspond to the r largest eigenvalues of $\mathbf{XX}'$. Let $f_t' = (f_{1t}, \ldots, f_{rt})$ denote the t-th row of $F_{T\times r}$. We replace $X_t = (1, Y_{1t}, \ldots, y_{N_1 t})'$ by $f_t = (f_{1t}, \ldots, f_{rt})'$ and estimate the counterfactual outcome based on the following model

$$y_{0t}^0 = f_t'\lambda + v_t, \qquad t = 1, \ldots, T_1 - 1, \quad (5)$$

where $f_t = (f_{1t}, \ldots, f_{rt})'$ and λ is an $r \times 1$ vector of unknown coefficients. Let $\hat{\lambda}$ denote the least squares estimator of λ based on (5). We estimate the counterfactual outcome y_{0t}^0 by $\hat{y}_{0t,FM}^0 = f_t'\hat{\lambda}$ and the treatment effects at time $t \geq T_1$ is estimated by

$$\hat{\Delta}_{0t,FM} = y_{0t} - \hat{y}_{0t,FM}^0 \qquad t = T_1, T_1 + 1, \ldots, T_2 - 1. \quad (6)$$

We can estimate the average treatment effects on the treated (ATT) by

$$\widehat{ATT}_{FM} = \frac{1}{T_2 - T_1} \sum_{t=T_1}^{T_2-1} \hat{\Delta}_{0t,FM}. \tag{7}$$

Similarly, we can estimate the 2018-policy treatment effects using the factor model approach. Again, by noting that the pre-treatment periods are $\{T_1, \ldots, T_2 - 1\}$ and the post-treatment periods are $\{T_2, T_2 + 1, \ldots, T\}$.

The ATT inference theory using a factor model method is developed in Bai and Ng (2021) for stationary data, and by Li and Sonnier (2023) for more general data type including nonstationary data.

When the number of factors is unknown, we select r by minimizing the modified Bai and Ng (2002) criterion as suggested by Li and Sonnier (2023). This criterion puts more weight on the penalty term proposed by Bai and Ng (2002) and it improves finite sample performance of Bai and Ng's original criterion.

4. EMPIRICAL RESULTS

4.1. The 2016-Policy

The HCW method with forward step-wise selection chooses 19 control units: Shijiazhuang, Harbin, Nanjing, Hefei, Jinan, Zhengzhou, Chongqing, Xi'an, Dandong, Jinzhou, Xuzhou, Jiujiang, Pingdingshan, Huizhou, Nanning, Beihai, Haikou, Yinchuan, and Urumqi. The FM method selects 22 factors. Figures 2 and 3 plot the counterfactuals estimated by the HCW method and the FM method, respectively.

FIG. 2. Counterfactual Estimated by the HCW Method for the 2016-Policy

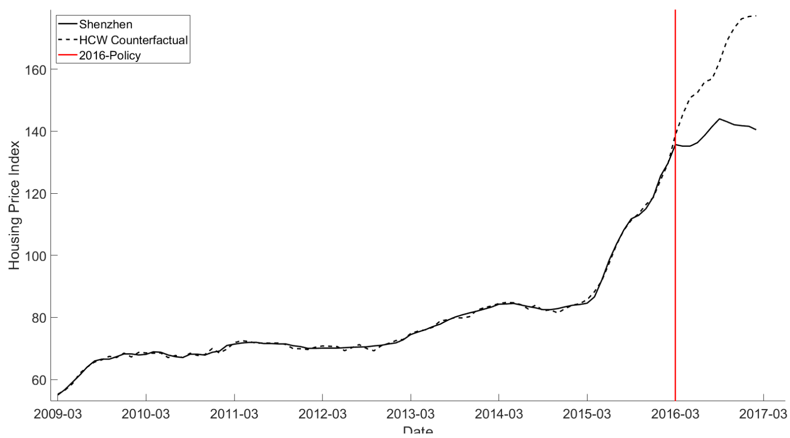
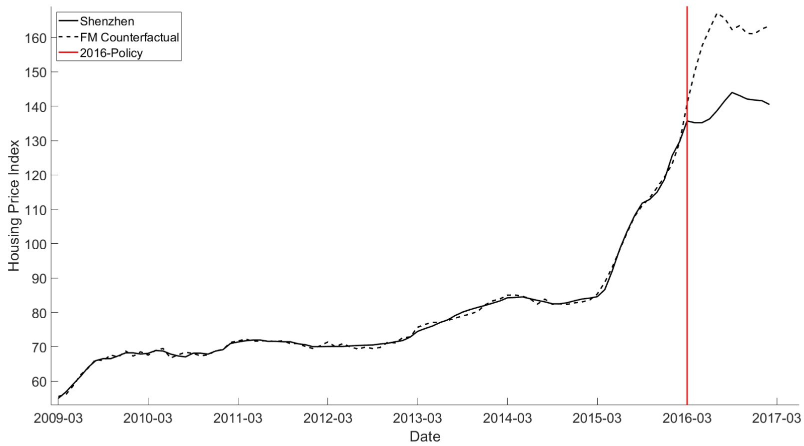


TABLE 2.

The Comparison Between Actual and HCW Predicted Values for the 2016-Policy

Date	Actual	HCW Predicted	Difference	Prediction S.E.	Difference in %
2016-03	135.7	138.8	−3.1	1.6	−2.2
2016-04	135.2	145.3	−10.1	2.3	−7.0
2016-05	135.2	150.8	−15.6	2.8	−10.3
2016-06	136.3	152.4	−16.1	3.2	−10.6
2016-07	138.7	155.9	−17.2	3.8	−11.0
2016-08	141.5	156.8	−15.3	4.5	−9.8
2016-09	144	162.3	−18.3	5.9	−11.3
2016-10	143.1	169.1	−26.0	6.7	−15.4
2016-11	142.1	173.3	−31.2	6.9	−18.0
2016-12	141.8	176.2	−34.4	7.0	−19.5
2017-01	141.6	177.0	−35.4	6.8	−20.0
2017-02	140.5	177.2	−36.7	6.9	−20.7
Average			−21.6		−13.0

FIG. 3. Counterfactual Estimated by the FM Method for the 2016-Policy



Tables 2 and 3 report the estimated treatment effects and the corresponding standard errors by the HCW and FM methods, respectively. Both methods suggest that there are significant treatment effects of the 2016-policy on Shenzhen housing prices. The percentage difference between the actual and HCW-predicted outcomes decreases over the first year after the treatment from -2.2% to -20.7%. The average percentage treatment effect is $ATT_{HCW} = -13.0\%$. For the FM method, the percentage difference decreases from -3.6% to -17.0%, with an average of $ATT_{FM} = -12.5\%$.

TABLE 3.

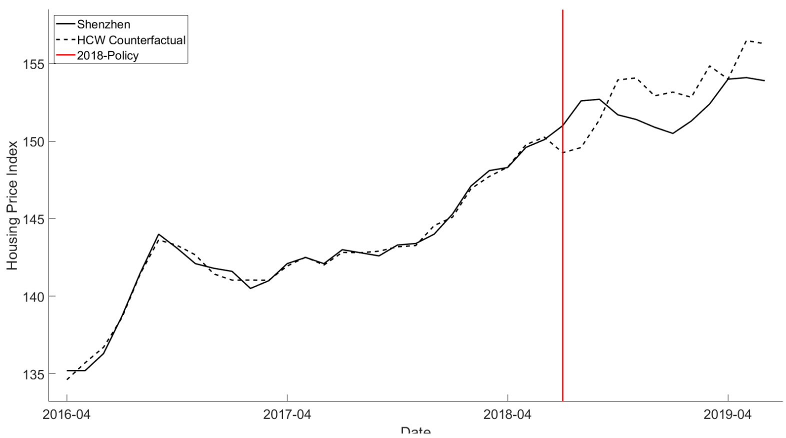
The Comparison Between Actual and FM Predicted Values for the 2016-Policy

Date	Actual	FM Predicted	Difference	Prediction S.E.	Difference in %
2016-03	135.7	140.7	-5.0	2.0	−3.6
2016-04	135.2	149.9	−14.7	2.9	−9.8
2016-05	135.2	157.6	−22.4	3.7	−14.2
2016-06	136.3	162.5	−26.2	4.4	−16.1
2016-07	138.7	167.1	−28.4	5.2	−17.0
2016-08	141.5	165.7	−24.2	7.1	−14.6
2016-09	144	162.3	−18.3	10.8	−11.3
2016-10	143.1	163.4	−20.3	12.1	−12.4
2016-11	142.1	161.2	−19.1	12.4	−11.8
2016-12	141.8	161.1	−19.3	12.7	−12.0
2017-01	141.6	162.5	−20.9	12.6	−12.9
2017-02	140.5	163.4	−22.9	13.1	−14.0
Average			−20.1		−12.5

4.2. The 2018-Policy

The HCW method with forward step-wise selection chooses 7 control units: Tianjin, Taiyuan, Hangzhou, Lanzhou, Baotou, Ganzhou, and Luoyang. The FM method selects 7 factors. Figures 4 and 5 report the counterfactuals estimated by the HCW and FM methods, respectively.

FIG. 4. Counterfactual Estimated by the HCW Method for the 2018-Policy



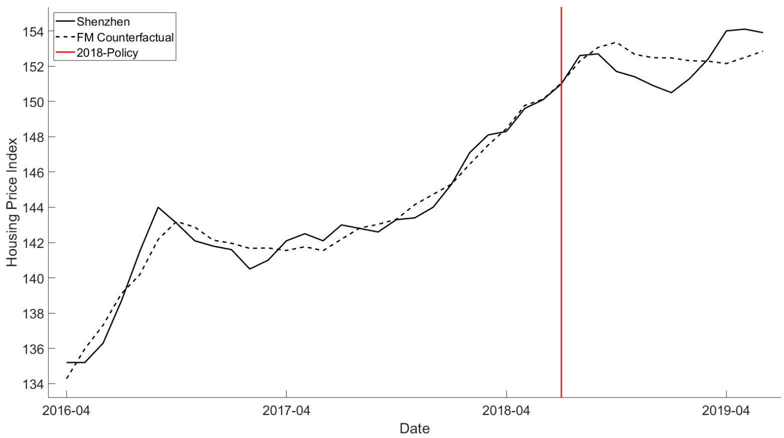
Tables 4 and 5 report the estimated treatment effects and the corresponding standard errors by the HCW and FM methods, respectively. Both

TABLE 4.

The Comparison Between Actual and HCW Predicted Values for the 2018-Policy

Date	Actual	HCW Predicted	Difference	Prediction S.E.	Difference in %
2018-07	151	149.3	1.7	0.5	1.2
2018-08	152.6	149.6	3.0	0.9	2.0
2018-09	152.7	151.4	1.3	1.5	0.9
2018-10	151.7	154.0	−2.3	2.0	−1.5
2018-11	151.4	154.1	−2.7	2.7	−1.7
2018-12	150.9	152.9	−2.0	3.0	−1.3
2019-01	150.5	153.2	−2.7	3.0	−1.7
2019-02	151.3	152.8	−1.5	2.9	−1.0
2019-03	152.4	154.9	−2.5	2.9	−1.6
2019-04	154	154.0	0.0	3.0	0.0
2019-05	154.1	156.5	−2.4	3.2	−1.5
2019-06	153.9	156.3	−2.4	3.3	−1.5
Average			−1.0		−0.7

FIG. 5. Counterfactual Estimated by the FM Method for the 2018-Policy



methods suggest that there are no significant treatment effects of the 2018-policy on Shenzhen housing prices.

4.3. Discussion

We find that the 2016-policy has significantly slowed down Shenzhen's housing price upward trends. This shows that increasing the land supply and increasing the down payment requirement are effective measures that help tame the rising housing price. For the 2018-policy, since it only im-

TABLE 5.

The Comparison Between Actual and FM Predicted Values for the 2018-Policy

Date	Actual	FM Predicted	Difference	Prediction S.E.	Difference in %
2018-07	151	151.0	0.0	1.5	0.0
2018-08	152.6	152.3	0.3	2.6	0.2
2018-09	152.7	153.1	−0.4	4.1	−0.2
2018-10	151.7	153.4	−1.7	5.0	−1.1
2018-11	151.4	152.7	−1.3	7.0	−0.8
2018-12	150.9	152.5	−1.6	8.2	−1.0
2019-01	150.5	152.5	−2.0	9.2	−1.3
2019-02	151.3	152.3	−1.0	10.2	−0.7
2019-03	152.4	152.3	0.1	10.7	0.1
2019-04	154	152.1	1.9	11.7	1.2
2019-05	154.1	152.5	1.6	12.6	1.1
2019-06	153.9	152.9	1.0	13.0	0.7
Average			−0.2		−0.2

poses a delay restriction in selling newly purchased houses, it may reduce the total sales of houses,[1] but its effect on reducing housing prices is quite limited. People are willing to hold properties until it passes the restriction time to put it on market, there is no incentive for them to reduce housing prices because even if they reduce the price, they still cannot put the house on market due to the 3-year restriction for reselling newly purchased houses. Hence, it is understandable that the 2018-policy is not an effective measure for slowing down the upwards trends of Shenzhen's housing prices.

5. CONCLUSION

The Chinese housing market has experienced significant growth over the past 20 years, driven by government policies aimed at promoting urbanization and economic growth. However, speculation and concerns about a potential housing bubble have led to government efforts to regulate the market. The housing market remains a crucial factor in the Chinese economy and a subject of ongoing debate and scrutiny. This paper focuses on the impact of two major local government policies implemented during 2016-2018 on housing prices in Shenzhen, one of the largest cities in China. Our empirical results suggest that, by increasing land supply and down payment requirements, the 2016-policy had significant effects on reducing housing prices, while the 2018-policy, which imposes a three-year restriction in delaying sales of newly purchased houses, had no significant

[1] We do not have housing sales data. Therefore, we cannot verify this conjecture.

effects. The insights from this study may provide valuable information for policymakers in designing and implementing effective housing policies in China.

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