# How does the COVID-19 pandemic affect housing prices in China?

by

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# How does the COVID-19 pandemic affect housing prices in China?[§]

**Terence Tai-leung Chong and Hengliang Liu**[*]

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**Abstract:** COVID-19 was first reported in Wuhan in late December 2019, and then spread throughout China, which has had great influence on many aspects of the economy. This paper uses the two-way fixed effects model to investigate the non-linear relationship between the death toll of COVID-19 and the changes in housing prices using monthly panel data from November 2019 to May 2020. The results suggest that there is a "U-shaped" relationship between monthly death toll of COVID-19 and the percentage changes of housing prices in cities; In addition, the housing markets of New First-tier cities are more sensitive to the COVID-19 pandemic than Second-tier and Third-tier cities, which the pandemic has had little effect on. Similarly, monthly confirmed cases of COVID-19 come to the same conclusions.

Keywords: COVID-19; housing prices; non-linear relationship; New First-tier cities

JEL Code: R31



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# 1 Introduction

There is no doubt that the novel coronavirus (COVID-19) outbreak is the hottest topic in early 2020 and has engendered profound and widespread economic ramifications. Since the report of the first confirmed case of COVID-19 in Wuhan of China in late December 2019, as of 31 May 2020, a total of 83,022 cases have been confirmed, and 4,634 people have died in China. The outbreak of COVID-19 has brought the globalized world to a standstill, claiming hundreds of thousands of lives and confining millions to their homes. (See Francke and Korevaar, 2020). Ren (2020) argued that the lockdown is a last resort, and clearly an expensive one, to rein in the pandemic, citing the different degrees of success in controlling the outbreak in China, Italy and the United States. Nicola et al. (2020) summarised the socio-economic effects of COVID-19 and suggested that even though the real estate industry should not have been immune from the considerable uncertainty brought by COVID-19, the housing market has hitherto shown little signs of distress. In contrast, Yoruk (2020) found that new home listings and pending home sales in the United States have started to decline from the second half of March 2020. Ozili and Arun (2020) believe that the increasing number of confirmed coronavirus cases has not had a significant impact on the level of economic activities. Unlike other advanced economies such as the United States and Europe, the pandemic in China has had a relatively short inflection duration of surging. It took less than two months from the first reported case of COVID-19 to the inflection point of confirmed cases in China. Thus, it is worth exploring whether the COVID-19 pandemic had a significant impact on China's housing market and how this impact differs across cities of China.

This paper investigates the non-linear relationship between the death toll of COVID-19 and the percentage changes of housing prices using monthly panel data of mainland China. Moreover, we explore the main determinants of housing price changes and their rates of change among different cities during the pandemic. To the best of our knowledge, no study has been conducted on the non-linear relationship between COVID-19 casualties and housing prices especially in China, and our study contributes to the existing literature by filling this gap. We merge the 4 top first-tier cities and the 15 new first-tier cities identified in the *Ranking of Cities Business Attractiveness 2019* [1] into a novel group called "New First-tier" cities. In total, we split

[1] *Ranking of Cities Business Attractiveness 2019* was released by the New First-tier

92 cities into three groups, namely New First-tier, Second-tier and Third-tier cities, according to the Ranking. As shown in subsequent sections of this paper, we find that both confirmed cases and deaths of COVID-19 have significant influences on housing prices of Chinese cities as a whole but their effects on housing prices vary across different groups of cities.

**Table 1**
Variables and their Descriptions

| Variables | Descriptions |
|---|---|
| $Y_{it}$ | Monthly percentage changes of average housing prices from Nov-2019 to May-2020 , where $Y_{it} = \ln P_{it} - \ln P_{i,t-1}$ |
| $P_{it}$ | Monthly average housing prices from Oct-2019 to May-2020 |
| $Confirm_{it}$ | Monthly confirmed cases of COVID-19 in each city |
| $Death_{it}$ | Monthly deaths of COVID-19 in each city |
| $GRP_i$ | Gross regional product or regional GDP |
| $HosBed_i$ | Number of hospital beds |
| $School_i$ | Number of regular higher education institutions |
| $Tertiary_i$ | Output from the tertiary industry as a percentage of GRP |
| $POP_i$ | Population |
| $IMP_i$ | Annual import volume of goods |

## 2 Data

The monthly average housing prices of 92 cities in China from October 2019 to June 2020 were obtained from Anjuke[2], the leading real estate information service platform in China. The monthly COVID-19 data was collected from the National Health Commission of China, the regional Health Commission, the World Health Organization (WHO) and the Johns Hopkins University. In addition, all other variables are mainly sourced from the National Bureau of Statistics of China, China City Statistical Yearbook 2019, China City Construction Statistical Yearbook in 2019, China Economic Information Network, Trading Economics and Qianzhan database.

The dependent variable is the monthly percentage changes of average housing prices in each city ($Y_{it}$) from November 2019 to May 2020. The eight independent variables can be classified into two categories (see Table 1),

Cities Research Institute of YiMagazine at the summit on May 24, 2019

[2]Anjuke's website: www.anjuke.com

namely key variables and control variables. The former includes monthly confirmed cases of COVID-19 ($Confirm_{it}$) and monthly deaths of COVID-19 ($Death_{it}$). They are analyzed separately in different models. Control variables encompass the annual gross regional product of each city ($GRP_i$) and its tertiary industry as a percentage of GRP ($Tertiary_i$), which reflects the level of economic development and the economic structure directly; the annual import volume of goods ($IMP_i$); the number of hospital beds ($HosBed_i$), which allows us to assess the level of local medical services; and the number of regular higher education institutions ($School_i$), which is a useful proxy of the regional education level; and finally the population of cities ($POP_i$).

**Table 2**

Descriptive statistics (observations: 644)

| Variables | Unit | Mean | Min | Max | Std.dev. |
|---|---|---|---|---|---|
| $Y_{it}$ | – | 0.001 | -2.312 | 2.305 | 0.187 |
| $P_{it}$ | RMB | 13677.250 | 4609.000 | 59126.000 | 9773.025 |
| $Death_{it}$ | – | 6.238 | 0.000 | 2003.000 | 95.678 |
| $Confirm_{it}$ | – | 95.110 | 0.000 | 45907.000 | 1813.731 |
| $GRP_i$ | hundred million RMB | 7424.299 | 1284.910 | 89879.230 | 10293.470 |
| $HosBed_i$ | thousand | 37.698 | 8.840 | 162.147 | 67.288 |
| $School_i$ | – | 20.663 | 0.000 | 92.000 | 21.488 |
| $Tertiary_i$ | % | 50.733 | 29.480 | 80.980 | 8.881 |
| $POP_i$ | hundred thousand | 81.940 | 17.654 | 1116.900 | 117.592 |
| $IMP_i$ | million RMB | 1424.589 | 1.013 | 22303.930 | 3540.194 |

Basic descriptive statistics are presented in Table 2. Notice that there are vast differences between the maximum and the minimum values of confirmed cases and deaths caused by COVID-19, but the mean percentage changes of average housing prices ($Y_{it}$) is close to 0. It shows that the housing prices were steady in the first half of 2020 in general but varied obviously by month in mainland China. To better understand the price dynamics, we divide the sample into three periods: the *Pre-cov* period, which is before 2020 and regarded as the control group; the *Early-cov* period, which is January 2020 to March 2020, the most severe wave of pandemic sweeping through the country; and the *Post-cov* period, including April and May 2020, relatively stable and favourable with only a handful of cases each day. The housing prices in these three periods are depicted in Figure 1: (a) In Wuhan, the worst-hit city, housing prices dropped from the *Pre-cov* period and have continued to drop through out the *Early-cov* period and the *Post-cov* period, although they rebounded around the end of *Post-cov* period, near May 2020. Some cities such as Hangzhou and Nanjing have had similar changes but with obviously earlier rebounds. (b) The housing markets of cities like Beijing were largely unaffected by the pandemic.

# 3 Empirical analysis

## 3.1 Models

A two-way error component model can mitigate the problems of both time-invariant but individual varying and individual-invariant but time varying omitting variables (Chen, 2014). Thus, we estimate the relationship between the percentage changes of monthly house prices and the deaths ( as well as confirmed cases ) using a two-way error component model. The model is constructed as:

$$Y_{it} = \alpha + \mathbf{x}_{it}'\beta + \mathbf{z}_i'\delta + v_t + u_i + \varepsilon_{it} \qquad (1)$$

In this model, $i$ and $t$ represent cities and months respectively, and $i = 1, ..., N$; $t = 1, ..., T$; $n = NT$. [3] The dependent variable is percentage changes of average housing prices; $\mathbf{x}_{it}$ is a time-varying vector of key variables while $\mathbf{z}_i$ is a vector containing time-invariant control variables; $\beta$ is a $(k \times 1)$ vector of unknown coefficients; The unobserved individual-specific effect $\{u_i\}$ is an i.i.d. sequence, with a zero mean and finite variance. Analogously, the unobserved time-specific effect $v_t$ is also i.i.d. and has a zero mean and finite variance. Additionally, $\{\varepsilon_{it}\}$ are idiosyncratic (i.i.d.) errors.

Using Hausman (1978) test, we reject the strictly exogenous assumption of $\mathbf{x}_{it}$ and $\mathbf{z}_i$, and conclude that the fixed effects model is better than the random effects model since $u_i$ is associated with independent variables. Subsequently, in order to account for individual-specific effects and to avoid omitted variable bias as little as possible, we use the least square dummy variable (LSDV) models to construct and estimate the coefficients. We define a dummy variable for each month and introduce (T-1) time dummy variables

[3] t=1 represents November 2019, t=2 represents December 2019, t=3 represents January 2020, t=4 represents February 2020, ... , t=7 represents May 2020.

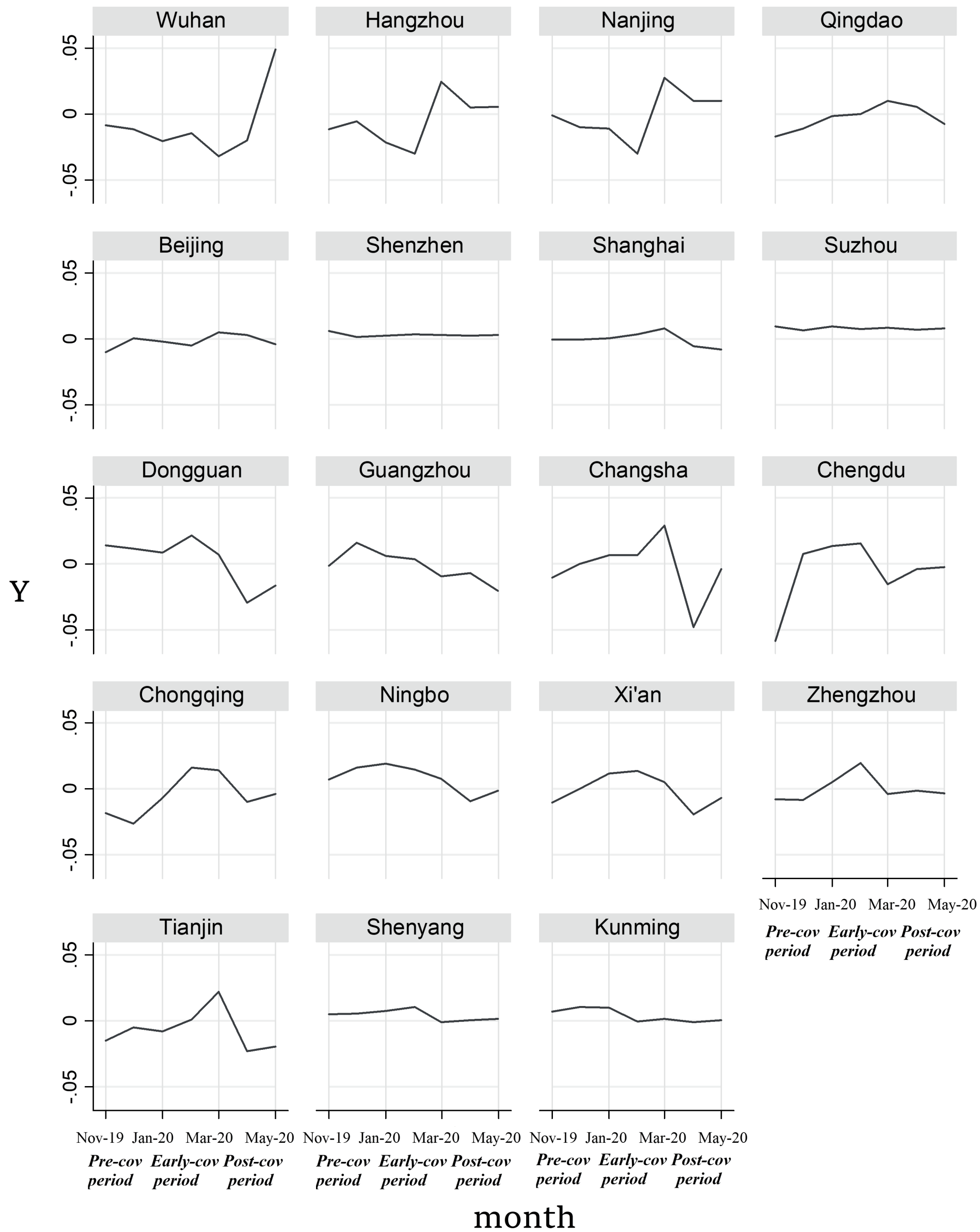


**Figure 1**. Percentage changes of average house prices in New First-tier cities by periods

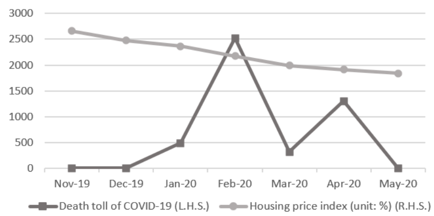


**Figure 2** Trends of the COVID-19 death toll and housing price index in China

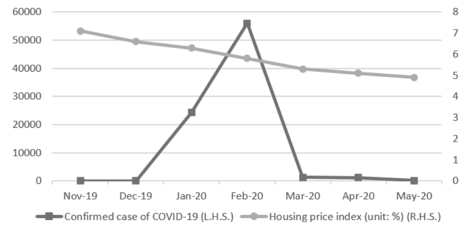


**Figure 3** Trends of the COVID-19 confirmed cases and housing price index in China

into model (1) to form a two-way fixed effects model.

$$Y_{it} = \alpha + \mathbf{x}'_{it}\beta + \mathbf{z}'_{i}\delta + \sum_{j=2}^{7} \gamma_j Dj_t + u_i + \varepsilon_{it} \tag{2}$$

where $Dj_t = 1$ if $j = t$, $Dj_t = 0$ if $j \neq t$.

Figures 2 and 3 show that there was an constantly downward trend in China's housing prices throughout the entire sample period. In the meantime, we find that the trends of variations associated with COVID-19, monthly deaths and confirmed cases of the whole of China, are similar but asynchronous where monthly deaths has two inflection points whereas confirmed cases has one. Note from Figure 1 that the percentage changes of housing prices are not monotonous among cities. Therefore, we see both $Death_{it}$ and $Confirm_{it}$ as key independent variables, namely $\mathbf{x}_{it}$, and explore the relationships among cities by month. However, on grounds of a strong correlation (0.833) between these two variables (see Table 3), we do not include both of them in the same equation and analyze them separately. Thus, the two-way fixed effects (FE) models at the city level is formulated as follows:

$$\begin{aligned} Y_{it} = {} & \alpha + \beta_1 Death_{it} + \beta_2 Death_{it}^2 + \delta_1 \ln GRP_i + \delta_2 HosBed_i \\ & + \delta_3 School_i + \delta_4 Tertiary_i + \delta_5 POP_i + \delta_6 \ln IMP_i \\ & + \sum_{j=2}^{7} \gamma_j Dj_t + u_i + \varepsilon_{it} \end{aligned} \tag{3}$$

In model (3), we use $Death_{it}$, and its quadratic to measure the impact of the COVID-19 pandemic. On the other hand, in model (4), $Confirm_{it}$

enters the model in the same way as model (3).

$$
\begin{aligned}
Y_{it} =& \alpha + \beta_1 Confirm_{it} + \beta_2 Confirm_{it}^2 + \delta_1 \ln GRP_i + \delta_2 HosBed_i \\
&+ \delta_3 School_i + \delta_4 Tertiary_i + \delta_5 POP_i + \delta_6 \ln IMP_i \\
&+ \sum_{j=2}^{7} \gamma_j Dj_t + u_i + \varepsilon_{it}
\end{aligned} \tag{4}
$$

Since our main research focus is how casualties of COVID-19 affect the housing market, model (4) is mainly used as a robustness check. In the interests of brevity, we will report the results of model (4) in Table 4 without delving much into the details in the main text.

**Table 3**
Correlation between independent variables

| Correlation | $Death_{it}$ | $Confirm_{it}$ | $lnGRP_i$ | $HosBed_i$ | $School_i$ | $Tertiary_i$ | $POP_i$ | $lnIMP_i$ |
|---|---|---|---|---|---|---|---|---|
| $Death_{it}$ | 1.000 | | | | | | | |
| $Confirm_{it}$ | 0.833 | 1.000 | | | | | | |
| $lnGRP_i$ | 0.084 | 0.063 | 1.000 | | | | | |
| $HosBed_i$ | 0.036 | 0.028 | 0.464 | 1.000 | | | | |
| $School_i$ | 0.183 | 0.130 | 0.687 | 0.472 | 1.000 | | | |
| $Tertiary_i$ | 0.027 | 0.022 | 0.424 | 0.283 | 0.664 | 1.000 | | |
| $POP_i$ | 0.015 | 0.016 | 0.654 | 0.266 | 0.504 | 0.359 | 1.000 | |
| $lnIMP_i$ | 0.033 | 0.026 | 0.689 | 0.331 | 0.484 | 0.340 | 0.307 | 1.000 |

## 3.2 LSDV estimation results

We start by analyzing the effect of deaths during the pandemic period on the housing market using the full sample. After that, we explore the relationships in the subgroups. The estimation results of model (3) are presented in Table 4 (full sample) and Table 5 (subsamples by city group). Considering the unobserved or possibly omitted heterogeneity among cities, we cluster observations at the city level, and use a two-way fixed effects model to conduct the analysis. Table 4 shows the LSDV results of a series of two-way FE models (full sample).

For the full sample, the coefficients of $Death_{it}$ and its quadratic term are -1.40E-04 and 6.29E-08 respectively from Table 4, implying that there is likely to be a "U-shaped" relationship between the monthly death toll of COVID-19 and the percentage changes of housing prices. In other words, the higher the casualties, and the lower the percentage changes of the average housing prices when there are few deaths each month during the COVID-19 pandemic while the relationship will reverse as the death toll further increases. The key variable, $Confirm_{it}$, has a similar effect on housing prices.

For the subsamples by cities, we find that the effects on housing prices differ across the categories. In New First-tier cities, comparatively developed cities or metropolises, monthly death toll and confirmed cases of COVID-19 had significant effects on the housing market, while the effects are insignificant and nearly indiscriminate in Second-tier and Third-tier cities (see Table 5 and Table 6).

From Table 4, we can see that the negative impact of COVID-19 on the housing price occurs in December 2019 and May 2020, but generally not significant statistically.

## 3.3 Endogeneity

While a panel data structure can alleviate the problem of omitted variable bias, endogeneity may still exist in our models. However, the percentage changes in housing prices do not affect death toll and the number of confirmed cases of COVID-19; Therefore, we can rule out the possibility of reverse causality, which can cause endogeneity. In order to solve the problem of endogeneity, we use Hausman (1978) test again to test the key variables. We conclude that there are weakly endogenous in our models and the exogenous assumption can be accepted since we are primarily interested in key variables.

## 3.4 Robustness Checks

Based on models in Section 3.1, we can use (T-1) dummy variables to allow for characteristics of cities which are individual-invariant but time varying. From Table 4, we find that the time dummy variables are jointly significant at 1% both in model (3) and model (4), estimated by LSDV method; besides, we reach the same result when using $v_t$ in LSDV. Thus, we suggest that there is a robust time trend in the two models.

We can use model (4) to check the robustness of model (3). From Table 4, we find that the coefficients of $School_i$ and $POP_i$ are positive whereas other independent variables are negative. In addition, we can see both $Death_{it}$ and its quadratic term can influence monthly housing price growth significantly, which indicates a "U-shaped" relationship between $Y_{it}$ and $Death_{it}$, and the

**Table 4**

LSDV results for two-way FE models (full sample)—— model (3) and model (4)

| Variables | model (3) | | | model (4) | | |
|---|---|---|---|---|---|---|
| | Coef. | Robust Std. Err. | P-value | Coef. | Robust Std. Err. | P-value |
| $Death_{it}$ | -1.40E-04** | 6.36E-05 | 0.029 | | | |
| $Death_{it}^2$ | 6.29E-08** | 2.85E-08 | 0.030 | | | |
| $Confirm_{it}$ | | | | -1.13E-05*** | 3.51E-06 | 0.002 |
| $Confirm_{it}^2$ | | | | 2.37E-10*** | 7.51E-11 | 0.002 |
| $lnGRP_i$ | -1.91E-02*** | 1.01E-05 | 0.000 | -1.90E-02*** | 1.07E-05 | 0.000 |
| $HosBed_i$ | -6.40E-04*** | 1.60E-06 | 0.000 | -6.49E-04*** | 1.86E-06 | 0.000 |
| $School_i$ | 5.89E-04*** | 5.75E-07 | 0.000 | 5.88E-04*** | 1.97E-07 | 0.000 |
| $Tertiary_i$ | -1.28E-03*** | 3.03E-06 | 0.000 | -1.25E-03*** | 6.72E-06 | 0.000 |
| $POP_i$ | 6.46E-04*** | 1.03E-06 | 0.000 | 6.53E-04*** | 1.50E-06 | 0.000 |
| $lnIMP_i$ | -7.10E-04*** | 1.96E-06 | 0.000 | -5.97E-04*** | 3.50E-05 | 0.000 |
| cons | 2.10E-01*** | 1.28E-03 | 0.000 | 2.32E-01*** | 2.73E-02 | 0.000 |
| Observations | | | 644 | | | 644 |
| R-squared | | | 0.019 | | | 0.016 |
| Robust MSE | | | 0.146 | | | 0.201 |
| Months: time dummy variables | | | | | | |
| Dec-19 (t=2) | -1.82E-03 | 1.77E-03 | 0.305 | -1.82E-03 | 1.76E-03 | 0.305 |
| Jan-20 (t=3) | 4.34E-03 | 2.92E-03 | 0.141 | 4.08E-03 | 2.91E-03 | 0.165 |
| Feb-20 (t=4) | 4.25E-03 | 3.03E-03 | 0.163 | 3.90E-03 | 3.01E-03 | 0.198 |
| Mar-20 (t=5) | 2.32E-03 | 4.52E-03 | 0.609 | 1.83E-03 | 4.52E-03 | 0.686 |
| Apr-20 (t=6) | 3.16E-02 | 2.87E-02 | 0.273 | 3.08E-02 | 2.83E-02 | 0.279 |
| May-20 (t=7) | -3.51E-02 | 2.83E-02 | 0.217 | -3.51E-02 | 2.83E-02 | 0.217 |
| Joint significance of all months | Prob>F | | 0.000 | Prob>F | | 0.000 |
| Use $v_t$ to replace time dummy variables | | | | | | |
| Joint significance of all months | Prob>F | | 0.000 | Prob>F | | 0.000 |

Note: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

**Table 5**
LSDV results for two-way FE models (subsamples by city group)—— model (3)

| Variables | New First-tier city | | Second-tier city | | Third-tier city | |
|---|---|---|---|---|---|---|
| | Coef. | P-value | Coef. | P-value | Coef. | P-value |
| $Death_{it}$ | -6.90E-05*** | 0.000 | 3.79E-03 | 0.307 | 3.19E-03 | 0.175 |
| | (7.88E-06) | | (3.65E-03) | | (2.32E-03) | |
| $Death^2_{it}$ | 3.09E-08*** | 0.000 | -8.90E-04 | 0.325 | -9.00E-05 | 0.177 |
| | (4.32E-09) | | (8.86E-04) | | (6.52E-05) | |
| $lnGRP_i$ | 1.51E-02*** | 0.000 | 1.39E-02*** | 0.000 | -3.61E-02*** | 0.000 |
| | (2.97E-03) | | (4.93E-04) | | (7.41E-04) | |
| $HosBed_i$ | 1.42E-06 | 0.343 | 2.95E-04*** | 0.000 | 3.29E-03*** | 0.000 |
| | (1.46E-06) | | (1.23E-05) | | (6.00E-06) | |
| $School_i$ | 2.86E-04*** | 0.000 | 9.65E-04*** | 0.000 | 1.08E-02*** | 0.000 |
| | (1.92E-05) | | (5.01E-05) | | (9.49E-05) | |
| $Tertiary_i$ | 1.89E-04** | 0.032 | -9.50E-05*** | 0.005 | 1.08E-03*** | 0.000 |
| | (8.16E-05) | | (3.11E-05) | | (1.70E-05) | |
| $POP_i$ | -4.40E-04*** | 0.000 | -4.20E-04*** | 0.000 | -7.70E-04*** | 0.000 |
| | (4.65E-05) | | (7.03E-06) | | (4.67E-07) | |
| $lnIMP_i$ | 6.66E-03*** | 0.000 | -2.63E-03*** | 0.000 | -1.26E-02*** | 0.000 |
| | (2.71E-04) | | (3.10E-05) | | (3.08E-05) | |
| cons | -2.39E-01*** | 0.000 | -6.77E-02*** | 0.000 | 3.89E-01*** | 0.000 |
| | (2.62E-02) | | (5.47E-03) | | (5.77E-02) | |
| Observations | 133 | | 203 | | 308 | |
| R-squared | 0.2417 | | 0.0522 | | 0.0261 | |
| Root MSE | 0.1395 | | 0.25536 | | 0.20403 | |

Note: (·) represents the robust standard errors.
* significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

**Table 6**
LSDV results for two-way FE models (subsamples by city group)——model (4)

| Variables | New First-tier city | | Second-tier city | | Third-tier city | |
|---|---|---|---|---|---|---|
| | Coef. | P-value | Coef. | P-value | Coef. | P-value |
| $Confirm_{it}$ | -1.16E-05*** | 0.000 | -5.96E-04 | 0.379 | 9.54E-06 | 0.754 |
| | (1.51E-06) | | (6.66E-04) | | (3.03E-05) | |
| $Confirm_{it}^2$ | 2.43E-10*** | 0.000 | 2.33E-06 | 0.371 | -5.76E-09 | 0.865 |
| | (3.11E-11) | | (2.57E-06) | | (3.36E-08) | |
| $lnGRP_i$ | 1.05E-02*** | 0.002 | 1.36E-03 | 0.920 | -3.54E-02*** | 0.000 |
| | (2.94E-03) | | (1.35E-02) | | (1.04E-03) | |
| $HosBed_i$ | 1.90E-05 | 0.170 | 1.64E-04 | 0.321 | 3.31E-03*** | 0.000 |
| | (1.33E-05) | | (1.62E-04) | | (5.50E-05) | |
| $School_i$ | 2.25E-04*** | 0.000 | 1.06E-03*** | 0.000 | 1.07E-02*** | 0.000 |
| | (2.48E-05) | | (4.86E-05) | | (2.03E-04) | |
| $Tertiary_i$ | 1.37E-04*** | 0.006 | -2.22E-04** | 0.047 | 1.10E-03*** | 0.000 |
| | (4.37E-05) | | (1.07E-04) | | (2.10E-05) | |
| $POP_i$ | -3.70E-04*** | 0.000 | -1.82E-04 | 0.506 | -7.81E-04*** | 0.000 |
| | (2.85E-05) | | (2.70E-04) | | (2.24E-05) | |
| $lnIMP_i$ | 6.90E-03*** | 0.000 | -1.69E-03 | 0.132 | -1.26E-02*** | 0.000 |
| | (5.22E-04) | | (1.09E-03) | | (8.59E-05) | |
| cons | -2.03E-01*** | 0.000 | 2.01E-02 | 0.828 | 3.81E-01*** | 0.000 |
| | (2.02E-02) | | (9.19E-02) | | (5.73E-02) | |
| Observations | 133 | | 203 | | 308 | |
| R-squared | 0.207 | | 0.0522 | | 0.026 | |
| Root MSE | 0.0142 | | 0.25459 | | 0.20363 | |

Note: (·) represents the robust standard errors.
* significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

results are relatively robust as shown in Table 4. Therefore, the non-linear relationship in model (3) is also consistent with Figure 1.

# 4 Conclusion

The shock of the COVID-19 pandemic on the housing market in China is an important topic to explore. Our results of 92 cities suggest a significant "U-shaped" relationship between COVID-19 casualties and the percentage changes of housing prices in China, which is new to the literature. The effects of both death toll and confirmed cases on housing prices vary across different groups of cities, and the New First-tier cities, with higher level of availability and diffusion of information and media reports of the outbreak, have more obviously volatile housing markets compared with Second-tier and Third-tier groups; Within same group, especially the New First-tier cities, the effects on housing prices during the *Early-cov* period are more likely to depend on the COVID-19 pandemic rather than city's individual factors compared with the *Pre-cov* and *Post-cov* periods.

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