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HOW DO HOUSING PRICES AFFECT A CITY'S INNOVATION CAPACITY? THE CASE OF CHINA

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Abstract. Using panel data from 269 Chinese cities, this study examined the impact of housing prices (*HP*) on cities' innovation capacity (*IC*) in China. Firstly, a fixed effect model was used to analyze the effect of *HP* on cities' *IC* in China, revealing that *HP* positively impacts cities' *IC*. Next, several robustness tests were conducted to verify the finding's reliability. Thirdly, the analysis empirically tested mediating mechanisms between *HP* and cities' *IC* in China. The results show that, on the one hand, higher *HP* can improve cities' *IC* by attracting talents and stimulating the growth of local fiscal revenue. On the other, increasing *HP* can inhibit cities' *IC* in China by attracting funds into the real estate market and impeding residents' consumption ability. Finally, the heterogeneous nature of the *HP*–*IC* link in China was further explored. This study's results provide recommendations for the government of China on how to promote cities' innovation performance.

Keywords: housing prices, innovation, fixed effect, mechanism analysis, heterogeneity analysis, China.

JEL Classification: O18, O30, O53, R21, R31.

Introduction

The "new normal" has made the transformation from a factor- and investment-driven economy to an innovation-driven economy an important condition for China's sustained and stable economic growth (Ding et al., 2022b). As centers of regional economic activity, cities attract various production factors (e.g. human capital) and bring together multiple industries. Thus, cities are now the core drivers of a country's innovation activities (Caragliu & Del Bo, 2019; Yao et al., 2020), meaning that a city's innovation capacity (hereafter *IC*) is vital for regional economic growth in China. At the same time, since the reform of the Chinese hous-

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ing market in the 1990s, China's housing prices (hereafter *HP*) have experienced exponential growth. Although the Chinese government has taken a number of measures to abate the property market, the situation of high *HP* in China has not been significantly improved. As such, scholars have conducted extensive research on China's high *HP*, but only a few studies have paid attention to the possible influence of *HP* on cities' *IC* in China. Against the dual backgrounds of China's continuously rising *HP* and cities' critical need for *IC* for economic growth, it is necessary to test the path from *HP* to cities' innovation performance in China.

High *HP* may impact cities' *IC* through the following five ways. First, high *HP* may inhibit cities' *IC* by crowding out innovation funds. Compared to the real estate industry's low risk and high return, innovation investment has higher risk, which is mainly reflected in the high failure rate of innovation activities (Castellion & Markham, 2013). As such, rising *HP* may attract investors to transfer more funds to the real estate industry (Wong et al., 2019), which squeezes out innovation input and inhibits cities' innovation output (Yu & Cai, 2021). Notably, with the increase of *HP*, the squeezing-out effect tends to be stronger because higher *HP* means higher expected returns on housing investments (Abelson et al., 2005). Second, rising *HP* may affect cities' *IC* by attracting or crowding out talents. On the one hand, cities with pricier houses usually have more employment opportunities and better development prospects (Lin et al., 2021). At the same time, high *HP* reflects the capitalization of public services (Boettke & Marciano, 2017); that is, higher *HP* in a city usually means that the city has better public facilities such as education, infrastructure, and healthcare. Additionally, as an investment product, the rapid rise in the price of housing can bring higher expected returns (Ding et al., 2022b). As such, when the price of housing in a city rises from a low level, it could attract talents and thus have a positive effect on the innovation performance of the city (Yang & Pan, 2020a). However, with the continuous rise of *HP*, the threshold for the labor force to survive in the city will be raised (ibid). When the city's *HP* rises to a relatively high level, talents may have to move out of the city due to the unaffordable housing cost, and the innovation performance of the city will be negatively affected (Yang & Pan, 2020b). In short, the rise of *HP* may affect cities' *IC* by affecting the migration of talents; this effect is manifested in an inverted U-shaped curve of promotion first and then inhibition (Ding et al., 2022b). Third, the increasing cost of housing may boost cities' innovation capabilities by easing the financing constraints of the enterprises located in cities. According to Chaney et al. (2012), higher *HP* adds value to enterprises' mortgageable property, which in part alleviates the financing constraints of enterprises, increases the credit funds available to enterprises for R&D, and thus, boosts the innovation output of enterprises. In turn, the improvement of enterprises' innovation output increases the innovation performance of the cities where the enterprises are located. Fourth, higher *HP* may promote cities' *IC* by promoting the growth of local fiscal revenue. Wen and Goodman (2013) stated that rising *HP* can promote the increase of land prices, which augments the fiscal revenue of local governments in China[1]. The increase of local fiscal revenue means that local governments have more funds to be used to support innovation, which may improve the innovation performance of cities. Finally, *HP* may affect cities' *IC* by affecting residents' consumption ability. According to Fisher (1930), the current consumption ability of consumers is subject to their borrowing ability to

[1] "Land prices" here refers to the price of the leased land use rights. The land is owned by the state in China and the income from renting land use rights is owned by China's local governments.

a certain extent. When the price of houses rises from a low level, the value of houses held by consumers as collateral can increase, which eases consumers' borrowing constraints and thus improves consumers' consumption ability – this illustrates the collateral effect (Attanasio et al., 2009). The improvement of consumption power can increase consumption demand and subsequently, the profitability of enterprises. More profits mean enterprises have more funds available for R&D, which can positively affect their innovation output. As mentioned earlier, greater enterprise innovation output will improve the *IC* of the cities where the enterprises are located. However, when *HP* rises to a relatively high level, home-buyers are likely to apply for a housing loan from banks, which means that they have to make monthly house payments (Fung et al., 2006). At this time, the collateral effect will change to the liquidity constraint effect; that is, residents have to reduce their consumption to make monthly house payments (Louise, 1995; Wong et al., 2015). Correspondingly, cities' *IC* will be negatively affected. In short, *HP* may affect cities' *IC* by affecting consumption, and this effect takes an inverted U-shape.

So far, to our knowledge, only two literatures have focused on the *HP*–*IC* nexus among cities in China (Lin et al., 2021; Yu & Cai, 2021). Specifically, using the fixed effect approach to analyze data from 51 cities in China from 2005 to 2014, Lin et al. (2021) found a positive effect of *HP* on cities' innovation output in China. In contrast, Yu and Cai (2021) posited that this effect is not a simple linear one, but takes an inverted U-shape. Although the two literatures did not reach a unanimous conclusion, they both showed that *HP* does impact cities' *IC*. In order to re-evaluate the possible relationship between *HP* and cities' *IC* in China, we used static estimation and dynamic estimation to investigate the unbalanced panel data of 269 Chinese cities from 2003 to 2018, wherein the dynamic estimation alleviated any potential endogeneity. In addition, a series of robustness checks were implemented to validate the above analyses' findings. Different from the existing two studies, in addition to directly testing the effect of *HP* on cities' *IC* in China, we also empirically tested, for the first time, the five aforesaid mechanisms through which *HP* alters cities' *IC*. Finally, the full-sample was divided into several sub-samples for heterogeneity analysis, in which we found unique results.

There are four remaining sections of this article. The second section presents a literature review relevant to the concepts under study. The third section introduces the data and methodology used in this study, followed by the fourth section which reports and discusses the empirical results. The conclusion and implications for policy makers are shown in the fifth section. In order to depict the framework of this study more intuitively, the framework is illustrated in Figure 1 as a diagram.

1. Literature review and hypothesis development

1.1. The influencing factors of cities' innovation capacity (*IC*)

The research on regional *IC* began with Solow's (1957) measurement of national innovation capability. Since then, the concept of city innovation capability has gradually developed and been evaluated by researchers (Henderson et al., 1995). Most of the influencing factors of a city's *IC* are economic factors. First, some studies have pointed out the relationship between industrial structure and cities' *IC*. According to Antonelli (2003), industrial development is

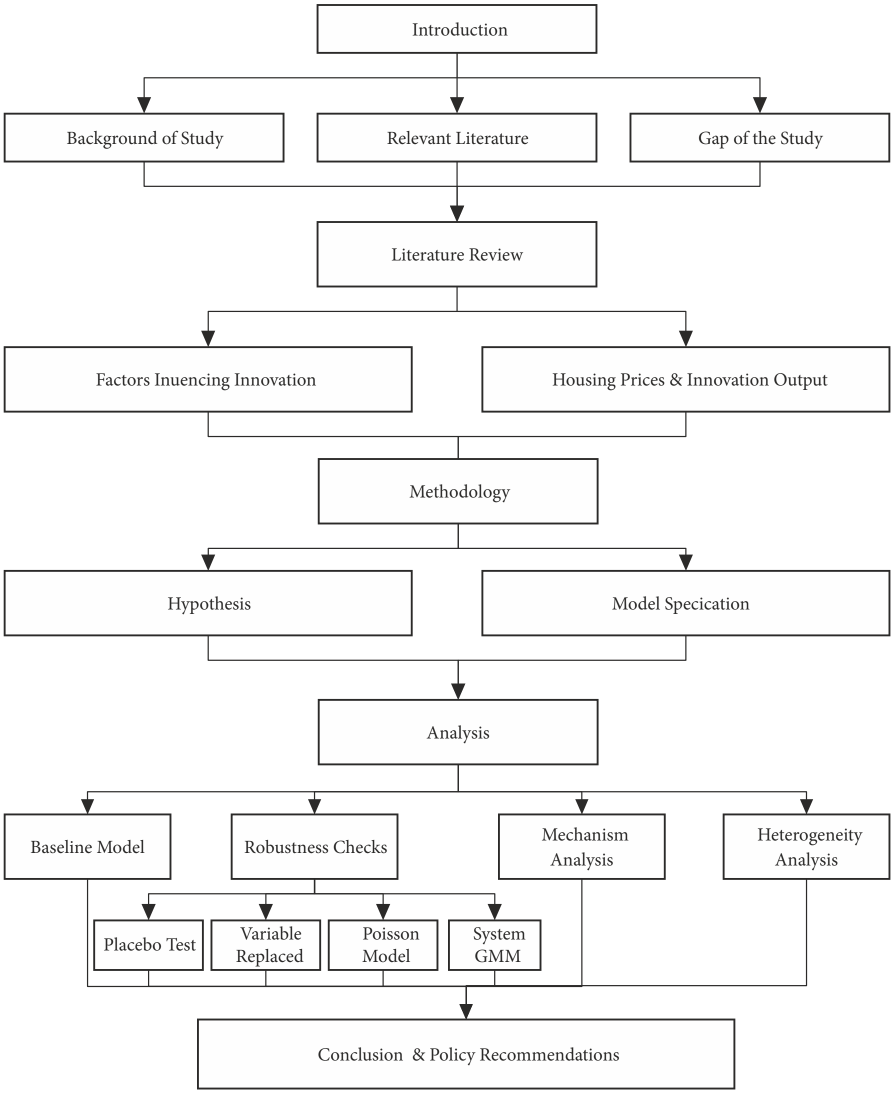

Figure 1. The research framework diagram

an important driving force for technological progress. Supporting this, Ning et al. (2016) conducted a series of empirical tests on the panel data of 181 China's cities from 2005 to 2011, and found that a diversified industrial structure can promote cities' innovation performance by optimizing the innovation environment. Second, industrial clusters can promote cities' *IC* by promoting competition, exchange, and cooperation within clusters (Iammarino & McCann, 2006), which was empirically confirmed by Hsieh-Sheng (2011). Third, the relationship between foreign direct investment (*FDI*) and cities' *IC* has also been found by some literature. According to Autor et al. (2016) and Liu and Liu (2016), *FDI* can promote technological innovation in host regions by training the hosts' employees and introducing advanced production technology and management concepts to the host regions. Supporting this, Yu and Cai (2021) used a simultaneous equation model to empirically explore panel data from 288 Chinese cities during the 2001 to 2016 period, and confirmed *FDI*'s positive effect on cities' *IC*. Finally, the increasing fiscal expenditure on R&D is also an important factor for the improvement of cities' *IC* (Li & Zhang, 2020). Castellion and Markham (2013) reported that while the implementation of innovation activities depends on the support of innovation investment, the high failure rate of innovation activities reduces the willingness of innovation subjects to carry out innovation activities. The government's financial support can reduce the losses caused by innovation failure and promote innovation activities. In addition to economic factors, greening (Li & Zhang, 2020), education (Lin et al., 2021) and government behavior (Yu & Cai, 2021) also impact cities' innovation output.

1.2. The effect of housing prices (*HP*) on innovation capacity (*IC*)

Existing research on the relationship between *HP* and innovation has mainly been carried out from two perspectives, namely enterprise innovation at the micro level and city innovation at the meso level. From the micro perspective, since the higher *HP* is helpful to alleviate the financing constraints of enterprises (Chaney et al., 2012), there can be a positive correlation between *HP* and enterprise *IC*. Extant literature supports this view by validating the relationship between the value of collateral (including housing) and the scale of enterprise investment. For example, Gan (2007) found that collateral appreciation promotes enterprises' expansion of investment scale by investigating manufacturing firms in Japan. Supporting this, Chaney et al. (2012) found that the investment amount enterprises in the U.S. increased with the value of real estate they own. However, there can also be a negative correlation of *HP* and enterprise *IC*. Specifically, rising *HP* can induce short-sighted enterprise managers to transfer more funds from R&D to real estate, which will lead to insufficient innovation input and inhibit the innovation output of enterprises (Aghion et al., 2013). By exploring the panel data of Chinese corporations from 2003 to 2010, Shi et al. (2016) corroborated this by concluding that the growing *HP* significantly crowds out the innovation output of enterprises.

From the meso perspective, Lin et al. (2021) tested *HP*'s impact on innovation output in 51 Chinese cities using municipal panel data and came to the conclusion that rising *HP* promotes cities' innovation performance by attracting talents. However, Yu and Cai (2021) believed that this link is not linear but inverted U-shaped. There also exists another macro-perspective to study innovation, which is national innovation performance. However, perhaps due to the large differences in *HP* among various cities in the same country, we have not found any literature on the *HP*–innovation nexus at the national level.

So far, only Lin et al. (2021) and Yu and Cai (2021) have tested *HP*'s effect on cities' *IC* in China, but have failed to reach a unanimous conclusion. In addition, Yu and Cai (2021) only directly analyzed this relationship without exploring its mechanisms. Although Lin et al. (2021) made a useful attempt to explore the mechanism of this relationship from the perspective of talent migration, it was not comprehensive. As such, we used unbalanced panel data from 269 Chinese cities from 2003 to 2018 to re-examine the effect of *HP* on cities' *IC* in China and comprehensively test this effect's mechanisms from the five perspectives of real estate investment, talent flow, enterprise financing constraints, local fiscal revenue, and residents' consumption ability. In doing so, we do not only enrich the empirical evidence in this field, but also make up for the insufficiency of mechanism analyses on the *HP*–*IC* nexus in China.

1.3. Hypothesis development

As discussed earlier, *HP* may affect cities' *IC* in five ways, such that this relationship depends on the net effect of the five indirect effects. When *HP* rises from a low level, on the one hand, it may improve cities' *IC* by easing the financing constraints of enterprises, increasing local fiscal revenue, attracting talents, and stimulating residents' consumption. On the other hand, although rising *HP* may attract investors to invest more in real estate and generate a negative impact on cities' innovation input and output, this negative impact is not very strong when *HP* is at a relatively low level. As such, when *HP* rises from a low level, the net effect of *HP* on cities' *IC* is likely to be positive. On the basis of these arguments, Hypothesis a was proposed.

However, when *HP* rises to a relatively high level, it may have a negative impact on brain drain and residents' consumption ability, and thus inhibit cities' *IC*. In addition, as *HP* grows further, its inhibitory effect on cities' *IC* by attracting funds into the real estate market would be strengthened. As such, when *HP* rises to the point where the positive effects of the easing of enterprise financing constraints and the increase of local fiscal revenue on cities' *IC* are offset by the negative effects of brain drain, lower consumption power, and the loss of innovation funds on cities' *IC*, rising *HP* will no longer show a positive effect on cities' *IC*, but would instead impede it. In line with these arguments, Hypothesis b was put forth. In summary, *HP*'s effect on Chinese cities' *IC* may be positive or inverted U-shaped, depending on whether *HP* has risen high enough.

Hypothesis A: The increase of *HP* has a positive impact on cities' *IC* in China.

Hypothesis B: The increase of *HP* has an inverted U-shaped effect on cities' *IC* in China.

2. Data and methodology

2.1. Dependent variable

City's innovation capacity (*CIC*): This study aimed to examine the possible effect of *HP* on cities' *IC* in China. *CIC* was the explained variable of this paper, the proxy of which was the annual number of patent applications at the city level. Patents can reflect regional innovation activity to a certain extent (Farre-Mensa et al., 2020). Although patent applications (Chang et al., 2015; Wen et al., 2021) and patent authorizations (Tian & Wang, 2018; Liang et al., 2019) have both been used to measure the *IC* of cities or enterprises, compared to the latter, the former can intermediately mark the output of the innovation process (Jalles, 2010), and has stronger stability, reliability and timeliness (Li & Zheng, 2016). As such, this paper selected the number of annual patent applications of cities to measure *CIC*, the data of which was derived from cities' statistical yearbooks and the official website of the China National Intellectual Property Administration.[2]

[2] The website is https://www.cnipa.gov.cn/.

2.2. Independent variable

Housing price (*HP*): *HP* was the main construct of this research. The proxy of *HP* was the mean annual sales price of commercial housing at the city level. The data of *HP* came from China's real estate information network, which is organized by the State Information Center of China. *HP* can affect cities' *IC* in five ways, which has been discussed in detail in Section 1.

2.3. Control variables

Economic growth (*EG*): Good economic growth momentum can promote innovation activities by providing favorable social expectations (Luo & Cheng, 2013). As such, *EG* was regarded as a control variable in this study and is predicted to have a positive effect on cities' *IC*. In line with Aghion et al. (2007), we employed per capita GDP at the city level to measure *EG*. The data of *EG* was derived from China's real estate information network.

Education (*Edu*): Education may affect regional innovation from two aspects. On the one hand, higher education is helpful to cultivate more scientific research talents (Bianchi & Giorcelli, 2020), thus promoting scientific and technological innovation. On the other, Lin et al. (2021) stated that cities with higher education standards can draw talents via continuing education for talents and elementary education for talents' children, thus improving the innovation performance of cities. As such, we took *Edu* as a control variable and predicted cities with higher education standards to have better innovation performance. We used the fiscal expenditure on education at the city level to measure *Edu*. The data of *Edu* was from the statistical yearbooks of cities.

Foreign direct investment (*FDI*): Howell (2020) proposed that a large amount of *FDI* is often a result of substantial cheap labor in the host region. These host regions offer large-scale cheap labor, and are often poor and have weak innovation ability (Davidov & Semyonov, 2017). As such, there may be a negative relationship between *FDI* and regional *IC*. On the contrary, *FDI* can promote the hosts' technological innovation by training the hosts' employees (Autor et al., 2016) and bringing advanced production technology and management concepts into the host regions (Liu & Liu, 2016). Correspondingly, Wen et al. (2021) indicated a positive correlation between *FDI* and local technological innovation. We thus took *FDI* as a control variable, with its estimation sign being both positive and negative. *FDI* is measured by the actual amount of foreign direct investment at the city level. The original data of *FDI* was measured in USD, which we converted into RMB through the annual mean exchange rate issued by the National Bureau of Statistics of China. The original data of *FDI* measured in USD can be obtained from the statistical yearbooks of cities.

Service industry cluster (*SIC*): According to Cai et al. (2021), a developed service industry cluster can promote cities' *IC* by providing professional services for innovation activities, such as legal, consulting, and financial services in the process of patent application. Supporting this, Yang and Bao (2019) proved that a specialized and diversified service industry significantly improves regional *IC*. As such, this paper took *SIC* as a control variable in the analysis framework and expected *SIC* to have a positive sign. As per Cai et al. (2021), *SIC* was calculated as the percentage of the tertiary industry's output of GDP at the city level. The data of *SIC* is accessible at the Chinese real estate information network.

International trade (*IT*): International trade enhances the growth of local fiscal revenue in the long term (Zhang & Liu, 2017). As such, local governments can invest more to develop new techniques, thereby encouraging regional *IC*. Meanwhile, according to Grossman and Helpman (1995), international trade can promote innovative output by promoting the exchange of ideas and technology transfer between trading parties. Supporting this, Schneider (2005) found that the import of high-tech products can significantly promote local innovation performance. As such, *IT* was incorporated in the regression model as a control variable, with the prediction that higher *IT* can lead to better regional innovation performance. *IT* was computed as the total volume of export-import at the city level. The data of *IT* was taken from the statistical yearbooks of cities.

Permanent Population (*PP*): In China, compared to cities with a small population, cities with a larger population are generally more developed and more attractive to talents (Gu et al., 2020). As a result, cities with larger populations tend to have more talents, who have a greater possibility of finding collaborators. Relative to independent research, cooperation among researchers can significantly improve innovation efficiency (Sanchez-Gonzalez & Herrera, 2015). However, the crowding effect holds that although higher population density can have positive effects when population density is low, a population density that is too high can also produce negative effects. Consistent with this, Simms and Nichols (2014) deemed that when too many people complete a task together, participants would prevaricate each other and make insufficient efforts, resulting in low work efficiency. As such, *PP* was added as a control variable in the regression model, albeit with an unclear specific direction. *PP* was measured by the year-end permanent resident population at the city level. The data of *PP* was also derived from cities' statistical yearbooks.

Based on the information discussed from Sections 2.1 to 2.3, a comprehensive analytical framework is presented in Figure 2.

2.4. Data description

We employed unbalanced panel data on 269 cities in China from 2003 to 2018. List A1 in the Appendix names these cities. The results of the study variables' descriptive analysis are shown in Table 1. In addition, a multicollinearity test was conducted, the output of which is presented in Table A1 in the Appendix. According to the results, the VIF values obtained by the study variables were all below 5.0, thus ruling out any potential estimation bias stemming from multicollinearity.

2.5. Methodology

This study collected the unbalanced panel data of 269 Chinese cities from 2003 to 2018 to study the possible effect of *HP* on the cities' *IC*. In order to test Hypothesis b, the squared term of *HP* was added to our estimation model. Additionally, all the variables except *SIC* were taken as logarithms to minimize heteroscedasticity effects, and all the variables involving price factors, namely *HP*, *EG*, *Edu*, *FDI*, and *IT*, were treated with CPI for de-inflation. Lastly, a panel data model was constructed, as shown in Equation (1). If the impact of *HP* on cities' *IC* in China takes an inverted U-shape, α_2 should be negative and statistically significant.

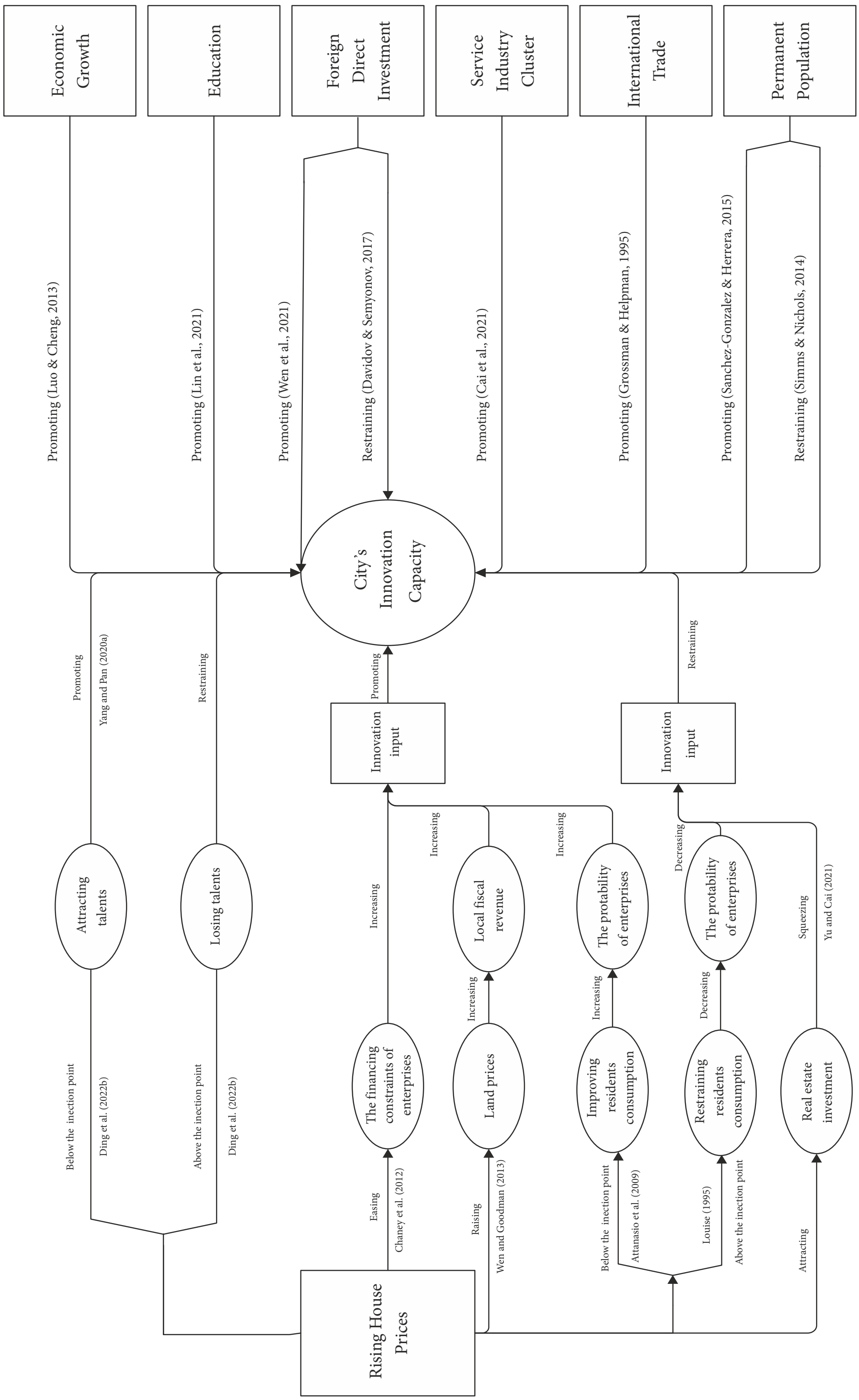

Figure 2. Comprehensive analytical framework

Table 1. Descriptive statistics of full-sample

Category	Variable Name	Measurement	Mean	Standard Deviation	Min	Max	Expected Sign
Dependent variable	CIC	Piece	4,178.09	11,968.30	5.00	1.82E+05	
Independent variable	HP	RMB per metre square	3,909.56	3,081.84	168.00	47,936.01	
Control variables	EG	RMB	35,648.48	28,280.85	2,370.00	196,728.00	+
	Edu	10,000 RMB	4.29E+05	6.66E+05	834.00	1.03E+07	+
	FDI	10,000 RMB	4.89E+05	1.16E+06	0.00	2.05E+07	+/–
	SIC	Ratio	0.38	0.09	0.11	0.81	+
	IT	10,000 RMB	7.37E+06	2.77E+07	738.31	3.33E+08	+
	PP	10,000 people	457.94	402.48	16.37	11,098.40	+/–

If α_2 is not statistically significant, Hypothesis b would be excluded. If the inverted U-shaped link is excluded, the squared term of *HP* would be deleted from the model, and a new model would be set up as presented in Equation (2) for re-estimation.

$$Ln(CIC_{it}) = \alpha_0 + \alpha_1 Ln(HP_{it}) + \alpha_2 (Ln(HP_{it}))^2 + \beta Z_{it} + \mu_i + \nu_t + \varepsilon_{it}; \quad (1)$$

$$Ln(CIC_{it}) = \alpha_0 + \alpha_1 Ln(HP_{it}) + \beta Z_{it} + \mu_i + \nu_t + \varepsilon_{it}. \quad (2)$$

In Equations (1) and (2), Z denotes the control variables explained earlier. μ_i and ν_t are the fixed effects for city and year, respectively. ε_{it} is the error term. α_0, α_1, α_2 and β are the coefficients to be estimated.

In order to affirm the benchmark estimation findings' robustness, we conducted a series of robustness tests. Due to unidentified flaws in the study's design, the benchmark regression results on the *HP–IC* link of cities in China could be a mere placebo effect (Ding et al., 2022c). As such, once the effect of *HP* on cities' *IC* in China was verified by the benchmark regression, the placebo test was implemented. Following Cornaggia and Li (2019), we began by removing *HP* data from all the samples before randomly assigning the data to every sample. Then, we re-estimated Equation (1) or (2). If the impact of *HP* on cities' *IC* in China is just a placebo, the results of the placebo test would match that of the benchmark regression.

China's urban and industrial innovation report, jointly issued by Yicai Research Institute and Fudan University in 2017, shows the index of cities' *IC*, which was constructed in terms of two groups of micro big data, i.e., patents and newly registered enterprises (Yicai Research Institute, 2017). Compared with only using patent application quantity to characterize cities' innovation capability, the index of cities' *IC* that accounts for both big data groups may be more comprehensive. As such, we changed the proxy variable of *CIC* from patent application quantity to cities' *IC* index, and re-estimated Equation (1) or (2) as a robustness test. Since the index of cities' *IC* is only updated to 2016, the time span of this robustness check was from 2003 to 2016.

According to Wen et al. (2018), a normal distribution among variables is a significant limitation of the general panel fixed effect model. To test whether the *HP–IC* relationship in

China still exists when there is a diversified distribution, the Poisson model was used for a robustness check, for which Equations (3) and (4) were developed. All the variables in Equations (3) and (4) have the same meaning as in Equation (1).

$$CIC_{it} = \alpha_0 + \alpha_1 Ln(HP_{it}) + \alpha_2 (Ln(HP_{it}))^2 + \beta Z_{it} + \mu_i + \nu_t + \varepsilon_{it}; \quad (3)$$

$$CIC_{it} = \alpha_0 + \alpha_1 Ln(HP_{it}) + \beta Z_{it} + \mu_i + \nu_t + \varepsilon_{it}. \quad (4)$$

Although the fixed effect model offers reasonable static estimation outcomes, the static estimation neglects to address the endogeneity problem, which could lead to biased estimation findings (Ding et al., 2022a). In addition, Landry (2001) believed that a good innovation foundation and atmosphere is an vital element for innovation. In other words, the innovation output in the later stage may be improved on the basis of existing innovation achievements in the earlier stage. That is, later innovation outputs may be affected by earlier ones. Therefore, following Arellano and Bond (1991), we added the lagged value of the dependent variable into the model as an instrumental variable, and then used the System GMM to estimate Equation (5) or (6) to alleviate the potential endogenous problem. In Equations (5) and (6), $CIC_{i,t-1}$ is the lagged value of the dependent variable, while the rest of the variables carry the same connotations as Equation (1).

$$Ln(CIC_{it}) = \alpha_0 + \alpha_1 Ln(CIC_{i,t-1}) + \alpha_2 Ln(HP_{it}) + \alpha_3 (Ln(HP_{it}))^2 + \beta Z_{it} + \varepsilon_{it}; \quad (5)$$

$$Ln(CIC_{it}) = \alpha_0 + \alpha_1 Ln(CIC_{i,t-1}) + \alpha_2 Ln(HP_{it}) + \beta Z_{it} + \varepsilon_{it}. \quad (6)$$

3. Empirical results and discussion

3.1. Baseline regression results

Initially, we used the panel fixed effect approach to estimate Equation (1), the results of which are shown in Columns I and II of Table 2, where Column I excludes the control variables and Column II includes them. Based on the results, we can see that the coefficients obtained by the squared term of *HP* in Columns I and II are both statistically insignificant, which indicates that the influence of *HP* on Chinese cities' *IC* is not inverted U-shaped; thus, we rejected Hypothesis b. We then estimated Equation (2) to re-explore the *HP* and cities' *IC* nexus. The results are in Columns III and IV of Table 2, where Column III excludes the control variables while Column IV includes them. It was found that the coefficients of *HP* are both significant and positive regardless of the inclusion of control variables, which indicates that an increase in *HP* can significantly improve cities' *IC* in China. This finding verifies Hypothesis a and supports the conclusion of Lin et al. (2021).

As for the control variables, all the variables hold the expected signs except *EG*. According to Luo and Cheng (2013), a good economy can promote innovation by creating good social expectations. However, the negative coefficient held by *EG* shows that per capita GDP hinders cities' *IC*. Consistent with this result, when Wen et al. (2021) estimated the effect of bureaucracy quality on innovation, per capita GDP also recorded a negative sign as a control variable. The unexpected negative sign obtained by *EG* in this study is justifiable. According to Heijster (2020), in China, local governments face great pressure in their performance evaluation, in which GDP is the primary measured item. Driven by the huge pressure to achieve GDP performance, Chinese local governments may ignore the law of economic growth. Specifically, to stimulate the rapid growth of urban GDP in the short term, Chinese local governments may ignore the decisive role of innovation in economic development and excessively channel capital to real estate and other investment fields, which inhibits the innovation enthusiasm of cities and eventually leads to cities' poor innovation performance. Consistent with Ayres et al. (2007), the statistically significant positive sign held by *Edu* points to a significant positive effect of education investment on cities' *IC*, which means that higher innovation output may come from more talents with good education background. It is worth noting that in contrast to the conclusion of Zhang et al. (2020) that human capital accumulation promotes regional innovation output, the variable *PP* in this study holds a statistically significant negative sign, which indicates that Chinese cities are overcrowded. To address the effect of this crowding effect on innovation, population control may need to be considered by the Chinese government.

3.2. Robustness checks

To test the robustness of the baseline regression results, we conducted a series of robustness tests, the outcomes of which are presented in Columns V to XII of Table 2. In the table, the odd columns do not contain the control variables, whereas the even columns include the control variables. Before discussing the results, it is necessary to state that during the robustness checks, we excluded the squared term of *HP* from our models because the baseline regression results confirmed the linear relationship between *HP* and Chinese cities' *IC*. Columns V and VI present the placebo test findings, which indicate that both coefficients of *HP* are not statistically significant. There are also great differences from the benchmark estimation results, which suggests that the panel fixed effect model's conclusion that *HP* has a positive impact on cities' *IC* in China is not a placebo, but reliable. From Columns VII to X, it is observable that regardless of whether the control variables are included in the analysis framework, after replacing the explained variable with the index of cities' *IC* (Columns VII and VIII) and the estimation model with the Poisson model (Columns IX and X), the coefficients of *HP* are all positive and significant at the 1% level. This supports the baseline regression results, proving once again that the conclusion obtained by the panel fixed effect model is robust. The estimated results of System GMM are shown in Columns XI and XII, which reveal that whether the control variables are included or not, the Sargan value is insignificant at the 10% level, proving that the instrumental variable is effective and does not cause the over-identification problem. Moreover, in both Column XI and XII, AR (1) is significant at the 1% level, whereas AR (2) is insignificant at the 10% level, demonstrating the feasibility of the dynamic panel data model and the absence of any auto-correlation issue from the error term. According to Columns XI and XII, the coefficients of *HP* are both positive and significant at the 1% level, corroborating the baseline regression results and once again proving the robustness of the conclusion that higher *HP* increases cities' *IC* in China. In addition, the lagged variable *Patent* in Columns XI and XII holds statistically significant positive coefficients, which implies that cities with higher *IC* also obtain more innovation production in the future. Consistent with this finding, Wen et al. (2018) found that regions with outstanding innovation performance are expected to obtain higher innovation output in the coming period.

Table 2. Baseline regression and robustness test results

	Baseline regression				Robustness checks							
	Fixed effect				Placebo effect		Variable replacement		Poisson model		System-GMM	
	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
$Ln(HP_{it})$	0.579*** (3.47)	−0.093 (−0.24)	2.458*** (99.71)	0.441*** (10.08)	−0.010 (−0.292)	0.006 (0.422)	1.144*** (53.27)	0.110*** (2.97)	0.387*** (28.93)	0.110*** (4.39)	0.253*** (8.76)	0.013*** (3.56)
$(Ln(HP_{it}))^2$	0.116 (1.18)	0.029 (1.11)										
$Ln(EG_{it})$		−0.084*** (−2.82)		−0.075** (−2.48)		−0.058* (−1.917)		0.351*** (6.31)		0.042** (2.44)		−0.035*** (−21.16)
$Ln(Edu_{it})$		1.200*** (39.31)		1.231*** (40.16)		1.434*** (61.234)		0.498*** (12.61)		0.095*** (5.45)		0.233*** (120.20)
$Ln(FDI_{it})$		−0.012 (−1.22)		−0.022** (−2.29)		−0.027*** (−2.819)		−0.078*** (−9.29)		0.015** (2.44)		−0.002** (−2.56)
SIC_{it}		0.362*** (5.93)		0.457*** (7.52)		0.499*** (8.121)		4.594*** (28.26)		0.009 (0.21)		−0.012 (−1.59)
$Ln(IT_{it})$		0.080*** (5.50)		0.070*** (4.74)		0.084*** (5.674)		−0.014 (−1.11)		0.024*** (3.83)		0.039*** (27.91)
$Ln(PP_{it})$		−0.093* (−1.70)		−0.121** (−2.41)		−0.058 (−1.036)		0.438*** (6.55)		0.031 (1.41)		−0.039*** (−10.64)
Constant	−5.039*** (−2.80)	−2.850* (−1.90)	−12.603*** (−65.10)	−5.636*** (−12.30)	6.756*** (25.826)	−4.045*** (−9.090)	−7.982*** (−47.61)	−9.033*** (−14.27)	−1.162*** (−10.93)	−0.619*** (−2.86)	−1.251*** (−7.09)	−0.468*** (−17.26)
$Ln(Patent_{i,t-1})$											0.919*** (101.88)	0.857*** (839.39)
R-squared	0.740	0.845	0.728	0.841	−0.075	0.825	0.459	0.681				
city FE	YES	YES	YES	YES	YES	YES	YES	YES				
year FE	YES	YES	YES	YES	YES	YES	YES	YES				
Sargan test											0.104	0.113
AR(1)											0.000	0.000
AR(2)											0.876	0.823

Note: t-statistics are in parenthesis; ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

3.3. Further analysis

3.3.1. Mechanism analysis

Deeper than the existing literature, we paid more attention to how *HP* affects cities' *IC* in China. As discussed earlier, *HP* may affect cities' *IC* in five ways: real estate investment, talent flow, bank credit, local fiscal revenue, and residents' consumption ability. Referring to Wen et al. (2021), we empirically tested these five mechanisms by adding two independent variables into Equation (2). Specifically, in order to verify whether higher *HP* could inhibit cities' *IC* by attracting funds into the real estate sector and thus crowding out innovation funds, as shown in Equation (7), we added investment in real estate ($Ln(IRE_{it})$) and the interaction term of *HP* and investment in real estate ($Ln(HP_{it})*Ln(IRE_{it})$) into Equation (2). To verify whether the rise of *HP* could affect cities' *IC* by affecting the city's choice of talents, as shown in Equation (8), we added the number of talents ($Ln(NT_{it})$) and the interaction term of *HP* and the number of talents ($Ln(HP_{it})*Ln(NT_{it})$) into Equation (2). To verify whether rising *HP* could improve cities' *IC* by easing enterprise financing constraints, as shown in Equation (9), we added bank credit scale ($Ln(BC_{it})$) and the interaction term of *HP* and bank credit scale ($Ln(HP_{it})*Ln(BC_{it})$) into Equation (2). To verify whether the rise of *HP* could encourage cities' *IC* by promoting the rise of land price and thus increasing local fiscal revenue, as shown in Equation (10), we added local fiscal revenue ($Ln(LFR_{it})$) and the interaction term of *HP* and local fiscal revenue ($Ln(HP_{it})*Ln(LFR_{it})$) into Equation (2). To verify whether rising *HP* could affect cities' *IC* by affecting residents' consumption ability, as shown in Equation

(11), we added residents' consumption ability ($Ln(CA_{it})$) and the interaction term of *HP* and residents' consumption ability ($Ln(HP_{it})*Ln(CA_{it})$) into Equation (2). In Equations (7) to (11), the proxy of *IRE* was annual completed investment in real estate development; the proxy of *NT* was the number of university students per 10 thousand citizens; the proxy of *BC* was the balance of RMB credit funds of monetary institutions at year-end; the proxy of *LFR* was the annual general budget revenue of municipal finance; and the proxy of *CA* was the per capita consumption expenditure of urban residents. The data of *IRE*, *NT*, *BC*, *LFR* and *CA* are available from China's real estate information network.

$$Ln(CIC_{it}) = \alpha_0 + \alpha_1 Ln(HP_{it}) + \alpha_2 Ln(IRE_{it}) + \alpha_3 (Ln(HP_{it}) * Ln(IRE_{it})) + \beta Z_{it} + \mu_i + \nu_t + \varepsilon_{it}; \quad (7)$$

$$Ln(CIC_{it}) = \alpha_0 + \alpha_1 Ln(HP_{it}) + \alpha_2 Ln(NT_{it}) + \alpha_3 (Ln(HP_{it}) * Ln(NT_{it})) + \beta Z_{it} + \mu_i + \nu_t + \varepsilon_{it}; \quad (8)$$

$$Ln(CIC_{it}) = \alpha_0 + \alpha_1 Ln(HP_{it}) + \alpha_2 Ln(BC_{it}) + \alpha_3 (Ln(HP_{it}) * Ln(BC_{it})) + \beta Z_{it} + \mu_i + \nu_t + \varepsilon_{it}; \quad (9)$$

$$Ln(CIC_{it}) = \alpha_0 + \alpha_1 Ln(HP_{it}) + \alpha_2 Ln(LFR_{it}) + \alpha_3 (Ln(HP_{it}) * Ln(LFR_{it})) + \beta Z_{it} + \mu_i + \nu_t + \varepsilon_{it}; \quad (10)$$

$$Ln(CIC_{it}) = \alpha_0 + \alpha_1 Ln(HP_{it}) + \alpha_2 Ln(CA_{it}) + \alpha_3 (Ln(HP_{it}) * Ln(CA_{it})) + \beta Z_{it} + \mu_i + \nu_t + \varepsilon_{it}. \quad (11)$$

The estimation results of the mechanisms underlying the *HP-IC* link in Chinese cities are shown in Table 3. Columns I and II show the results of the intermediary role of real estate investment between *HP* and cities' *IC*. The significant negative coefficient of *IRE* in Column I indicates that real estate investment has an inhibitory effect on cities' *IC* in China. The interaction term $Ln(HP_{it})*Ln(IRE_{it})$ in Column II has a significant negative coefficient as well. This means that increasing *HP* can worsen cities' innovation performance by attracting more money into the real estate industry. Columns III and IV show the results of the intermediary role of talents between *HP* and cities' *IC* in China. The estimation coefficient of *NT* in Column III is positive and significant, revealing that talent is an important element to enhance cities' *IC*. According to Column IV, the interaction term $Ln(HP_{it})*Ln(NT_{it})$ has a significant positive coefficient, such that a rise in *HP* augments cities' *IC* in China by attracting talents. Columns V and VI show the estimated findings of the intermediary role of bank credit between *HP* and cities' *IC* in China. As per our expectation, the growth of *HP* enhances enterprises' mortgageable real estate value, which can alleviate enterprises' financing constraints to a certain extent, and thus increase credit funds available for innovation. The increase of enterprises' innovation input is conducive to the improvement of enterprises' innovation output. As a result, the innovation performance of the cities where the enterprises are located can be improved. The coefficient of *BC* in Column V is significantly positive, meaning that credit support is another important factor for the improvement of cities' *IC*. However, the estimation coefficient obtained by the interaction term $Ln(HP_{it})*Ln(BC_{it})$ in Column VI is not statistically significant, showing that higher *HP* cannot improve cities' *IC* in China by expanding the scale of bank credit, which is inconsistent with our expectation. This may be because although in theory, the appreciation of enterprises' real estate that can be mortgaged would enable enterprises to obtain more loans from banks for innovation investment, collateral is not the only condition for obtaining loans. Especially when the central bank's policy aims to tighten bank credit, the increase in the value of real estate will not facilitate enterprises in securing more funds for innovation. Columns VII and VIII show the estimated results of the intermediary role of local fiscal revenue between *HP* and cities' *IC*

Table 3. Mechanism tests

	Investment in real estate		The number of talents		Bank credit		Local fiscal revenue		Consumption ability	
	I	II	III	IV	V	VI	VII	VIII	IX	X
$Ln(HP_{it})$		0.138** (2.46)		0.473*** (3.25)		0.322*** (4.26)		0.207*** (3.99)		0.120*** (3.84)
$Ln(EG_{it})$	−0.076** (−2.51)	−0.102*** (−3.40)	1.869*** (21.98)	1.823*** (21.07)	−0.080*** (−2.88)	−0.090*** (−3.24)	−0.075** (−2.48)	−0.098*** (−3.30)	−0.076** (−2.39)	−0.097*** (−3.08)
$Ln(Edu_{it})$	1.311*** (42.45)	1.108*** (31.42)	0.478*** (8.10)	0.450*** (7.52)	0.903*** (31.16)	0.788*** (23.92)	1.268*** (37.29)	1.087*** (28.21)	1.409*** (54.65)	1.230*** (37.86)
$Ln(FDI_{it})$	−0.035*** (−3.59)	−0.018* (−1.85)	−0.048*** (−3.96)	−0.049*** (−4.03)	−0.005 (−0.60)	−0.003 (−0.35)	−0.030*** (−3.09)	−0.013 (−1.35)	−0.026*** (−2.59)	−0.009 (−0.90)
SIC_{it}	0.482*** (7.87)	0.365*** (5.99)	3.414*** (15.37)	3.361*** (15.00)	0.268*** (4.72)	0.253*** (4.44)	0.508*** (8.30)	0.382*** (6.27)	0.479*** (7.79)	0.390*** (6.35)
$Ln(IT_{it})$	0.084*** (5.71)	0.078*** (5.33)	−0.015 (−0.77)	−0.020 (−1.02)	0.070*** (5.12)	0.060*** (4.42)	0.077*** (5.23)	0.073*** (5.00)	0.090*** (5.85)	0.080*** (5.21)
$Ln(PP_{it})$	−0.074 (−1.33)	−0.111** (−2.03)	1.846*** (20.09)	1.802*** (19.37)	−0.092* (−1.80)	−0.091* (−1.80)	−0.081 (−1.45)	−0.120** (−2.20)	−0.074 (−1.30)	−0.101* (−1.82)
$Ln(IRE_{it})$	−0.128*** (−6.08)	−0.054*** (−6.36)								
$Ln(HP_{it})*Ln(IRE_{it})$		−0.082*** (−7.91)								
$Ln(NT_{it})$			0.024* (1.67)	0.553** (2.34)						
$Ln(HP_{it})*Ln(NT_{it})$				0.067** (2.26)						
$Ln(BC_{it})$					0.699*** (27.14)	0.717*** (7.57)				
$Ln(HP_{it})*Ln(BC_{it})$						−0.005 (−0.48)				
$Ln(LFR_{it})$							0.100*** (6.70)	0.379*** (6.09)		
$Ln(HP_{it})*Ln(LFR_{it})$								0.059*** (7.87)		
$Ln(CA_{it})$									0.062*** (3.00)	0.056*** (2.72)
$Ln(HP_{it})*Ln(CA_{it})$										−0.172*** (−5.36)
Constant	−3.259*** (−7.26)	−2.394*** (−4.18)	−27.581*** (−28.53)	−30.294*** (−21.31)	−3.938*** (−9.92)	−5.275*** (−7.76)	−2.814*** (−6.02)	−2.622*** (−4.86)	−4.152*** (−8.80)	6.926*** (2.88)
R-squared	0.839	0.845	0.781	0.783	0.864	0.866	0.839	0.846	0.836	0.841
city FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: t-statistics are in parenthesis; ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

in China. The significant positive coefficient of *LFR* in Column VII shows that the financial support of local governments can significantly improve the innovation performance of cities, which indicates that government funds may play a guiding role in innovation activities. The statistically significant positive coefficient held by the interaction term $Ln(HP_{it})*Ln(LFR_{it})$ in Column VIII points out that higher *HP* can improve cities' *IC* by increasing local fiscal revenue. Columns IX and X show the estimated results of the intermediary role of residents' consumption ability between *HP* and cities' *IC* in China. *CA* shows a significant positive coefficient in Column IX, which indicates that the improvement of residents' consumption ability has a positive effect on cities' *IC*. The interaction term $Ln(HP_{it})*Ln(CA_{it})$ in Column X has a significant negative coefficient, which can be inferred as the rise of *HP* impeding cities' *IC* by inhibiting residents' consumption ability in China.

3.3.2. Heterogeneity analysis

Due to the huge difference in resource endowment among Chinese cities, there is significant heterogeneity in urban development in China, which is reflected in the discrepancies in cities' real estate market activity, talent attraction, financial industry development, local fiscal revenue, and resident consumption power. As such, the impact of *HP* on cities' *IC* in China may not be generalizable. In other words, cities with different development levels could vary in terms of if and how *HP* affects their innovation performance. Referring to Huang et al. (2021), this paper defines four types of cities, namely megacities (i.e., first-tier cities and new first-tier cities), large cities (i.e., second-tier cities), medium-sized cities (i.e., third-tier cities) and small cities (i.e., fourth- and fifth-tier cities) for heterogeneity analysis[3]. Specifically, the full-sample of 269 cities involved in this study were divided into the aforesaid four sub-samples by city type. Then, the four sub-samples were estimated with Equation (1) to examine whether an inverted U-shaped link exists between *HP* and innovation output in the four categories of cities. If the inverted U-shaped effect is excluded in some (or all) sub-samples, Equation (2) would be used for re-estimation.

We first employed Equation (1) to regress the four sub-samples individually, the results of which are depicted in Columns I, II, IV, and VI of Table 4. The results reveal that *HP* and the squared term of *HP* in Column I have a significant positive and negative coefficient, respectively, which preliminarily implies that *HP* has an inverted U-shaped effect on the innovation output of China's megacities. According to Lind and Mehlum (2010), It is not sufficient to conclude that a U-shaped relationship exists solely based on the presence of a significant quadratic term, as other types of relationships such as convex and monotonic can also produce a U-shaped pattern and an extreme point. As per their suggestion, a Utest was conducted to further confirm the inverted U-shaped relationship in China's megacities (see Table 5). As shown in Table 5, the extreme point lies in the interval and is significant. At the same time, one of the slopes is negative in the interval. Therefore, we rejected the null hypothesis of the monotone or U-shape relationship, and confirmed the existence of an inverted U-shaped link. In addition, according to Table 5, the extreme point for *HP* is 10.06[4]. This means that when *HP* is lower than RMB 23,388.51, rising *HP* can promote the *IC* of these cities, while when *HP* exceeds RMB 23,388.51, rising *HP* will inhibit the *IC* of these cities. As of 2018, among these megacities in China, the *HP* in Beijing and Shenzhen exceeded RMB 23,388.51[5], which indicates that high *HP* has begun to restrain the innovative performance of Beijing and Shenzhen. However, based on Columns II, IV and VI of Table 4, the coefficients for the squared term of *HP* in these three columns are insignificant, negating the inverted U-shaped pattern of *HP*'s effect on innovation output in the sub-samples of large, medium-sized, and small cities. As such, Equation (2) was used to re-estimate the three sub-samples, for which the results are presented in Columns III, V and VII of Table 4. Consistent with the baseline regression output, *HP* holds significant positive coefficients in the three columns, verifying that rising *HP* can improve the innovation performance of large, medium-sized, and small cities in China.

[3] The four types of cities are presented in List A1 of Appendix.

[4] The anti-log of 10.06 is 23,388.51.

[5] *HP* here refers to real housing prices, not nominal housing prices.

In a word, *HP* has a positive influence on the *IC* of China's non megacities, but an inverted U-shaped influence on the *IC* of the megacities in China. This varying relationship could be caused by the fact that *HP* in the megacities far exceeds that of other cities in China. As discussed in Section 1.3, *HP* could have a positive or inverted U-shaped impact on cities' *IC*, which depends on whether *HP* has crossed the point where the positive effects of loosened enterprise financing constraints and increased local fiscal revenue (as a result of higher *HP*) on cities' *IC* are offset by the negative effects of brain drain, declined consumption power, and loss of innovation funds (as a result of higher *HP*) on cities' *IC*. Notably, the inverted U-shaped effect detected in the sub-sample of megacities suggests that it is unsustainable to increase cities' *IC* by raising *HP*.

Table 4. Heterogeneity analysis

	Megacities	Large cities		Medium-sized cities		Small cities	
	I	II	III	IV	V	VI	VII
$Ln(HP_{it})$	9.455*** (15.63)	0.083 (0.12)	0.392*** (3.56)	3.225** (2.46)	0.413*** (4.12)	3.382*** (3.94)	0.511*** (8.80)
$(Ln(HP_{it}))^2$	−0.470*** (−14.30)	0.001 (0.02)		−0.191 (−0.47)		−0.272 (−0.60)	
$Ln(EG_{it})$	0.580*** (3.43)	0.127 (1.33)	0.112 (1.17)	−0.035 (−0.70)	−0.035 (−0.69)	0.036 (1.03)	0.029 (0.82)
$Ln(Edu_{it})$	0.836*** (7.09)	1.177*** (13.55)	1.136*** (13.36)	0.801*** (14.01)	0.812*** (14.23)	0.913*** (23.75)	0.915*** (23.70)
$Ln(FDI_{it})$	−0.058 (−1.07)	−0.061** (−2.25)	−0.069** (−2.53)	−0.060*** (−3.04)	−0.063*** (−3.18)	0.009 (0.86)	0.009 (0.82)
SIC_{it}	0.211* (1.97)	0.250** (2.19)	0.297*** (2.64)	0.190* (1.74)	0.180* (1.65)	0.148* (1.69)	0.149* (1.70)
$Ln(IT_{it})$	0.057 (0.75)	0.109 (1.62)	0.074 (1.13)	0.126*** (4.14)	0.131*** (4.33)	0.029* (1.87)	0.031* (1.93)
$Ln(PP_{it})$	0.421* (1.78)	−1.649*** (−3.13)	−1.186** (−2.47)	−0.291*** (−2.71)	−0.282*** (−2.62)	0.724*** (9.66)	0.694*** (9.26)
Constant	−10.978* (−1.86)	15.689** (2.06)	1.067 (0.37)	−16.291*** (−3.38)	−6.140*** (−6.33)	−14.349*** (−4.94)	−2.524*** (−3.26)
R-squared	0.928	0.918	0.917	0.906	0.905	0.860	0.820
city FE	YES	YES	YES	YES	YES	YES	YES
year FE	YES	YES	YES	YES	YES	YES	YES

Note: t-statistics are in parenthesis; ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5. Utest for the sub-sample of megacities

Extreme point	10.06	
	Lower bound	Upper bound
Interval	7.07	10.43
Slope	2.65	−0.68
t-value	19.75	−6.01
P > t	0.00	0.00
t-value	6.01	
P	0.00	

Note: Test: H_1: Inverted U-shape vs. H_0: Monotone or U-shape.

Conclusions

Endogenous growth theory puts innovation in an extremely important position, holding that technological progress is the decisive factor of sustainable economic growth. The changes in a city's *HP* may affect its *IC* through the five ways of real estate investment, talent flow, enterprises' financing constraints, local fiscal revenue, and residents' consumption ability. Due to insufficient innovation momentum and the overall slowdown of economic growth in China, it is of extreme practical importance of examine how *HP* can affect cities' *IC* in China. As such, this paper utilized the fixed effect model, placebo test, Poisson model, and System GMM to analyze the unbalanced panel data of 269 Chinese cities from 2003 to 2018, with the aim of empirically validating the possible effect of *HP* on cities' *IC* in China. To more accurately describe the influence of *HP* on cities' *IC*, a series of control variables were included in the analysis framework. Our estimation results revealed that *HP* has a significant positive effect on the *IC* of cities. As for the control variables, education, service industry cluster, and international trade all improve the *IC* of cities, while economic growth, *FDI*, and permanent population inhibit the progress of *IC* in Chinese cities. Then, by adding interactions to the model, we explored how *HP* impacts cities' *IC* in China through various mechanisms. The results show that an increase in *HP* can improve the *IC* of cities by attracting talents and increasing local fiscal revenue. At the same time, rising *HP* can curb the *IC* of cities by drawing funds to the real estate market and curbing residents' consumption ability. In addition, perhaps due to the tight bank credit scale, rising *HP* cannot improve cities' *IC* by easing the financing constraints of enterprises in China. Finally, the full-sample was divided into four city sub-samples for heterogeneity analysis. The results report that an increase in *HP* is favorable for the *IC* of large, medium-sized, and small cities in China, but has an inverted U-shaped effect on the *IC* of megacities in China.

Our findings offer alternative measures for Chinese local authorities to boost cities' *IC*. First, given the finding on the heterogenous link between *HP* and cities' *IC* in different categories of cities, we believe that urban innovation promotion is a place-based policy practice. Specifically, since higher *HP* augments the *IC* of non megacities in China, from the perspective of urban innovation promotion, house price regulation in these cities is not necessary for the time being. At the same time, increasing *HP* exerts an inverted U-shaped effect on the *IC* of China's megacities. In Beijing and Shenzhen where *HP* has crossed the inflection point, these cities should immediately take measures to regulate *HP* to alleviate the negative impact of a further rise in *HP* on their innovation performance. For instance, studies have found that certain methods, such as land price control, housing credit scale limitation, and home purchase restrictions[6], are effective in regulating *HP* in China. Second, as higher *HP* can inhibit the improvement of cities' *IC* in China by attracting funds into the property market, Chinese local authorities must adequately restrain real estate investment. Third, due to the potentially tight bank credit scale, rising *HP* cannot promote the *IC* of cities where enterprises are located by easing enterprises' financing constraints. As such, Chinese local governments should appropriately expand the scale of bank credit to increase the availabil-

[6] Home purchase restrictions include restrictions on outsiders' house purchases and on second house purchases, which can effectively curb speculation in the housing market and achieve *HP* regulation.

ity of loans for innovation. Finally, due to the great pressure on China's local governments regarding GDP assessment, they tend to over-guide capital to areas that can quickly increase regional GDP in the short term, such as real estate investment, while ignoring the decisive role of innovation in the process of long-term economic growth. As such, per capita GDP has an unexpected negative effect on the *IC* of cities in China. In order to correct this abnormal result, China's central government should minimize the position of GDP in local governments' performance appraisal and take cities' *IC* as a component of their performance.

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APPENDIX

List A1. The city list

Megacities: Beijing, Shanghai, Guangzhou, Shenzhen, Chengdu, Chongqing, Hangzhou, Wuhan, Xian, Suzhou, Tianjin, Nanjing, Changsha, Zhengzhou, Dongguan, Qingdao, Foshan, Ningbo, Hefei

Large cities: Shenyang, Changchun, Changzhou, Dalian, Guiyang, Haerbin, Haikou, Huizhou, Jiaxing, Shijiazhuang, Jinan, Jinhua, Kunming, Lanzhou, Nanchang, Nanning, Nantong, Quanzhou, Shaoxing, Taiyuan, Wenzhou, Wuxi, Xiamen, Xuzhou, Yangzhou, Yantai, Zhongshan, Zhuhai

Medium-sized cities: Anqing, Anshan, Baoding, Baotou, Bengbu, Cangzhou, Chaozhou, Chenzhou, Chuzhou, Daqing, Fuyang, Ganzhou, Guilin, Handan, Hengyang, Huaian, Huhehaote, Huzhou, Jiangmen, Jieyang, Jilin, Jingzhou, Jining, Jiujiang, Langfang, Lianyungang, Linyi, Lishui, Liuzhou, Luoyang, Maanshan, Meizhou, Mianyang, Nanchong, Nanyang, Ningde, Putian, Qingyuan, Qinhuangdao, Sanya, Shangqiu, Shangrao, Shantou, Suqian, Taian, Taizhou, Tangshan, Weifang, Weihai, Wuhu, Wulumuqi, Xiangtan, Xianyang, Xinxiang, Xinyang, Yancheng, Yichang, Yinchuan, Yueyang, Zhangzhou, Zhanjiang, Zhaoqing, Zhenjiang, Zhoushan, Zhuzhou, Zibo, Zunyi, Suzhou, Taizhou, Xiangyang

Small cities: Ankang, Anshun, Anyang, Baicheng, Baise, Baiyin, Baoji, Baoshan, Bazhong, Beihai, Benxi, Binzhou, Bozhou, Changde, Changzhi, Chaoyang, Chengde, Chifeng, Chizhou, Chongzuo, Dandong, Datong, Dazhou, Deyang, Dezhou, Dingxi, Dongying, Eerduosi, Fangchenggang, Fushun, Fuxin, Fuzhou, Guangan, Guangyuan, Guigang, Hanzhong, Hebi, Yulin, Hechi, Hegang, Heihe, Hengshui, Heyuan, Heze, Hezhou, Huaibei, Huaihua, Huainan, Huangshi, Huanggang, Huangshan, Huludao, Hulunbeier, Jiamusi, Jian, Jiaozuo, Jiayuguan, Jinchang, Jincheng, Jingdezhen, Yichun, Jingmen, Jinzhong, Jinzhou, Jiuquan, Kaifeng, Laibin, Laiwu, Leshan, Liaocheng, Liaoyang, Liaoyuan, Lijiang, Lincang, Linfen, Liuan, Liupanshui, Longnan, Loudi, Luohe, Luzhou, Lvliang, Maoming, Mudanjiang, Neijiang, Panjin, Panzhihua, Pingdingshan, Pingliang, Pingxiang, Puyang, Qingyang, Qiqihaer, Qitaihe, Qujing, Quzhou, Rizhao, Sanmenxia, Shangluo, Shanwei, Shaoguan, Shaoyang, Shuangyashan, Shuozhou, Siping, Suihua, Suining, Suizhou, Tianshui, Tieling, Tongchuan, Tonghua, Tongliao, Tongling, Weinan, Wuhai, Wulanchabu, Wuzhou, Xianning, Xiaogan, Xingtai, Xining, Xinyu, Xinzhou, Xuancheng, Xuchang, Yaan, Yan, Yanan, Yangjiang, Yangquan, Yibin, Yichun, Yingkou, Yingtan, Yiyang, Yongzhou, Yuncheng, Yunfu, Yuxi, Zaozhuang, Zhangjiajie, Zhangjiakou, Zhangye, Zhaotong, Zhoukou, Zhumadian, Zigong, Ziyang, Zuishan, Puer, Yulin.

Table A1. Multicollinearity test

Variable Name	VIF	1/VIF
HP	3.81	0.262443
EG	3.30	0.303362
Edu	3.16	0.316476
FDI	2.78	0.359287
SIC	2.08	0.480175
IT	1.96	0.510464
PP	1.21	0.827565
Mean VIF	2.61	