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# THE SPATIAL INTERRELATIONSHIP BETWEEN HOUSING AND LAND PRICES: EVIDENCE FROM CHINA

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**Abstract.** The interrelationship between housing and land prices has long been a puzzle in China. Using a panel dataset of 286 prefecture-level cities from 2011 to 2020, we construct a spatial simultaneous-equations model and estimate it with the feasible generalized spatial three- stage least squares (FGS3SLS) approach. Results show significant mutual causality and spatial spillovers between housing and land prices. A 1% rise in local housing prices increases local land prices by about 0.71%, with a comparable effect from neighboring housing markets. Regional heterogeneity is evident: the housing-to-land price effect is strongest in western cities (0.93%) and weaker in eastern cities (0.53%), reflecting differences in local government incentives and market structures. By capturing both bidirectional causality and spatial-temporal variation, this study offers new evidence on the mechanisms linking housing and land markets and provides insights for regionally differentiated housing and land policies in China.

**Keywords:** spatial panel simultaneous-equations model, housing price, land price, FGS3SLS, geo-economic weights, China.

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## 1. Introduction

The sustainable and healthy development of land and housing markets has long been a key objective for both local and central governments in China. Following the termination of welfare-based housing allocation in 1998 as part of housing reform, China established a market-based housing system (Man, 2011). Since then, the average living space per capita in urban areas has risen from 17 in 1996 to 40 square meters in 2019.[1] Concurrently, residential house prices and land prices have surged, leading to significant socio-economic challenges (Chen & Wen, 2017). Local governments are under pressure from both central authorities and residents to control housing prices (Yang et al., 2015; Wang & Hui, 2017). In this context, local governments typically focus more on regulating land markets than directly controlling housing prices, as all land in China is state-owned. Therefore, land market regulation plays a crucial role in stabilizing the housing market, and the subsequent adjustments in housing prices pro- vide key insights for policymakers. The simultaneous interactions between housing and land prices have made their interrelationship an important area of academic inquiry and policy discussion.

The literature on pricing housing and land in urban areas has been expanding significantly. A substantial body of research has explored the economic fundamentals that determine housing prices, including income (Ortalo-Magne & Rady, 2006), employment (Saks, 2008), population (Jeanty et al., 2010), construction costs (Hwang & Quigley, 2006), and proximity to educational resources (Shen & Turner, 2018). In addition to housing prices, numerous studies have examined the factors influencing land values, such as household income (Hardie et al., 2000), population density (Clapp et al., 2001), urbanization rates (Fan et al., 2020), and air pollution (Huang & Du, 2022). Beyond examining housing and land prices separately, recent research has focused on the causality between the two, marking a significant contribution to literature. Some studies argue that a mutually causal relationship exists between land and housing prices (Zeng & Zhang, 2006). The interdependence between land lease and housing prices has also been observed in the UK and the German Erbbaurecht system (Alexander, 2014). Long and Guo (2009) outlines a

[1] http://www.stats.gov.cn/english/

theoretical framework suggesting that land prices initially drive housing prices, which, in turn, lead to a subsequent rise in land prices. Several empirical methods have been used to test the mutual causality between housing and land prices, including linear city models (Kuang, 2005), Granger-causality models (Zeng & Zhang, 2006), error-correction models (ECM) (Song & Gao, 2007), and vector autoregressive (VAR) models (Long & Guo, 2009).

Given the rapidly expanding literature on housing and land prices, consistently and accurately quantifying their causality remains challenging for several reasons. First, the relation- ship is often plagued by the well-known simultaneity problem, which leads to estimation bias if not properly addressed (Anselin, 2013). Second, previous studies have highlighted strong spatial dependence in both housing and land prices, suggesting that local housing markets are likely influenced by neighboring markets (Yu et al., 2016). Ignoring this spatial structure can result in substantial misspecification bias. Additionally, local markets in certain regions may experience unobserved exogenous shocks that are geographically correlated, leading to spatially dependent price disturbances. If not accounted for, spatial dependence in error terms can also result in inconsistent estimates. Moreover, the degrees of mutual influence between housing and land prices remain debated. Some studies argue that the impact of land prices on housing prices is more significant (Zeng & Zhang, 2006), while others suggest the reverse that argue that housing prices have a greater impact on land prices (Long & Guo, 2009). This paper addresses these challenges by considering simultaneity, spatial dependence, and the ambiguity surrounding the direction and magnitude of their mutual influences.

Recent studies have advanced the understanding of the housing-land price nexus by moving beyond simple causality tests and examining the broader institutional, spatial, and policy environments that shape this relationship. In the Chinese context, scholars have documented how land prices transmit to housing prices through expectations, supply constraints, and developer bidding behavior. For example, Wu et al. (2016) show that China's land auction system systematically fuels housing price appreciation by embedding price expectations into land bids. Internationally, Sivitanidou and Sivitanides (2000) and Fernández-Avilés et al. (2012) provide evidence from the U.S. demonstrating that stringent land-use regulation and constrained land availability amplify the pass-through from land prices to housing prices, highlighting the global relevance of this mechanism.

Beyond these foundational studies, newer research emphasizes the institutional and spatial contingencies embedded in the housing-land price relationship. Xiao et al. (2024) show how neighborhood externalities and industrial proximity jointly shape residential land and housing prices, while Han and Feng (2024) demonstrate that affordable housing land supply exerts differentiated price effects across cities of varying sizes. Policy interventions also play a critical role. Wang et al. (2024) finds that housing purchase restrictions reshape land supply dynamics across city tiers, and Chen et al. (2025) shows that house-price conditions imposed during land granting influence second-hand housing markets by altering buyer and seller expectations. Comparative evidence from other emerging markets, such as Lu et al. (2024) on Chiang Mai, further illustrates how urban land-use planning mediates housing price formation. Collectively, these studies underscore that the interrelationship between housing and land prices is not only causal but also deeply conditioned by spatial heterogeneity, institutional design, regulatory frameworks, and market structure. Our study builds on and extends this literature by quantifying cyclical dynamics in the housing-land price nexus and comparing the heterogeneous effects across Chinese cities at different development stages.

While the broad conclusion that housing and land prices are closely interrelated is consistent with existing literature, our study contributes novelty in both methodology and scope. To the best of our knowledge, no previous research has rigorously examined the spatial and causal interrelationship between housing and land prices across Chinese markets using the FGS3SLS framework. By employing a system of simultaneous equations, we explicitly model the bidirectional causality between the two markets, while addressing endogeneity with carefully selected socioeconomic instruments and controlling for spatial dependence within and across equations. Compared with single-equation or conventional panel methods used in earlier studies, this approach yields more reliable and nuanced estimates, thereby strengthening empirical inference and offering new insights into the structural linkages of China's real estate system. Using a unique panel dataset of housing and land prices in 286 prefecture-level cities in China from 2011 to 2020, combined with local socioeconomic indicators from multiple data sources, we comprehensively explore the causal effects between housing and land prices, as well as other key price determinants.[2] To motivate the empirical strategy and justify our econometric setup, we propose a conceptual model describing the utility-consistent behaviors of local governments that regulate housing and land markets. Empirical results confirm the existence of positive causality and spatial dependence between housing and land prices. We find that, on average, the influence of urban housing prices on local land prices is more significant than the reverse, controlling for other local attributes. The geographically and temporally heterogeneous causal effects of the two prices are also explored and confirmed.

Several identification methods have been developed in the literature to address spatial dependence in price variables and unobservables. These two types of spatial relationships, commonly identified in the literature, can

[2] Prefecture-level cities are considered second-level geographical units in China's administrative structure (Ye & Wu, 2014). There are 339 prefecture-level divisions in China. Due to data availability, we select 286 prefecture-level cities in our sample (Ye & Wu, 2014).

introduce bias and inefficiency in empirical estimation if not appropriately accounted for (Anselin, 2013). To address this, Kelejian and Prucha (1998) propose a spatial autoregressive model with spatial autoregressive disturbances. Another source of bias in estimation arises from endogeneity due to simultaneous causality between land and housing prices. To resolve this issue and obtain consistent estimates, Kelejian and Prucha (1998) also developed the feasible generalized spatial two-stage least squares (FGS2SLS) method. However, FGS2SLS uses limited information from separate markets, which may lead to inefficiency. In addition to spatial dependence on unobserved price determinants within each market, inter-market spatial interactions in these unobservables might also exist. To fully address such inter-market spatial dependence, Kelejian and Prucha (2004) proposed the generalized spatial three-stage least squares (GS3SLS) method, which was later improved by Gebremariam et al. (2010) to make it empirically feasible. The FGS3SLS method yields consistent and efficient estimates for an over-identified simultaneous-equations system by utilizing full system-wide information (Irwin et al., 2014). Since its development, FGS3SLS has been employed in various contexts, such as analyzing the relationship between social capital and poverty (Harrison et al., 2019) and the spatial interaction between employment and income growth (Gebremariam et al., 2010).

Compared to the existing literature, our study contributes in four key ways. First, it is the first paper to develop a spatial panel simultaneous-equations model estimated with FGS3SLS, the state-of-the-art technique, to quantify the causality between housing and land prices in China. Second, unlike previous studies that focus only on major cities and earlier data (Wen & Goodman, 2013; Wu et al., 2015), we present broader, more up-to-date empirical results covering most of China's prefecture-level cities. This enables us to uncover hidden geographical heterogeneity in spatial market interactions.[3] Third, by fully considering complex spatial interactions, we construct a novel asymmetric mixed geography-economy weighting matrix that accounts for both geographical and economic correlations across areas.[4] Finally, our work offers insights into the regulation of land and housing markets, which can help mitigate the political pressure faced by local governments in China. It contributes to a better understanding of the interactions between these two markets and provides valuable policy recommendations for local policymakers.

The remainder of this paper is organized as follows. Section 2 provides a summary of empirical background and data. Section 3 presents the methodology. Section 4 discusses empirical results. Finally, Section 5 concludes the paper with a summary of key findings and policy implications.

## 2. Empirical background and data

### 2.1. Land and housing markets in China

An important feature of land markets in China is that governments formally own and regulate all lands. The current urban land allocation system, initiated in 1992 as part of China's economic reform, allows private entities to purchase land use rights from local governments through leaseholds that usually last 40–70 years (Zhu & Dong, 2005). In the 1990s, most land-use rights were allocated through under-the-table negotiations between local governments and developers (Cai et al., 2017), generating widespread corruption. To fix this problem, the Ministry of Natural Resources in China banned negotiated sales and announced that all urban land-use rights must be allocated through public auctions in 2004 (Xu et al., 2009).[5] The pricing of land use rights, since then, has become a very "hot" research area.

At the city level, the auctions of land use rights are implemented by local bureaus of planning and natural resources. Profits from sales of land use rights go directly to local governments with no need to be shared with the state government or administrations at higher levels. There are two types of auctions frequently used in land sales, i.e., the English auction ("*paimai*" in Chinese) and the two-stage auction ("*guapai*" in Chinese). Even if a public auction is an excellent way to prevent corruption in most cases, previous studies have found strong evidence suggesting that officials and developers can still potentially benefit from collusion (Cai et al., 2013; Chen & Kung, 2019). Despite the corruption problem, revenue from land sales has increased steadily over the past two decades. As documented by Ping et al. (2015), the revenue from land sales only took up less than 5% of the total fiscal revenue in 2000 but increased rapidly to over 30% in 2013. In some cities, such as Kunming, Wenzhou, and Taiyuan, land financing has become a dominant component of income resources by local governments, with the ratio of land sales to the local general public budget even exceeding 100%.

As with land prices, housing prices have also risen dramatically nationwide as China's economy has grown over tenfold in the last twenty years. Rising housing expenses and unaffordable housing have become severe socio-economic problems in many urban cities, especially those in more economically developed regions. According to the data from the National Bureau of Statistics of China, the average residential housing price increased from

[3] Some earlier studies on Chinese land and housing prices use data from only 21 provincial cities (Wen & Goodman, 2013) or 35 cities (Wu et al., 2015) in earlier periods (Ye & Wu, 2014; Chen & Chen, 2017).

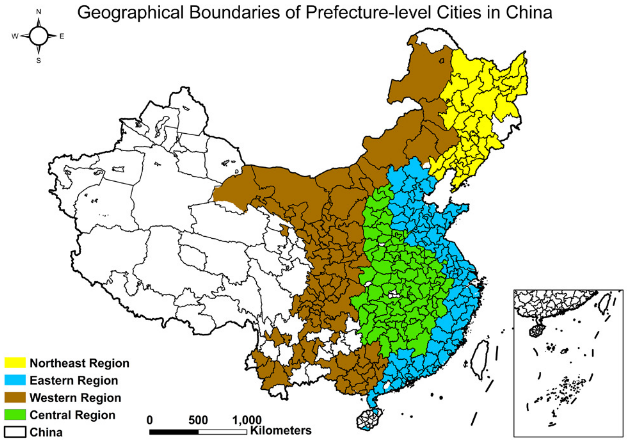
[4] A similar weighting method has been adopted to study the impact of natural resource sector booms on local and neighboring manufacturing sectors in China (Shao et al., 2020).

[5] In March 2004, the Ministry of Land and Resources and the Ministry of Supervision in China jointly issued "Order No. 71", requesting that all sales of urban land-use rights must be processed through public auctions after 08/31/2004.

2,112 Yuan/Meter$^2$ in 2000 to 9,960 Yuan/Meter$^2$ in 2020.[6] The central government, thus, has received significant pressure from ordinary people concerning high housing prices. Since most residents living in urban areas in China purchase residential apartments directly from property developers, multiple measures have been taken to suppress the rapid increase in housing prices, including a high proportion of downpayment, strict limits on purchase eligibility, and high mortgage rates on housing loans. However, the average national housing price growth rate remains very high, given these measures in China. Some studies propose that, on top of a variety of non-policy factors such as demand and speculation, the motivation of land financing that aims to maximize the revenue from land sales by Chinese local governments could be a vital component of the rising residential housing price (Yang et al., 2015; Wang & Hui, 2017). In 2013, the central government announced that officials in local governments need to be held accountable if housing prices in their jurisdictions rise too quickly (Huang & Du, 2018). Since then, local governments have started facing a trade-off between housing and land prices because a higher land price increases fiscal revenue and probably also enhances the probability of getting punished by the central government because of a subsequent increase in the housing price. Therefore, the utility-maximizing objective of the local governments on housing regulation should be considered when quantifying the causal relationship between land and housing prices.

## 2.2. Geography of the study area

We select prefecture-level cities in China as the sample for estimating the spatial panel simultaneous- equations model. Given data availability, we construct a panel dataset consisting of 286 prefecture-level cities, which account for over 70% of the total housing and land markets in China (Zheng et al., 2014). Figure 1 shows the spatial distribution and geographic boundaries of these prefecture-level cities. Many cities in western provinces, such as Tibet and Xinjiang, are sparsely populated and have limited economic fundamentals (Chen & Chen, 2017). Additionally, there is a lack of data on prices and other key variables in certain cities.[7] Consequently, the 286 prefecture-level cities with available data are selected for the sample, as shown in color in Figure 1. Due to the significant regional disparities in China, we categorize all prefecture-level cities into four regions, i.e., eastern, northeast, central, and western, as illustrated with different colors in Figure 1. This categorization helps explore geographical heterogeneity (Ye & Wu, 2014).




*Note*: All 286 prefecture-level cities with available data are shown in color. All Chinese prefecture-level cities are categorized into four regions, i.e., the eastern, northeast, central, and western regions.

**Figure 1.** Geographical boundaries of prefecture-level cities in China

## 2.3. Data

To estimate the pricing models of housing and land prices, we construct a unique dataset comprised of price variables and local socioeconomic indicators that impact these prices from multiple data sources.

**Housing and land prices:** The newly available data on two price variables are first collected for 286 prefecture-level cities, spanning from 2011 to 2020. The housing prices are proxied by all representative housing units' average sales prices across urban cities from China Real Estate Information (CREI), a database organized by State Information Center in China.[8] A prefecture-level housing price is computed by dividing the total residential house sales price by the total sales area, measured as Yuan/Meter$^2$. In addition to the housing price, we attain data on residential land prices in the urban land price monitoring system from China's Ministry of Land and Resources.[9] A land price equals the total payment on urban land use rights transferred to a local government divided by the total land area, measured as Yuan/Meter$^2$. The land price level adequately reflects the information on sales revenue and cost of urban lands across geographical regions.

**Price determinants:** On top of the price variables, we collect rich information on price determinants used to estimate the spatial panel simultaneous-equation model. The panel of local attributes is constructed by data from the China Statistical Yearbook (CSY), National Bureau of

6 http://www.stats.gov.cn/English

7 For example, real estate prices are only available for 286 prefecture-level cities and are missing for others in 2013.

8 The China Real Estate Information (CREI) collects data on a great number of economic and social variables in prefecture-level cities in China. See http://www.crei.cn

9 China's Ministry of Land and Resources is formally responsible for the regulation, preservation, and exploitation of natural resources, such as lands. See: https://www.mlr.gov.cn/mlrenglish

Statistics of China (NBSC)[10], and the China Land and Resources Statistical Yearbook (CLRSY)[11]. Due to the close relationship between the two prices, some overlaps exist between the two groups of price determinants. For the completeness of control variables, variables of urban economic fundamentals and local attributes are assumed to impact both.

Following the approach in Goodkind and West (2002), we select local GDP as the first variable affecting prices, serving as a proxy for the market value of all finished goods and services produced within a region. Additionally, we consider per-capita disposable income, which is calculated as the sum of final consumption expenditures and available savings divided by the total population (Hwang & Quigley, 2006). Urban housing and land prices can also be influenced by local housing investment, defined as the total investment in the real estate market (Goodkind & West, 2002). We include data on local fiscal revenue, representing the income from the financial participation in the distribution of local social products.[12] In addition to government revenue, we include the local residential house sales area, which is the total area of residential houses sold in a given period. Lastly, we account for population density to reflect the local aggregate demand for residential housing.

**Control variables:** To minimize the potential omission of variables and eliminate the bias in estimation, multiple controls in the dataset are extracted from the province or city statistical yearbooks published by the National Bureau of Statistics of China (NBSC). They involve the education expenditure, the number of doctors, the number of books, the number of university teachers, and the areas of road (Chen & Chen, 2017). Following Yuan et al. (2019), we also select a tertiary industry ratio, measured as the ratio of tertiary industry gross product to a local GDP.

## 2.4. Summary statistics

Table 1 presents the summary statistics for all the variables used in the model estimations. The dataset spans from 2011 to 2020 for 286 prefecture-level cities, with annual measurements. The statistics reveal considerable variation in land and housing prices, highlighting the significant spatial inequality in economic development across China. Figure 2 illustrates the spatial variation in land and housing prices averaged over the period 2011-2020. Eastern coastal cities exhibit higher prices, while midwestern inland cities are comparatively economically underdeveloped. In addition to the price variables, various local socio-economic indicators show geographical significance, helping to explain the inter-city disparities in housing and land prices.

**Table 1.** Summary statistics of the variables

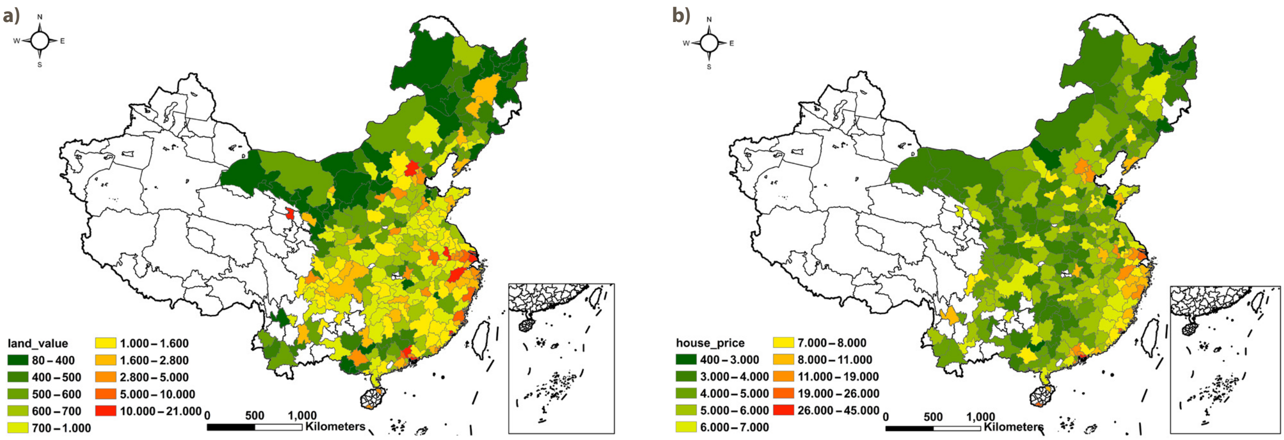
| Variable | Description | Unit | N | Mean | SD | Min | Max | Source |
|---|---|---|---|---|---|---|---|---|
| Price variables | | | | | | | | |
| *LP* | Land price | Yuan/m$^2$ | 2,860 | 1,227 | 1,614 | 20 | 27,150 | CREI |
| *HP* | Housing price | Yuan/m$^2$ | 2,860 | 5,814 | 2,714 | 276 | 50,286 | CREI |
| Price determinants | | | | | | | | |
| *GDP* | Local GDP | $10^9$ yuan | 2,860 | 205 | 279 | 8.79 | 3,128 | NBSC |
| *DI* | Per-capita disposable income | Yuan | 2,860 | 23,124 | 7,238 | 1,940 | 57,232 | CLRSY |
| *HI* | Housing investment | $10^9$ yuan | 2,860 | 174 | 290 | 6.33 | 25,129 | NBSC |
| *FR* | Fiscal revenue | $10^9$ yuan | 2,860 | 2,125 | 4,518 | 35.29 | 66,190 | NBSC |
| *SA* | House sales area | $10^4$ m$^2$ | 2,860 | 401 | 502 | 0.90 | 6,317 | CLRSY |
| *PD* | Population density | #/km$^2$ | 2,860 | 468 | 537 | 0.83 | 5,989 | NBSC |
| Control variables | | | | | | | | |
| *EE* | Education expenditure | $10^9$ yuan | 2,860 | 0.588 | 0.511 | 0.006 | 5.098 | NBSC |
| *Doc* | Number of doctors | # per $10^4$ | 2,860 | 18.09 | 9.89 | 9.09 | 29.03 | NBSC |
| *T* | Number of univ teachers | # per $10^4$ | 2,860 | 24.13 | 20.98 | 4.26 | 52.28 | NBSC |
| *Book* | Number of books | # per 100 | 2,860 | 48.27 | 112.76 | 11.71 | 90.72 | NBSC |
| *Road* | Area of road | m$^2$/# | 2,860 | 10.53 | 26.81 | 3.84 | 16.99 | NBSC |
| *TR* | Tertiary industry ratio | % | 2,860 | 36.91 | 10.98 | 3.79 | 81.13 | CSY |

*Note*: Over 2011–2020, there are a total of 10×286 = 2,860 observations in our balanced panel dataset. All economic variables are measured in the Chinese Yuan.

[10] http://www.stats.gov.cn

[11] https://www.chinayearbooks.com

[12] Revenues from land sales are excluded, as they would be directly related to the dependent variable.




The pattern of spatial variability in land prices

The pattern of spatial variability in housing prices

**Figure 2.** Average land and housing prices over 2011–2020 across prefecture-level cities

## 3. Methodology

### 3.1. Theoretical framework

To model the price dynamics in the housing and land markets, we adopt a comprehensive general equilibrium framework that captures both the mutual causality and spatial dependence within local markets and across neighboring markets (Zhu et al., 2022). Figure 3 illustrates the theoretical framework, showing the causal relationship between housing and land prices. For simplicity, the figure presents the spatial interrelationship between two cities, though the framework can easily be extended to multiple urban areas. We assume a reverse causality between housing and land prices, as documented in previous studies (Anselin, 2013). From the demand side, rising housing prices lead to an increase in land prices, while from the supply side, higher land prices drive up housing prices. Additionally, spatial dependence is incorporated to account for the autocorrelation of prices in neighboring markets. Both land and housing prices are thus determined by local price determinants as well as their spatial interactions with neighboring regions.

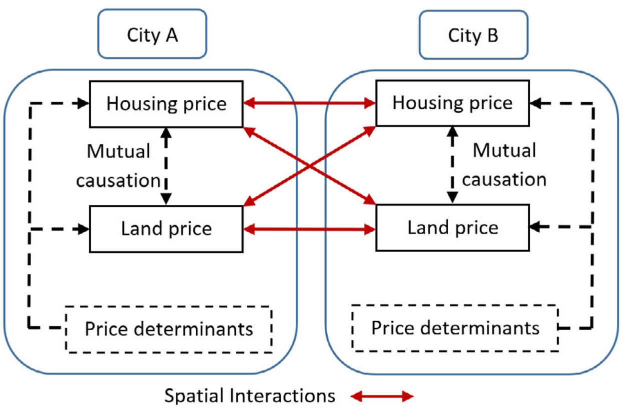



**Figure 3.** Theoretical framework of the causal relationship between housing and land prices

Quantitatively, this framework can also be rationalized by a novel government-centered model. Let $i = 1, ..., n$ denote the indexes for $n$ local governments. In each period $t$, officials in local governments observe land and housing prices of their own and other cities, as well as a set of city-level characteristics. As described in Section 2.1, local governments in China have substantial market power in local land markets as they have both incentives and abilities to affect land prices. Therefore, we assume they can adjust or even determine the equilibrium levels of land prices. Suppose that a local government $i$ has the following utility function:

$$U_{it}\left(,HP_{it}, LP_{-it}, HP_{-it}, Z_{it}, \mu_{it}\right) = \underbrace{\frac{1}{2}LP_{it}^{2} + f\left(Z_{it}, \mu_{it}\right) \times LP_{it}}_{\text{Utility gain from the local land market}} \underbrace{-\frac{1}{2}\left(LP_{it} - g_1\left(HP_{it}\right)\right)^2}_{\text{Utility loss from the local price deviation}} \underbrace{-\frac{1}{2}\left(LP_{it} - g_2\left(LP_{-it}, HP_{-it}\right)\right)^2}_{\text{Utility loss from the global price deviation}}, \quad (1)$$

where $LP_{-it}$ and $HP_{-it}$ denote land and housing prices in cities other than city $i$. The vector, $Z_{it}$, represents all observable market price determinants in city $i$. $\mu_{it}$ is the local market price disturbance only observed by officials in city $i$. $f$, $g_1$, $g_2$ are smooth functions.

The utility function of a local government consists of three terms. The first term is the utility gain from the local land market, which can be interpreted from the perspective of either potential corruption in the local land market (Chen & Kung, 2019) or the increase in the local government revenue (Ping et al., 2015). The second term quantifies the utility loss caused by a price deviation from the central government's signal of a proper local land price. It is motivated by the fact that officials in Chinese local governments face great pressure from the central government regarding housing price control and thus adopt a signal function, $g_1$, of the appropriate local housing price for the local land market. The price deviation in a local land market then incurs a utility loss if the local land price deviates from the corresponding target. The third term measures the utility loss caused by the price deviation from the corresponding signal of relevant markets that can be geographically or politically "close" to the city $i$. It shares a similar spirit with the classic literature on political tournaments in China (Chen et al., 2005; Li & Zhou, 2005; Zhou, 2010; Xu, 2011; Li et al., 2019). As with economic growth, local government officials are regularly evaluated by the upper-level administration for the performance of housing price control within their jurisdictions.[13] However, in contrast to the "economic growth" story in the political tournament literature, a local government's strategy regarding the land price is more ambiguous: it tends to maximize the local land price without getting noticed by the central government. Therefore, its best strategy is to not deviate from the land price signal $g_2(LP_{-it}, HP_{-it})$ delivered by relevant land markets.

The local government then maximizes its utility by determining an optimal local land price considering all three terms. Note that all local governments make decisions simultaneously. By deriving the first-order condition from the Equation (1), the equilibrium land price in city $i$ is given by:

$$LP_{it} = f(Z_{1it}, \mu_{1it}) + g_1(HP_{it}) + g_2(LP_{-it}, HP_{-it}), \tag{2}$$

where $Z_{1it}$ is the vector of local land price determinants and $\mu_{1it}$ is the local land price disturbance.[14] On the other hand, the empirical model of an equilibrium housing price in city $i$ is assumed to be as follows:

$$HP_{it} = h(LP_{it}, HP_{-it}, LP_{-it}, Z_{2it}, \mu_{2it}), \tag{3}$$

where $Z_{2it}$ represents the vector of local housing price determinants and $\mu_{2it}$ is the local housing price disturbance. $h$ is another smooth function for the housing price. Finally, combining the Equations (2) and (3), it becomes clear that the general equilibrium framework presented in Figure 3 is supported by the utility-maximizing behavior of a local government. We model the price dynamics in land and housing markets given this motivation.

## 3.2. Spatial panel simultaneous-equations model

We further develop a spatial panel simultaneous-equations model from the government-centered framework presented above. To mainly focus on linear relationships, assume that the functions, $f$, $g_1$, $g_2$, and $h$, are linear. To capture the relative importance of other markets nearby, $LP_{-it} = \sum_{j=1}^{n} w_{ij}\ln LP_{jt}$ and $HP_{-it} = \sum_{j=1}^{n} w_{ij}\ln HP_{jt}$, where $w_{ij}$ are spatial weights with $w_{ij} = 0$ if $i = j$. We also let $Z_{1it} = (X_{1it}, \delta_{1it}, \theta_{1it})$ and $Z_{2it} = (X_{2it}, \delta_{2it}, \theta_{2it})$, where $X_{1it}$ and $X_{2it}$ represent the exogenous price determinants for land and housing markets, respectively. $\delta_{1i}$ and $\delta_{2i}$ are locational fixed effects included to control for unobserved spatial features within each city, and $\theta_{1t}$ and $\theta_{2t}$ are yearly fixed effects accounting for the temporal dynamics in the two markets. Furthermore, we assume the price disturbances, $\mu_{1it}$ and $\mu_{2it}$, are spatially correlated both within and across two markets. Our econometric specification is presented as follows:[15]

$$\begin{cases} \ln LP_{it} = \alpha_0 + \alpha_1 \ln HP_{it} + \alpha_2 \sum_{j=1}^{n} w_{ij} \ln LP_{jt} + \alpha_3 \sum_{j=1}^{n} w_{ij} \ln HP_{it} + X_{1it}\Pi_1 + \\ \delta_{1i} + \theta_{1t} + \mu_{1it} \\ \ln HP_{it} = \beta_0 + \beta_1 \ln LP_{it} + \beta_2 \sum_{j=1}^{n} w_{ij} \ln HP_{jt} + \beta_3 \sum_{j=1}^{n} w_{ij} \ln LP_{it} + X_{2it}\Pi_2 + \\ \delta_{2i} + \theta_{2t} + \mu_{2it} \\ \mu_{1it} = \rho_1 \sum_{j=1}^{n} w_{ij}\mu_{1jt} + \varepsilon_{1it};\ \mu_{2it} = \rho_2 \sum_{j=1}^{n} w_{ij}\mu_{2jt} + \varepsilon_{2it} \\ \mathrm{var}\begin{pmatrix} \varepsilon_{1it} \\ \varepsilon_{2it} \end{pmatrix} = E\begin{pmatrix} \varepsilon_{1it}^2 & \varepsilon_{1it}e_{2it} \\ \varepsilon_{2it}\grave{o}_{1it} & \varepsilon_{2it}^2 \end{pmatrix} = \begin{pmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{pmatrix} \end{cases} . \tag{4}$$

Our main econometric interest is to estimate parameters ($\alpha$, $\beta$, $\Pi$, $\rho$) that capture the complex interactions between land and housing markets. The spatial weighting method becomes critical for accurately measuring the existing spatial interactions. The key component in the spatial econometric model, the spatial weighting matrix $W$, needs to be appropriately constructed as follows:

$$W_{(n\times n)} = \left[w_1' \ldots w_i' \ldots w_n'\right]' = \begin{bmatrix} 0 & w_{12} & \cdots & w_{1n} \\ w_{21} & 0 & \cdots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \cdots & 0 \end{bmatrix}, \tag{5}$$

[13] As early as 2007, the central government in China made an official announcement that required local governments to take charge of housing issues in their jurisdictions. If local governments fail to fix the problems, the central government will impose some political punishments on local government officials. Since then, the central government has never stopped making such efforts. For example, in the 2016 Central Economic Working Conference, the central government announced that "houses are for living in, not for speculation" and made a series of policies to motivate local governments to stabilize local housing markets. See: http://star.news.sohu.com/20070905/n251965013.html

[14] There exist some overlaps between two groups of price determinants for housing and land prices. However, to make the model more notationally clear, we separate the price determinants of lands from the housing and decompose $Z_{it} = (Z_{1it}, Z_{2it})$. $Z_{1it}$ and $Z_{2it}$ represent the land and housing price determinants, respectively. Similarly, $\mu_{it} = (\mu_{1it}, \mu_{2it})$ denote land and housing price disturbances, respectively.

[15] It is noteworthy that some setups similar to ours have also been adopted by Gebremariam et al. (2010) and Wen and Goodman (2013) in different contexts.

where $w_i = \left[w_{i1} \ldots w_{ij} \ldots w_{in}\right]'$ is the $n \times 1$ weighting vector. The diagonal elements of the matrix are set to zero since there exist no spillover effects on itself, while other non-diagonal elements, $w_{ij}$, are the measures of relative strengths of the linkages between cities $i$ and $j$.

To fully capture various kinds of spatial interactions introduced above, we adopt three sorts of most commonly used spatial weighting methods with typical features, i.e., an inverse-distance weight, an economic weight, and a novel geography-economy weight, as well as some other alternatives for robustness checks (Anselin, 2013).[16] The spatial links between two areas are typically dependent on their geographical distances. To compute distance-related weighting matrices, we first measure the distance between prefecture-level cities by attaining the exact city-specific longitudes and latitudes from the database of the Distance Matrix API in Google Map Platform.[17] Then, given the geographical coordinates, inter-city Euclidean distances are calculated using the ArcGIS, and the inverse-distance weights are defined as follows (Anselin & Bera, 1998):

$$w_{ij} = \frac{1}{d_{ij}}, \tag{6}$$

where $d_{ij}$ denotes an Euclidean distance between the geographical centroids of two urban cities, measured in miles.

On top of the geographical distance, an "economic" distance plays an important role since the strength of spatial interactions of housing and land markets could be affected by economic factors. Following the classic reference (Conway & Rork, 2004), we construct economic weights based on "economic distances" on the following criteria:

$$w_{ij} = \begin{cases} \dfrac{1}{\left|\overline{X_i} - \overline{X_j}\right|}, i \neq j \\ 0, i = j \end{cases}, \tag{7}$$

where $X_i$ represents the sample average of observations on some socioeconomic characteristics in city $i$, such as GDP, total consumption, and per-capita income (Qu & Lee, 2015; Ye et al., 2018). Considering the data availability and more relevance to land and housing prices, we select two economic variables, i.e., the local GDP and per-capita disposable income, to measure "economic distances".[18]

In addition to geographical and economic distances measured separately, the spatial correlation between two cities might relate to both distances simultaneously. For instance, two economically close but geographically distant cities might have a spillover effect on each other. Thus, we construct an asymmetric geography-economy weighting matrix, accounting for the complex geographical and economic linkages. Specifically, the inverse geographic and economic weighted spatial weighting matrix is calculated as follows (Shao et al., 2020):[19]

$$w_{ij} = \begin{cases} \dfrac{1}{d_{ij}\left|\overline{X_i} - \overline{X_j}\right|}, i \neq j \\ 0, i = j \end{cases}, \tag{8}$$

where $\overline{X_i}$ and $d_{ij}$ are defined the same as before. Given the elements $w_{ij}$, these (a)symmetric weighting matrices are then row-standardized, such that $\sum_j w_{ij} = 1$.[20] This normalization ensures that all the weights are between 0 and 1 and that the weighting operation can be interpreted as an average of the neighboring values.[21]

### 3.3. Estimation procedure

We estimate the spatial panel simultaneous-equations model (4) following the feasible generalized spatial three-stage least squares (FGS3SLS) estimation method, which is first put forward by Kelejian and Prucha (2004) and then improved by Gebremariam et al. (2010). The FGS3SLS estimation yields efficient and consistent estimates of the over-identified equation system with system-wide full information in a panel data fixed effect setting. It accounts for the simultaneity, spatial interactions across geographical areas, and spatial disturbances within and potentially between equations. The estimation procedure is outlined below, which is similar to Irwin et al. (2014):

**Step 1:** Taking all price determinants and controls as exogenous instrumental variables for endogenous price

[16] As with other studies, we also conduct robustness checks on several additional weighting methods, such as queen-based spatial contiguity weights, exponential distance weights, and power distance weights (Yu et al., 2016; Harrison et al., 2019; Fan et al., 2020). Most relevant empirical results turn out to be comparable. Due to the space limitation, they are not presented but available from the corresponding author upon request.

[17] https://cloud.google.com/maps-platform/routes/?apis=routes

[18] Given a high correlation between a local GDP and per-capita disposable income (0.96), the relevant empirical results are very similar. Due to the limited space, we choose to report results with the local GDP.

[19] Definitely, the geo-economic weights can be computed by combining the geographical and economic distances in a different method for the robustness checks (Wang & He, 2019). The empirical results turn out to be very robust across the geo-economic weights.

[20] In practice, the weights matrix is typically row-standardized due to the ease of computation (Anselin & Lozano-Gracia, 2008). Admittedly, many different definitions of the neighbor relation are also possible, and there is little formal guidance in the choice of the "correct" spatial weights. For instance, the spatial weight matrix W can also be column normalized. The interpretation for column and row normalized matrix is different. For row normalized weight matrix, the row gives the impact on a given unit by all other units. An element of a column normalized matrix gives the impact of a given unit on all other units (Mussa et al., 2017).

[21] To strengthen the robustness of the geo-economic weight construction, we conduct a sensitivity analysis to examine whether the weighting scheme influences the estimated spillover effects. In addition to the baseline 50% geographical / 50% economic specification, we test two alternative formulations: 40% geographical / 60% eco- nomic and 60% geographical / 40% economic. The results show that the estimated spillover coefficients and the identified regional heterogeneity patterns remain highly consistent across all specifications. These findings indicate that the interaction effects between geographical proximity and economic size are stable, and the main conclusions are not driven by the subjective choice of weight ratios.

variables, the following first-stage regressions are estimated:

$$\begin{cases} \ln LP_{it} = \lambda_0 + X_{1it}\Lambda_1 + \delta_{1i} + \theta_{1t} + u_{1it} \\ \ln HP_{it} = \gamma_0 + X_{2it}\Lambda_2 + \delta_{2i} + \theta_{2t} + u_{2it} \end{cases}, \quad (9)$$

where the coefficients, $\lambda$, $\Lambda$, $\delta$, and $\theta$, are first estimated and used to predict the prices, $\widehat{\ln LP_{it}}$ and $\widehat{\ln HP_{it}}$ .

**Step 2:** The predicted price variables are then used to replace the endogenous price variables in the equation system (4) when estimating the regression coefficients, $\hat{\alpha}$, $\hat{\beta}$, and $\hat{\Pi}$, as well as the spatial disturbances, $\widehat{\mu_{it}}$, in the main spatial pricing equations. Given the computed spatial disturbances, the spatial autoregressive parameters, $\widehat{\rho_1}$ and $\widehat{\rho_2}$, are estimated in a generalized moments procedure. The residuals, $\varepsilon_{it}$, are also computed to estimate the variance-covariance matrix of the disturbances, $E(\varepsilon_n \varepsilon n') = \Sigma \otimes I_n$, where $\Sigma = (\sigma_{it})$ and $\otimes$ denotes the Kronecker product.

**Step 3:** For simplicity, the pricing equation is first rewritten as $y_{it} = Z_{it}\Delta + \mu_{it}$, where $y_{it}$ is the price variable and $Z_{it}$ denotes the vector of all regressors. This equation is followed by the Cochrane-Orcutt transformation (Gebremariam et al., 2010), $y^*_{it}(\rho) = Z^*_{it}(\rho)\Delta + \varepsilon_{it}$, where $y^*_{it}(\rho) = y_{it} - \rho\sum_{j=1}^{n} w_{ij} y_{it}$ and $Z^*_{it}(\rho) = Z_{it} - \rho\sum_{j=1}^{n} w_{ij} Z_{it}$. In the third step, given the estimated spatial autoregressive parameters, $\hat{\rho}$, the FGS3SLS estimator, Δ, is computed in the transformed regression model as follows:

$$\hat{\Delta}^{FGS3SLS} = \left[\hat{Z}^*_{it}(\hat{\rho})'\left(\hat{\Sigma}_n^{-1} \otimes I_n\right)\hat{Z}^*_{it}(\hat{\rho})\right]\hat{Z}^*_{it}(\hat{\rho})'\left(\hat{\Sigma}_n^{-1} \otimes I_n\right) y^*_{it}(\hat{\rho}), \quad (10)$$

where $\hat{\Sigma}$ is the estimated variance-covariance matrix whose elements $\widehat{\sigma_{it}} = n^{-1}\widehat{\epsilon_{it}}'\widehat{\epsilon_{it}}$.

## 4. Empirical results

Following the Feasible Generalized Spatial Three-Stage Least Squares (FGS3SLS) estimation method, we present the empirical results based on the framework outlined in Figure 3.

### 4.1. Global estimation results

Before estimating the spatial models, we first confirm the endogeneity of price variables. To this end, we adopt a Durbin-Wu-Hausman test and reject the hypothesis of exogenous land and housing prices (Anselin, 2013).[22] Some might also be concerned about the invalidity and weakness of instrumental variables chosen in this paper. We then test and confirm the validity of the IVs in the first-stage regressions.[23]

Table 2 presents the estimation results of the spatial model (4) under the spatial econometric framework with varying weighting methods, as well as the relevant non-spatial models. It is seen in columns [1] and [2] that the non-spatial models yield some misleading estimates with- out controlling for spatial dependence. The effects of land and housing prices on each other have been substantially overestimated, while the estimates of a local GDP and housing investment turn out to be opposite to conventional wisdom. A Moran's *I* test is conducted for two endogenous price variables, confirming the existence of spatial autocorrelation (Kelejian & Prucha, 2001). On top of that, the statistical significance of estimated coefficients on spatial autocorrelations of prices and spatial autoregressive parameters of error terms, $\rho_{LP}$ and $\rho_{HP}$, further suggests the necessity of accounting for the spatial dependence. Combining both geographical and economic spatial linkages, the empirical findings with the geo-economic weights lie between two separate weights. Moreover, given the higher adjusted $R^2$, the FGS3SLS estimation method improves the model fit over the relevant non-spatial models. The goodness of fit also implies that the spatial geo-economic weights prove to be empirically preferred over the regular geographical and economic weights when estimating the spatial panel simultaneous-equations model. Therefore, we mainly focus on the empirical findings with the spatial geo-economic weights.

Table 2 shows that housing and land prices have a mutually endogenous and positive relationship, with each significantly affecting the other within an urban city. The impact of a city's housing price on its own land price is found to be more significant than the reverse relationship between land prices and housing prices. This finding is consistent with the main conclusions in Wen and Goodman (2013), though the estimates are larger when using the FGS3SLS estimation method. The Chinese housing market has experienced strong demand and rising prices over the past decade, with homebuyers and developers anticipating continued price growth. This expectation creates a feedback loop, driving higher investment demand for real estate. Consequently, housing developers are incentivized to place higher bids for residential land sold by local governments. Given the inelastic supply of residential land in the short term, any increase in housing prices is quickly capitalized into land values, resulting in significant increases in local land prices. In contrast, the responsiveness of local housing prices to changes in land prices is much weaker. This is primarily due to the fact that land values constitute only a fraction of housing prices, meaning that to equalize the change in housing price with that in land price, the land price must adjust more than the housing price. Additionally, local governments do not directly regulate housing prices, which are also influenced

[22] The Durbin-Wu-Hausman test statistic is 29.12 ($p$-value < 0.01), which implies the rejection of the null hypothesis that the prices are exogenous.

[23] Due to the overidentifying restrictions, we use *J*-test and fail to reject the null hypothesis of instrument exogeneity (Fernández-Avilés et al., 2012). The *J* statistic = $mF$ = 1.392 < 3.841 (critical value of $\chi^2$ at the 5% significance level). Then, we perform a *F* test to examine the relevance of the instruments. The prices are found to be jointly and significantly correlated to instrumental variables with high *F* statistics.

by homebuyers' preferences. As a result, housing prices respond to changes in land prices only in proportion to the land's share in overall housing prices.

On top of the positively mutual interrelationship and spatial autocorrelation of the two prices, we find their cross-regressive spatial lags. Housing prices in nearby cities have a spillover effect on the local land value, which, in reverse, impacts housing prices in neighboring urban cities. As with the own-city effects, the cross-city impact of nearby housing prices on the local land value is also larger than the spatial spillover effect of land prices in nearby cities on the local housing price. Following Anselin (2013), we further compute the marginal effects of price variables based on the estimated coefficients in the spatial models. To decom- pose the spatial interactions of land and housing prices, we calculate the direct ("own" effect), indirect (spatial spillover effect), and total impacts of land and housing prices on each other, as shown in Table 3 (Golgher & Voss, 2016). Overall, all own and spillover effects are statistically significant at the 1% level, and the impacts of land prices on housing prices are smaller than those on land prices. We first interpret the effect of a housing price on a land price and find that, under the geo-economic weights, a 1% increase in the own-city housing price raises the own-city land price by 0.71% on average. When considering the indirect effects, the response of the land price to nearby housing prices has a similar magnitude, and, specifically, a 1% increase in neighboring cities' housing prices raises the local land price by nearly 0.73% on average. A key implication of the indirect effects is that, holding other factors constant, since housing prices are so spatially interconnected, an increase in own-city housing prices could provide a strong positive signal for land prices in nearby cities across a much wider geographical area. Combining direct and indirect impacts results in an estimated total impact of 1.44% of a housing price on a land price on average. It is worth noting that lands become housing price-elastic if evaluating their total impact, confirming that local governments heavily regulate land prices under the influence of housing markets. Besides the housing price's impact on the land price, we also examine the effects of the land price on the housing price. It shows that, when the housing equation is geo-economically weighted, the own-city influence of a 1% rise on neighboring cities' land prices on the housing price is around 0.53% on average. The relevant cross-market impact of a land

**Table 2.** Global estimation results of non-spatial and spatial land and housing pricing models

| Dependent variables: In$LP_{it}$ and In$HP_{it}$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Non-spatial | | Spatial panel simultaneous-equations model | | | | | |
| | | | Geographical weights | | Economic weights | | Geo-economic weights | |
| | *LP* | *HP* | *LP* | *HP* | *LP* | *HP* | *LP* | *HP* |
| Variables | [1] | [2] | [3] | [4] | [5] | [6] | [7] | [8] |
| Price variables | | | | | | | | |
| In*LP* | | 0.9353*** | | 0.5427*** | | 0.4515*** | | 0.5253*** |
| | | (2.91) | | (2.89) | | (2.74) | | (2.71) |
| In*HP* | 1.2722*** | | 0.8166*** | | 0.7342*** | | 0.8612*** | |
| | (3.27) | | (3.71) | | (3.60) | | (3.02) | |
| $LP_{-it}$ | | | 0.4421*** | 0.3878*** | 0.7291*** | 0.3431** | 0.8910*** | 0.3409*** |
| | | | (8.90) | (7.52) | (3.38) | (2.31) | (3.11) | (2.98) |
| $HP_{-it}$ | | | 0.8319*** | 0.7191*** | 0.8121** | 0.8692*** | 0.9220*** | 0.8617*** |
| | | | (8.41) | (5.12) | (2.13) | (3.89) | (3.32) | (3.08) |
| Price determinants | | | | | | | | |
| In*GDP* | 0.0112** | –0.0292* | 0.0202** | 0.0190** | 0.0782** | 0.0580*** | 0.0671** | 0.0419*** |
| | (2.10) | (–1.80) | (1.99) | (2.39) | (2.01) | (5.21) | (1.99) | (4.11) |
| In*DI* | 0.0239* | 0.0119 | 0.0119** | 0.0340** | 0.0119** | 0.1741*** | 0.0876** | 0.1290*** |
| | (1.80) | (1.29) | (2.16) | (1.99) | (1.98) | (5.82) | (2.15) | (5.21) |
| In*HI* | 0.0211* | –0.0102 | 0.0087*** | 0.0187** | 0.0098*** | 0.0253*** | 0.0087*** | 0.0209** |
| | (1.72) | (–0.92) | (2.97) | (2.16) | (2.90) | (2.75) | (2.75) | (2.21) |
| In*FR* | 0.0347** | 0.0123* | 0.0721** | 0.0345** | 0.0901*** | 0.0455** | 0.0912*** | 0.0575** |
| | (2.41) | (1.79) | (2.11) | (1.99) | (5.41) | (2.31) | (5.13) | (2.13) |
| In*SA* | 0.0214* | 0.0941** | 0.0362*** | –0.0789 | 0.1496*** | 0.0123 | 0.2362*** | 0.0076* |
| | (1.86) | (2.06) | (3.91) | (–0.36) | (7.02) | (0.87) | (8.21) | (1.71) |
| In*PD* | 0.0004 | 0.0004** | 0.0003** | 0.0012*** | 0.0002*** | 0.0009*** | 0.0007*** | 0.0015*** |
| | (1.43) | (2.10) | (2.20) | (4.12) | (6.31) | (4.21) | (4.10) | (5.39) |

*End of Table 2*

| Dependent variables: ln$LP_{it}$ and ln$HP_{it}$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Non-spatial | | Spatial panel simultaneous-equations model | | | | | |
| | | | Geographical weights | | Economic weights | | Geo-economic weights | |
| | *LP* | *HP* | *LP* | *HP* | *LP* | *HP* | *LP* | *HP* |
| Variables | [1] | [2] | [3] | [4] | [5] | [6] | [7] | [8] |
| Control variables | | | | | | | | |
| ln*EE* | 0.0119 | 0.0213** | 0.0691** | 0.2379** | 0.0893*** | 0.2191** | 0.0811*** | 0.0321*** |
| | (1.24) | (1.74) | (2.16) | (2.24) | (3.85) | (2.09) | (3.37) | (3.41) |
| ln*Doc* | 0.0099** | 0.0029* | 0.0191** | 0.0521*** | 0.0832*** | 0.0220*** | 0.0451*** | 0.0509*** |
| | (2.01) | (1.76) | (2.06) | (3.24) | (3.81) | (4.24) | (4.71) | (5.41) |
| ln*T* | 0.0191* | 0.0012** | 0.0312** | 0.0199** | 0.0221*** | 0.0023** | 0.0011*** | 0.0012** |
| | (1.74) | (2.10) | (2.02) | (1.98) | (4.05) | (2.14) | (5.71) | (2.01) |
| ln*Book* | 0.0002 | 0.0003** | 0.0091** | 0.0011** | 0.0013** | 0.0012** | 0.0231** | 0.0021** |
| | (0.94) | (2.09) | (2.10) | (1.99) | (2.15) | (2.13) | (2.31) | (2.23) |
| ln*Road* | 0.0019** | 0.0210 | 0.0211** | 0.0231** | 0.0203** | 0.0210** | 0.0218*** | 0.0290*** |
| | (2.31) | (1.04) | (2.13) | (2.11) | (2.75) | (2.21) | (3.71) | (4.14) |
| ln*TR* | 0.0091 | 0.0111** | 0.0201*** | 0.0011** | 0.0008** | 0.0691** | 0.0811*** | 0.0009** |
| | (0.94) | (2.01) | (2.28) | (2.13) | (1.98) | (2.19) | (2.71) | (2.23) |
| ρ*LP* | | | 0.2112*** | 0.2389*** | 0.2091*** | 0.2891*** | 0.2912*** | 0.2929*** |
| | | | (3.87) | (4.01) | (3.99) | (4.18) | (3.99) | (4.18) |
| ρ*HP* | | | 0.1923*** | 0.1319*** | 0.3409** | 0.2389*** | 0.2314*** | 0.2491*** |
| | | | (3.98) | (4.98) | (2.49) | (3.28) | (2.95) | (3.83) |
| City FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y | Y | Y |
| *N* | 2,860 | 2,860 | 2,860 | 2,860 | 2,860 | 2,860 | 2,860 | 2,860 |
| Adj-$R^2$ | 0.0527 | 0.0571 | 0.1821 | 0.1711 | 0.1790 | 0.1745 | 0.1981 | 0.1907 |

*Notes*: This table presents the estimation results of non-spatial and spatial models with the geographical, economic, and geo-economic weights in our panel data setting. The *LP* and *HP* represent the land and housing pricing models, respectively. The *t* statistics are presented in parentheses, with the robust standard errors clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table 3.** Direct, indirect, and total impacts for the spatial models

| Dependent variables: ln$LP_{it}$ and ln$HP_{it}$ | | | | |
|---|---|---|---|---|
| | *HP* in *LP* model | | *LP* in *HP* model | |
| | Coefficient | Robust St Error | Coefficient | Robust St Error |
| Geographical weights | | | | |
| Direct | 0.7203*** | (0.1249) | 0.5502*** | (0.1002) |
| Indirect | 0.7211*** | (0.1212) | 0.3909*** | (0.0828) |
| Total | 1.4414*** | (0.2122) | 0.9411*** | (0.1922) |
| Economic weights | | | | |
| Direct | 0.6703*** | (0.0209) | 0.5219*** | (0.0302) |
| Indirect | 0.7563*** | (0.1042) | 0.3609*** | (0.0348) |
| Total | 1.4266*** | (0.2082) | 0.8828*** | (0.1712) |
| Geo-economic weights | | | | |
| Direct | 0.7103*** | (0.0913) | 0.5329*** | (0.0340) |
| Indirect | 0.7322*** | (0.1112) | 0.3891*** | (0.0438) |
| Total | 1.4425*** | (0.3282) | 0.9220*** | (0.1092) |

*Notes*: This table shows the estimated direct, indirect, and total effects with geo- graphical, economic, and geo-economic weights in the spatial models. LP and HP represent the land and housing pricing models, respectively. The robust standard errors are presented in parentheses and clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

price is nearly 0.39%, suggesting that residential housing is less price elastic than land among the cross-market spatial interactions. The total impact of land on housing remains less than 1% in terms of prices, which implies that housing is always less responsive to land price than the reverse.

In addition to the mutual causality between land and housing prices, Table 2 shows the effects of price determinants and local controls on both housing and land prices. The coefficients for most of these variables align with conventional expectations and are statistically significant. Among the price determinants, local GDP and fiscal revenue have a more substantial positive impact on land prices, while disposable income, housing investment, and local population density exert a stronger influence on housing prices. These latter factors more directly reflect short-term demand in the real estate market. The relationship between housing sales area and housing price is ambiguous, as it is influenced by both supply and demand for housing services, thereby representing a market equilibrium quantity. However, the total sales area has a clear positive effect on land prices, as it signals higher housing demand, prompting local developers to purchase more land. The spatial models are controlled by local attributes, many of which are also statistically significant. Specifically, Table 2 reveals that higher investments in education, more teachers, doctors, and books, a denser road network, and a higher share of the tertiary industry all contribute to raising both land and housing prices in a given city, *ceteris paribus*.

## 4.2. Analysis of spatial-temporal heterogeneity

This section investigates the spatial-temporal heterogeneity of the causal relationship between land and housing prices, as the levels of these two prices exhibit noticeable spatial variations over the past decade. Specifically, we explore how the interaction between land and housing prices differs across regions and time periods, acknowledging that factors such as local economic conditions, demographic shifts, and government policies contribute to these spatial disparities. By analyzing the dynamic changes in the relationship between land and housing prices, we aim to uncover how geographic and temporal factors influence the strength and direction of the mutual causality, offering a deeper understanding of the evolving market dynamics.

### 4.2.1. Analysis of geographical heterogeneity

Following the approach in Ye and Wu (2014), Chinese prefecture-level cities are categorized into four regions: eastern, northeast, central, and western, as shown in Figure 1. This regional division allows us to investigate the spatial-temporal heterogeneity in the causal relationship between land and housing prices. As illustrated in Figure 2, there is a significant regional variation in land and housing prices, with eastern cities such as Beijing, Shanghai, Guangzhou, Shenzhen, and Hangzhou experiencing overheated real estate markets. In contrast, cities in the central and western regions tend to have lower land and housing prices. Given the varying levels of economic development, policy influences, and market maturity across regions, the mutual causal relationship between housing and land prices is expected to differ. As the real estate markets in coastal cities are more developed and face stronger demand pressures, housing prices tend to drive land prices upwards. Conversely, in less-developed central and western regions, the causal dynamics may be weaker or operate differently due to more limited demand for real estate and land.

Table 4 presents the empirical results for each of these regions, derived from the spatial model (4). For brevity, we report only the estimation results using the geo-economic weighting method, which provides a better fit for the data. The regional heterogeneity is expected to reveal distinct causal relationships between housing and land prices, contributing valuable insights into the complex dynamics of real estate markets across China's diverse geographical areas. Empirical results show that the mutually causal effects between land and housing prices remain significant and positive in eastern, central, western, and northeast cities. Overall, we also find that there are large geographical variations in the magnitudes of both own effects and spillover effects. The region-specific estimates on the own-city effects suggest that a housing price has the greatest influence on a local land price among the western cities. Specifically, a 1% increase in a local housing price in eastern cities, on average, causes the local land price to increase by 0.53%, which rises to 0.93% in the western region. Compared to the eastern region with a more developed economy, the relatively lower economic development level in the western region gives local governments an incentive to promote the local economy by raising the land prices when selling residential lands. Thus, as local governments dominate the land markets and regulate their prices, lands become more price-sensitive to local housing prices (Wang & Hui, 2017). On the contrary, a land price impacts its own-city housing price the most among the eastern cities, followed by the effects in the central region. A 1% increase in a local land price raises the local housing price by 0.79% in eastern cities, while the direct impact declines to 0.32% in the western region. Land prices in the eastern region have a more pronounced effect on local housing prices due primarily to the higher disposable income and home purchasing power of the local population. Real estate developers take into consideration the local residents' demand for housing services and improvement of the living standard and raise the housing investment and prices more dramatically. Therefore, developed eastern cities typically feature a prosperous real estate industry and high land price elasticity of housing (Yuan et al., 2019). Moreover, the process of urbanization in the central region has been accelerating, making the interrelationship between housing and land prices similar to that in the eastern cities.

**Table 4.** Analysis of geographical heterogeneity with geo-economic weights

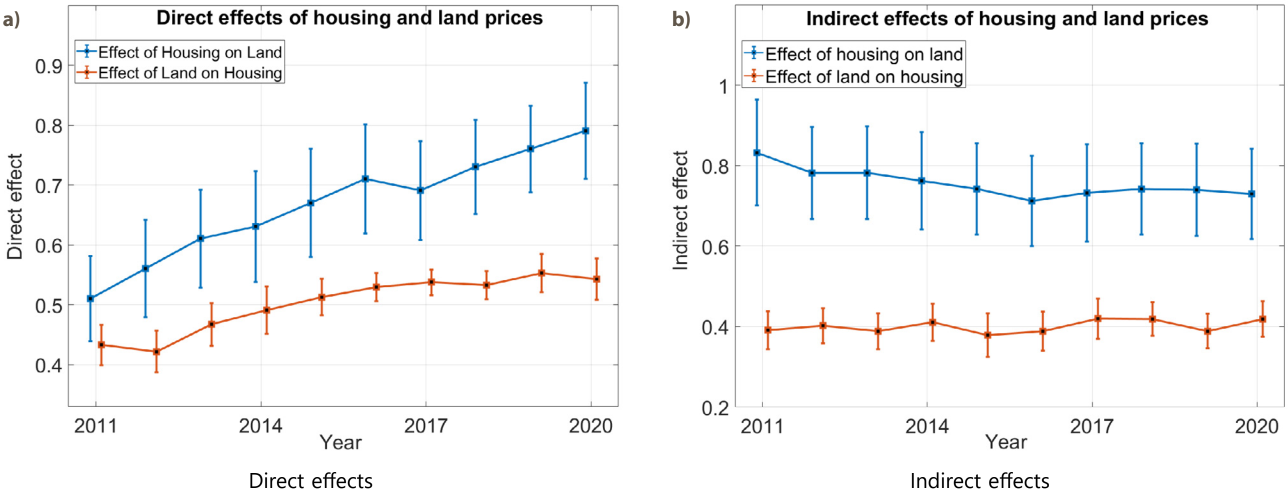
| Dependent variables: In$LP_{it}$ and In$HP_{it}$ | | | | |
|---|---|---|---|---|
| | 87 eastern cities | | 82 central cities | |
| | Coefficient | Robust St Error | Coefficient | Robust St Error |
| | *HP* in *LP* model | | *HP* in *LP* model | |
| Direct | 0.5311*** | (0.0949) | 0.7021*** | (0.0892) |
| Indirect | 0.5862*** | (0.0981) | 0.6991*** | (0.0811) |
| Total | 1.1173*** | (0.1022) | 1.4012*** | (0.1112) |
| | *LP* in *HP* model | | *LP* in *HP* model | |
| Direct | 0.7898*** | (0.0719) | 0.6712*** | (0.1202) |
| Indirect | 0.8114*** | (0.0831) | 0.6892*** | (0.0981) |
| Total | 1.6012*** | (0.1232) | 1.3604*** | (0.0911) |
| Price determinants | Y | | Y | |
| Controls | Y | | Y | |
| City & Year FE | Y | | Y | |
| *N* | 870 | | 820 | |
| Adj-$R^2$ | 0.0077 | | 0.0061 | |
| | 84 western cities | | 33 northeast cities | |
| | Coefficient | Robust St Error | Coefficient | Robust St Error |
| | *HP* in *LP* model | | *HP* in *LP* model | |
| Direct | 0.9312*** | (0.0891) | 0.7522*** | (0.0912) |
| Indirect | 0.9608*** | (0.0921) | 0.7191*** | (0.0781) |
| Total | 1.8920*** | (0.1812) | 1.4713*** | (0.1523) |
| | *LP* in *HP* model | | *LP* in *HP* model | |
| Direct | 0.3231*** | (0.1091) | 0.4432*** | (0.0976) |
| Indirect | 0.3198*** | (0.0322) | 0.3993*** | (0.1081) |
| Total | 0.6429*** | (0.0967) | 0.8425*** | (0.1212) |
| Price determinants | Y | | Y | |
| Controls | Y | | Y | |
| City & Year FE | Y | | Y | |
| *N* | 840 | | 330 | |
| Adj-$R^2$ | 0.0057 | | 0.0036 | |

*Notes*: This table shows the estimated direct, indirect, and total effects of the spatial models at the regional level with geo-economic weights. LP and HP represent the land and housing pricing models. The robust standard errors are presented in parentheses and clustered at the city level. *** $p < 0.01$.

In addition to the own-city effects between housing and land prices, Table 4 presents the region-specific estimates of spatial spillover and total effects. The results reveal positive spatial spillover effects between housing and land prices across regions, with the spatial patterns of these spillover effects closely mirroring those of the direct effects. Specifically, the spillover effect of housing prices on land prices in neighboring cities is smaller in the eastern region compared to other regions. Conversely, local housing prices in eastern cities are, on average, more strongly influenced by nearby land prices than in other regions. Moreover, the cross- market spillover effect of local housing prices on land prices in neighboring areas is generally higher than the reverse effect in most regions, except for the eastern region. In eastern cities, stronger aggregate housing demand allows real estate developers to capitalize on rising land prices, leading to more elastic housing price increases. On the other hand, local governments in more developed urban areas can generate greater fiscal revenue from sources other than land sales, which results in lower housing price elasticity in relation to land prices (Wu et al., 2015). Empirical findings of geographical heterogeneity at the regional level, using alternative weighting methods, align closely with those derived from geo-economic weights, and are not repeated here.

#### 4.2.2. Temporal dynamics of spatial dependence

Over the past decade, the average residential housing price in China has more than quadrupled, and the mutually causal effects between housing and land prices are likely to vary over time. In addition to geographical heterogeneity, we also examine temporally heterogeneous effects in their interrelationship. Figure 4 presents the year-specific estimates of the direct and indirect effects of land and housing prices. Panel (a) reveals upward trends in the own-city effects of both housing and land prices over




*Note:* The bars represent 95% confidence intervals of year-specific estimates on direct or indirect effects.

**Figure 4.** Analysis of temporal heterogeneity in the interrelationship between land and housing prices

time. The increasing direct effect of housing prices on local land prices suggests that local governments in China are now more reliant on land sales to finance public spending than in previous years. This reliance on land financing has amplified incentives for high levels of local public investment, driving land-centered urbanization in China over the past decade. Therefore, our empirical findings confirm that land financing has become more integral to China's economic growth (Cai et al., 2021). An increasing direct effect of land prices on housing is also observed, although the upward trend is less pronounced than the effect of housing prices on land prices.

As well as the own-city effects, we explore temporal heterogeneity in spatial spillover effects. As opposed to direct effects, we find a slightly downward trend in the spatial effect of housing on land until 2016. It suggests that, during the period, local governments have gradually tightened the regulation of land markets and gained more independence in land policy. Meanwhile, no evident temporal variations are found in the effect of land on housing over the entire study period. The ambiguity might be since two opposing forces might coexist. In- creasing land values reinforce the upward trend in nearby housing prices, on the one hand. On the other hand, the political tournament of a "proper" housing price incentivizes local governments to get less responsive to land prices in neighboring cities and maintain an effective housing price control in China (Zhou, 2010; Xu, 2011; Li et al., 2019).

## 5. Conclusions

Under a spatial econometric framework, this paper systematically documents the mutually causal effects between land and housing prices. We begin by establishing a conceptual framework to describe the underlying causal mechanisms between the land and housing markets, with a focus on local government incentives. Using newly available panel data from Chinese prefecture-level cities spanning 2011 to 2020, we construct a spatial panel simultaneous- equations model incorporating a novel asymmetric mixed geography-economy weighting method. To obtain consistent and efficient estimators, we employ a feasible generalized spatial three-stage least squares (FGS3SLS) approach, accounting for simultaneity, endogeneity, spatial dependence in prices, and spatial effects in intra- and inter-market disturbances. The geo-economic weighting method is found to be preferable over purely geographical or economic weighting, as it better reflects the actual spatial linkages in the data. The empirical findings advance our understanding of the spatially interdependent relationship between housing and land markets. Model estimation results confirm the existence of mutual and positive causality between housing and land prices in China. Over the past few decades, China's rapid economic growth has largely been driven by agglomeration economies in metropolitan areas, particularly in the eastern and central regions (Chen, 2009). The concurrent concentration of population and industry has significantly increased aggregate housing demand, which, in turn, has been a key driver of rising housing and land prices. Our findings also indicate that the own-city effect of housing prices on land prices is more significant than the reverse effect, confirming that land financing has played a central role in land-centered urbanization in China (Ye & Wu, 2014).

Beyond national-level analysis, we examine both geographically and temporally heterogeneous effects between housing and land prices. The results show that these prices exhibit positive and mutually causal effects across all regions, with geographical heterogeneity in their magnitude. Specifically, housing prices have the greatest impact on local land prices in western cities, primarily due to local government-led land financing. In contrast, land prices exert the strongest influence on housing prices in eastern cities, reflecting the faster pace of urban development in these regions. Additionally, rising housing prices in more developed eastern cities have been driven by stronger demand for improved living standards and high-quality housing services, leading to a relatively greater effect on local housing prices. Temporal variations in the effects further reveal that local governments' reliance on land financing has increased over time.

The empirical evidence in this paper provides important policy implications for regional urban planning in China. The first key takeaway is that urban policies concerning real estate and land markets should be systematically designed based on the interaction mechanisms identified in this study. Given their mutual causality, dynamic pricing schemes for housing and land should be improved to ensure stable and sustainable development of the real estate and land markets, as well as the broader local economy. Another crucial policy consideration is the role of urbanization and land financing in China. Land financing has long been a vital source of local fiscal revenue, facilitating urban economic growth during periods of rapid urban expansion. In economically stronger cities with aggressive real estate investment, land financing has driven large-scale urbanization, contributing to the rapid rise in housing and land prices (Ye & Wu, 2014). However, the primary goal of urbanization should be to enhance the quality of life for residents, not merely to generate revenue. Therefore, it is essential that ongoing land reforms and urbanization initiatives align with their intended goals, particularly in balancing political relations between central and local governments.

Although the dataset concludes in 2020, immediately prior to the nationwide downturn in China's real estate and land markets, the structural mechanisms identified in this study remain pertinent for interpreting subsequent developments. The documented mutual causality and spatial spillover effects between housing and land prices under stable market conditions provide a useful reference point for understanding the evolution of these relationships during the post-2021 downturn. While the sharp decline in property values and transaction activity may have altered the magnitude of these linkages, their underlying presence is unlikely to have disappeared. Moreover, the heterogeneity observed across cities suggests that the cur- rent downturn is also likely to exhibit differentiated spatial patterns. Future extensions of the dataset should incorporate key post-2021 variables to capture the structural adjustments that have occurred during this period. Particularly, we could collect the data on updated housing purchase and resale restriction policies, developer leverage indicators such as debt-asset ratios and off-balance-sheet financing, and changes in local government reliance on land-based revenues following the pronounced contraction in land sales. Integrating these variables would enable direct examination of how policy tightening, developer balance-sheet stress, and evolving fiscal conditions reshape the housing-land price nexus, thereby providing a more comprehensive basis for evaluating market dynamics across different phases of the real estate cycle.

Finally, our analysis of geographical heterogeneity has direct policy implications for local governments in China, particularly in formulating city-specific urban policies. Population characteristics, economic fundamentals, and land use patterns vary significantly between eastern coastal cities and western inland regions, resulting in heterogeneous effects of land supply shocks on housing markets. For example, in Shanghai, the land auction system and intense competition for premium land parcels have repeatedly amplified the pass-through from land prices to housing prices, demonstrating the stronger land price impact observed in eastern cities. In contrast, cities, such as Chengdu, which have experienced rapid in-migration and substantial land supply expansion, exhibit a high housing-to-land price elasticity, consistent with our findings for western metropolitan areas. These representative cases highlight the need for local governments to tailor housing and land policies to the specific development stage, market structure, and demographic dynamics of each city.

Overall, our findings reveal a mutually reinforcing relationship between housing and land prices, with notable spatial spillovers across cities, which carry clear policy implications across different phases of the real estate cycle. In boom periods, the housing-land price feedback mechanism may amplify risks of speculative bubbles, underscoring the need for coordinated regulatory tools such as tighter credit policies, stricter mortgage requirements, and prudent land supply management. During stabilization phases, consistent coordination between land allocation and housing affordability policies, such as transparent land auctions and predictable land supply, can help sustain balanced growth and reduce volatility. In downturn periods, the interdependence of housing and land markets may intensify downward pressure, particularly where fiscal reliance on land revenues is high, highlighting the importance of decoupling local government finances from land sales and adopting countercyclical measures such as fiscal transfers or targeted subsidies. By capturing both bidirectional causality and spatial interconnections, our analysis provides a basis for designing differentiated, cycle-specific regulatory interventions that promote long-term housing affordability and market stability.

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