Do Higher House Prices Crowd-Out or Crowd-In Manufacturing?
A Spatial Econometrics Approach

Ping Feng[*], Mahmut Yasar[†], and Jeffrey P. Cohen[‡]

Abstract

This paper examines the hypothesis that higher house prices lead to greater manufacturing concentration in Chinese cities. There are several innovations in our work, including our allowing for feedback and spillover effects across cities with spatial econometric modeling. We also address the endogeneity of house prices with a difference-in-differences approach that relies on house purchase restrictions imposed by some local governments, which limit the number of homes residents can purchase. These restrictions vary across cities and over time. Across various model specifications, we find evidence of significant crowding-in of manufacturing firms when house prices rise. This crowding-in impact tends to be dampened in cities with house purchase restrictions in effect. Our direct, indirect, and total effects of house price changes on manufacturing concentration imply significant feedback and spillover effects across cities when a city's house prices change and when a city experiences a house purchase restriction. These findings have important potential policy implications for real estate markets when local policymakers want to increase their city's manufacturing concentration. These include offering subsidies and/or other incentives for homeownership, and discouraging house purchase restriction policies by the local governments.

Keywords: Spatial Econometrics, House prices, Agglomeration, Manufacturing

JEL Classifications: R11, R32

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[*] School of Economics and Management, Changsha University of Science and Technology, Hunan, 410076, P.R.China
[†] College of Business, University of Texas at Arlington, TX,76019,USA
[‡] Center for Real Estate and Urban Economic Studies, University of Connecticut, Storrs, CT 06269 USA

I. Introduction and Literature Review

Do house price increases lead to greater or less geographic concentration in the manufacturing sector? We address this question from a spatial econometrics perspective, with a focus on housing and the booming manufacturing sector in Chinese cities during the period of 2000-2018. It is clear that there are significant differences between China's housing markets and manufacturing sector and those of Western countries such as the U.S. (Lai & Van Order, 2020). A careful analysis is warranted of what the Chinese data imply for the validity of various theories behind how house prices impact firm concentration. With the location being a key factor in housing markets, spatial econometrics modeling is crucial to precisely assess the relationship between house prices and industry concentration.

As motivation behind the need to study how housing prices impact industry concentration, some historical summary of city formation is helpful. There is a long history in the urban economics literature on the formation and development of cities in both the China and U.S. context. For instance, Zheng et al. (2009) use Chinese household-level survey data to compare the land rent and wage rate differentials across cities. Going back much further, in the U.S. context, the classic land rent models of Alonso (1964) and Muth (1969) assume a marketplace at the city center, and merchants would locate close to the center to sell their products. Often, as in the case of what are now major U.S. metropolises such as New York City, Boston, and Philadelphia, the train station would be located near the market so that merchants could ship their products at relatively low costs to other parts of the country, further reinforcing the desirability of the city center as a location for merchants. As these cities matured and goods markets developed further to include manufacturing goods, these firms tended to locate near the city center.

The theory attributes this concentration to the "leftover principle", which states that firms will spend on land rent all of their revenues net of non-land costs. This principle implied that manufacturing firms, with relatively high costs of transporting their goods to the marketplace and train station, had the ability to pay higher land rent in the urban center (where the train stations are located) to reduce the transportation costs. On the other hand, residents bid more for land further out. In such a model, a shock leading to higher house prices would result in lower demand for residential land, causing residents to move further away from the center and making it more financially attractive for manufacturing firms to take over some of the land previously used for housing. In this sense, the Alonso (1964) and Muth (1969) models imply a crowding-in of the manufacturing sector in response to higher house prices – higher house prices should lead to more manufacturing firms in or near the city center. That is the foundation of the functioning of early land markets in many U.S. cities, where land is privately owned – i.e., the land is sold to the highest bidder. The geographic layouts of many U.S. cities today still reflect, to some extent, these early models of urban economic theory. The train stations in many large cities (e.g., Washington DC and Chicago) are in the urban center, together with a substantial industry concentration, while the majority of residential neighborhoods are concentrated in and near the suburbs. These early theoretical models imply that house prices are endogenous, leading to a challenge in empirically testing the relationships between house prices and manufacturing firms' concentration in cities.

In China, land markets function quite differently. Specifically, the land is owned by the state or the collective[1]. The facts about land ownership and land allocation in China are, in some respects, quite different from the U.S. In particular, the governments (local and central) are essentially monopolies in land market transactions and are "the ultimate arbitrator" (Glaeser et al., 2017). More generally, China is an interesting case study for a city-level exploration of the relationship between house prices and manufacturing firms' locations, since, over the last two decades, China has experienced a long-term boom in the housing market. Since 1998, when China began its housing market reform, the average house prices of four first-tier cities (Beijing, Shanghai, Guangzhou, and Shenzhen) have grown by 12.5 percent annually. Among these, Shenzhen rose nearly twelvefold.[2] Nationwide, the average selling price of a residential house in 2021 was 10396 yuan per square meter, nearly 5.6 times that of the 1999 level. Studies have investigated some economic consequences of rising house prices in China, such as the causes and the fundamental conditions of the Chinese housing market (Wang, 2011; Fang et al., 2016; Wu et al., 2016), possible housing boom bubbles (Glaeser et al., 2017; Chen & Wen, 2017), and the effects of rising housing prices on private consumption, labor force participation and residential investment (Chen et al., 2010; Johnson, 2014; Li & Zhang, 2021; Zhou & Hui, 2022). Nevertheless, the impacts on regional manufacturing development are explored less comprehensively. The manufacturing industry is not only an important driving force for China's rapid economic growth but also the foundation of China's national economy.

[1] The Law of the People's Republic of China on Land Administration indicates all urban land will be owned by the government, but rural/suburban land (with the exception of state-owned land) is to be owned by "the collective". While residents may use the land, they are not allowed to own land..

[2] The average residential housing selling price is 5190 yuan/m^2 in 1998 and 72283 yuan/m^2 in 2022. The data is taken from https://fdc.fang.com/index/.

It is observed that some manufacturing enterprises moved from China's eastern city of Shenzhen, where the housing prices were high, to inland areas or even overseas, such as the phenomena of 'Foxconn Moving Inland' and 'HUAWEI Go North.' [3] However, Shenzhen's manufacturing industry is still flourishing. In 2021, the value added from industrial businesses above the designated size in Shenzhen reached 175.7 billion US dollars, which ranked it first among China's prefecture-level cities. The Shenzhen experience leads to the question of whether the rise of house prices has inhibited or promoted the growing manufacturing presence in that city (and others).

Related empirical studies on the impacts of house price changes on manufacturing in China offer no consensus. One point of view posits that continuously rising housing prices increase manufacturers' labor and land costs, forcing enterprises to move to regions with relatively lower factor prices, which in turn hinders the development of the local manufacturing industry (Gao et al., 2012). The findings are consistent with the theory of Helpman (1998), which holds that as inter-regional transportation costs decline, the difference in regional housing prices will push the manufacturing industry from the central region to peripheral areas, resulting in a more dispersed layout of the industry in the region. It is noteworthy that this prediction is the opposite of the implied outcomes of the Alonso (1964) and Muth (1969) models. Yet another theoretical point of view holds that most workers in Chinese manufacturing agglomeration regions are low-skilled rural migrants with relatively low incomes who cannot afford expensive houses.[4] High housing prices

[3] The Manufacturing base of both Foxconn and Huawei were located in the city of Shenzhen before. With the rapid rise of house prices in Shenzhen, the former went to the inland China mainland, while the latter moved to Dongguan, located in the north of Shenzhen.
[4] Sufficient working opportunities and relatively high earnings compared to those in the workers' hometown guarantee the continuous inflow of manufacturing labor.

have little impact on local manufacturing labor costs in these high-priced manufacturing hubs. Also, by monopolizing the land supply, the local government subsidizes industrial land with income from commercial and residential land selling to encourage local industrial growth (See Figure 1). Industrial land, which is owned by manufacturing firms, cannot be used to build residential housing. Therefore, increases in housing prices, in general, may be irrelevant to local industrial land prices and supply (Fan et al., 2015; Wang & Hou, 2021; Jia et al., 2021). But many regions with higher housing prices are still more attractive to the manufacturing industry.

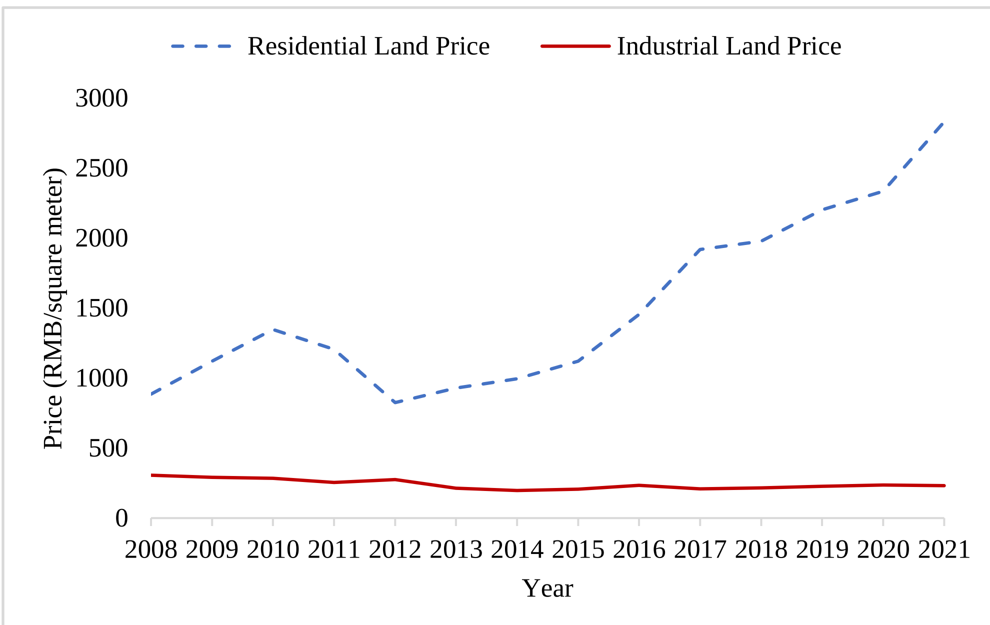

Figure 1 Average residential and industrial land price for cities in China
Source： Wind economic database.

Although the previous findings are mixed, these empirical studies highlight the mechanism – specifically, that the increase in housing prices can impact the development of the local manufacturing industry through its impact on land and labor costs. However, there is no clear consensus behind the reasons for the seemingly ambiguous findings.

This leads to the question of what theoretical underpinning – if any – more accurately describes the Chinese housing market's impacts on manufacturing. Our study complements earlier studies by considering these effects and testing which theoretical paradigm more closely aligns with the reality of China's land markets. First, the Alonso (1964) and Muth (1969) models, which at first glance do not reflect the structure of Chinese cities, have shown that higher house prices can lead to an expansion of manufacturing firms further concentrating in a city center. Alternatively, the theoretical analysis of Helpman (1998) implies a testable hypothesis that, in China, house price increases can crowd out local manufacturing industries.

In addition to our testing of which theoretical construct more closely reflects the relationship between Chinese house prices and manufacturing firms' agglomeration, we also contribute to the empirical analyses in this literature. Specifically, much of the previous Chinese research is based on large geographical unit data, such as national or provincial data. When using provincial-level data, it is hard to control the large heterogeneities within Chinese provinces. It is also difficult for provincial or national data to define a central region and its peripheral area. Our use of city-level data is an additional contribution beyond the province-level studies; it enables us to examine the manufacturing development impact of house price changes for different types of cities in different provinces. In most previous studies, the house price impact is examined by using national or provincial-level data. Only a few studies analyze about 70 large- and medium-sized Chinese cities (Yang et al., 2018; Funke et al., 2019). Our data contains information for 284 Chinese cities at the prefecture level and above from 2000 to 2018. Zhou et al. (2020) used panel data of 283 Chinese cities during 2000-2013 to test the impacts of housing prices on cities' total factor productivity, but our analyses of how house prices impact the number of manufacturing firms, and separately, how house prices impact manufacturing employment, are unique.

The issue of house prices and manufacturing firm concentration needs to be carefully modeled empirically. Specifically, there is a large literature on determinants of house prices in China, some of which use spatial econometrics methods. One of these studies is Hanink et al. (2012), who uses a spatial error model for global estimation of a hedonic house price model for Chinese housing, but geographically weighted regressions for more local modeling. The hedonic house price literature implies that house prices are endogenous. More generally, others have studied housing markets in other countries using spatial econometrics, such as Pace and Calabrese (2021), who highlight the importance of considering a spatial autoregressive error term. Liu (2013) finds that including a spatial lag enhances the "prediction power" of hedonic house price models.

We address causality in the reverse direction with house prices as an independent variable in a spatial model, in addition to addressing endogeneity due to a spatial lag of the dependent variable. We carefully control for potential endogeneity of house prices in a model of China's manufacturing industry concentration using a difference-in-differences identification strategy in a full spatial model. Our quasi-experiment for the difference-in-differences relies on house purchase restrictions at the city level in China, which vary over time and city. The spatial model includes spatial dependence in both the disturbances and a spatial lagged dependent variable. We find evidence that higher house prices in China "crowd-in" manufacturing firms. In other words, we find a positive and significant causal relationship between house prices and manufacturing firm concentration in Chinese cities from 2000 to 2018. In general, the effects of a 10% rise in house prices (as shown in Table 3) lead to a 0.3% to 0.9% rise in the number of manufacturing firms (and is statistically significant). For cities facing the house purchase restrictions, the effect of a 10% rise in house prices is roughly a 0.7% to 1.2% fall in the number of manufacturing firms. These offsetting effects imply that the house purchase restriction policies counteract (and in some cases overwhelm) the crowding-in effects of higher house prices. The implications are that policy makers should be encouraged to avoid implementing house purchase restriction policies if they are interested in enhancing manufacturing concentration in their city.

The rest of this paper is organized as follows. Section 2 describes the empirical models, identification strategies, and data. Section 3 presents the estimation results and main findings. Section 4 offers further discussions on different city characteristics and robustness checks. Section 5 concludes the paper.

Estimation strategy, data, and model selection

Housing prices and manufacturing industry development in one city may be spatially correlated with other cities. Using methods that do not allow us to control for such a spatial dependence across cities would lead to biased and inconsistent parameter estimates (Corrado and Fingleton, 2012).

Spatial regression models allow for such spatial interactions and thus yield unbiased and consistent estimates. Pace et al. (1998a, b) were among the first to explicitly integrate spatial econometrics modeling into the real estate literature. Case et al. (2004) and Sun et al. (2005) introduced spatial panel data modeling in real estate contexts for the space-time dimensions.[5] In general, with these models, a change in an observation (region) for one regressor will not only affect that region itself (which is considered a "direct impact"), but it also may have an impact on many or all of other the other regions in the sample (which is considered an "indirect impact") (LeSage and Pace, 2009). The manufacturing development in a city i may also depend on the development of manufacturing in its neighboring cities. Thus, to obtain unbiased and consistent estimates of the housing price effect on the manufacturing outcomes, we use spatial econometrics models that allow us to control for all sources of spatial interactions among the cities. In addition, these models will enable us to quantify both the direct and indirect housing price effects.

Estimation strategy

The spatial autoregressive model (SAR) and the spatial error model (SEM) are the most commonly used spatial models. The SAR uses a spatially lagged dependent variable as an explanatory variable, while the SEM contains a spatial autoregressive process in the error term. This paper nests both the SAR and the SEM. This nesting is accomplished with spatial lags of the explanatory variables and spatial error terms (which is referred to as the spatial Durbin model (SDM) as in equation (1) below. This SDM leads us to direct, indirect, and total marginal effects for each regressor (as in Elhorst, 2010b), which leads to rich information about the spatial relationships of interest (Mussa et al., 2017).

$$y = \alpha l_n + \rho \mathbf{W} y + X\beta + \mathbf{W} X\delta + \varepsilon \tag{1}$$

$$y = (I_n - \rho \mathbf{W})^{-1}(\alpha l_n + X\beta + \mathrm{WX}\delta) + (I_n - \rho \mathbf{W})^{-1}\varepsilon$$

$$\varepsilon \sim (0, \sigma^2 I_n)$$

[5] Francke and Vos (2004) also consider spatial dependence in a very specific context of hedonic housing price indexes.

where I_n denotes the identity matrix, l_n is a column of 1's, **W** is the spatial weights matrix representing the distance between neighbor regions or the structure of the spatial interactions among cities, and **W**y captures the spatial interdependence of the explanatory variable in the model. The SDM model allows for spatial interactions in the dependent variable, the explanatory variables, and the disturbances.

To obtain the direct and indirect marginal effects of X in the spatial model, Elhorst (2014) provides the following matrix of partial derivatives of the expectation of the dependent variable in the different units with respect to the kth explanatory variable in the different units (e.g., x_{ik} for $i = 1,\ldots, n$) :

$$\left[\frac{\partial E(y)}{\partial X_{1k}} \cdots \frac{\partial E(y)}{\partial X_{nk}}\right] = \begin{bmatrix} \frac{\partial E(y_1)}{\partial x_{1k}} \cdots \frac{\partial E(y_1)}{\partial x_{nk}} \\ \vdots \quad \ddots \quad \vdots \\ \frac{\partial E(y_n)}{\partial x_{1k}} \cdots \frac{\partial E(y_n)}{\partial x_{nk}} \end{bmatrix} = (I_n - \rho W)^{-1} \begin{bmatrix} \beta_k & w_{12}\delta_k & \cdots & w_{1n}\delta_k \\ w_{21}\delta_k & \beta_k & \cdots & w_{2n}\delta_k \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1}\delta_k & w_{n2}\delta_k & \cdots & \beta_k \end{bmatrix} \tag{2}$$

The diagonal elements represent direct effects, and the off-diagonal elements represent the indirect (spillover) effects. In the context of the housing price-manufacturing model, the direct impact is the average impact of the manufacturing development determinants (e.g., the changes in the housing prices of city i) on manufacturing in that city. The indirect impact is the manufacturing impact that stems from the changes in the housing prices of the neighboring cities. But Elhorst (2010b) notes that, in general, the values of the direct and indirect effects are not straightforward intuitively, and they vary with the sample size and spatial structure. Specifically, Elhorst (2014) notes that for the SDM model, the marginal effects and the direct effects "may be different due to the endogenous interaction effects **W**y. These interaction effects cause feedback effects, i.e.,

impacts affecting crime rates in certain neighborhoods that pass on to surrounding neighborhoods and back to the neighborhood instigating the change." (Elhorst (2014), page 31).

Empirical Implementation

This paper first elaborates on the necessity of using spatial econometric estimation models that allow us to obtain unbiased and consistent parameter estimates. It then estimates a panel data version of the SDM to obtain the direct, indirect, and total marginal effects of house price changes on manufacturing. The baseline model of this paper follows equation (3).

$$\begin{gathered} Men_{it} = \rho \mathbf{W} Men_{it} + Hp_{it} \cdot \delta_1 + HPR_{\mathrm{it}} \cdot \gamma_1 + Hp_{it} \cdot HPR_{it} \cdot \alpha_1 + \mathbf{X_{it}} \beta_1 + \mathbf{W} Hp_{it} \cdot \delta_2 \\ + \mathbf{W} HPR_{\mathrm{it}} \cdot \gamma_2 + \mathbf{W} Hp_{\mathrm{it}} \cdot HPR_{it} \cdot \alpha_2 + \mathbf{W} X_{it} \beta_2 + u_{it} \\ u_{it} = \lambda \mathbf{W} u_{it} + \varepsilon_{it} \end{gathered} \tag{3}$$

where Men_{it} is the number of manufacturing enterprises in the city *i* at year *t*; Hp_{it} is the housing price in the city *i* and year *t*; HPR_{it} is whether there is a house purchase restriction policy in the city *i* and year *t*; $\mathbf{X_{it}}$ is a vector of the other control variables in the city *i* and year *t*. This model also helps to deal with the omitted variable bias by including the spatial lag of both the dependent and error term.

There are two sources of endogeneity in the model (3). One of them, $\mathbf{W}Men_{it}$ is the (endogenous) spatial lag of the dependent variable that accounts for endogenous interaction effects. The manufacturing development in city *i* affects the manufacturing development in city *k*, which in turn affects the manufacturing development in city *j* and then impacts the number of manufacturing firms in city *i*. Each *Men* depends on the weighted average of other observations in the dependent variable over the neighboring cities. ρ is the spatial dependence parameter that measures the dependence of manufacturing development in city *i* on the neighboring cities' manufacturing. If ρ =0, there is no spatial dependence. A significant value of ρ indicates the existence of spatial dependence. **W** is the spatial weights matrix, described in more detail below.

The second source of endogeneity is the house price, Hp_{it} . We know Hp_{it} is endogenous because of the huge literature on hedonic studies that model house price as the dependent variable. For a recent example of a hedonic house price modeling approach in the context of a quasi-experimental framework, see Ambrose and Shen (2021). In the hedonic literature, house prices are modeled as a function of their characteristics. Therefore, in our application, where house prices are an explanatory variable, we need an identification strategy. We use a quasi-experimental approach – difference-in-differences – to identify the causal effect that Hp_{it} has on Men_{it} (the number of manufacturing firms).[6] To curb the rapid rise of housing prices, in April 2010, the Chinese central government issued the Notice of the State Council on resolutely curbing the excessive rise of house prices in some cities (GuoFa [2010] No. 10), explicitly requiring local governments to take effective measures to control the excessive rise of local housing prices. In the same month, the Beijing government introduced a purchase restriction policy, stipulating that from May 1, 2010, Beijing households can only buy a new residential house. This is the first "House Purchase Restriction" policy for families to purchase houses in China. Since then, the "House Purchase Restriction" (HPR) policy has been promoted throughout China. As of the end of 2011, 49 cities at prefecture level or above with "excessively high house prices or excessively fast rising house prices" have implemented the HPR policy.

By 2014, the house prices in various regions of China had begun to fall, the trading volume had shrunk, and the real estate stock had increased significantly. Therefore, by the

[6] Others, including Deng et al. (2022), have used the house price restriction as a quasi-experiment in other Chinese real estate studies.

end of 2014, except for five cities, Beijing, Shanghai, Guangzhou, Shenzhen, and Sanya, other cities had canceled the HPR policy. Then, house prices in all cities, especially in the first and second-tier cities, rebounded sharply. In the face of rising housing prices, since January 2016, cities have successively reintroduced the HPR policies. By the end of 2018, 46 cities at prefectures and above (including those five cities) had implemented a new round of HPR policies.

These policies (denoted as the indicator variable, HPR_{it} in (3)) vary over time (t) and city (i). Therefore, our quasi-experimental identification strategy relies on this exogenous policy, which was implemented at specific points in time for some cities and later withdrawn. It relies on the indicator HPR_{it} that equals 1 if the policy was in effect at time t and city i, and 0 otherwise. Therefore, the "treatment effect" of the policy is given as α_1, while the effect of house prices on number of manufacturing firms for cities with the policy in effect is given as $\delta_1 + \alpha_1$, and the effect of house prices on number of manufacturing firms without the policy in effect is given as δ_1.

Returning to the remaining details behind the spatial aspects of the model in (3), the spatial weight matrix **W** at any given point in time, t (assuming time-invariant spatial weights), is defined as:

$$\mathbf{W} = \begin{bmatrix} 0 & w_{ij} & \cdots & w_{ik} \\ w_{ji} & 0 & \cdots & w_{jk} \\ \vdots & & \ddots & \vdots \\ w_{ki} & w_{kj} & \cdots & 0 \end{bmatrix} \tag{4}$$

The row elements of the weight matrix are standardized so that they sum up to one, and the diagonal elements are set to zero.[7] We explore one spatial weight structure between any pair of the cities *i* and *j* (w_{ij}) based on the criteria of adjacent borders:

$$w_{ij} = \begin{cases} 1 & if\ \ city\ i\ and\ j\ share\ a\ border \\ 0 & otherwise \end{cases} \tag{5}$$

To control for the remaining potential endogeneity of the house price variable, we take the House Purchase Restriction (hereforth HPR) Policy enacted in some Chinese key cities as the exogeneous shock and estimate the SDM Difference-in-Difference model.

Data and Variables

In mainland China, cities can be classified into four groups according to their administrative levels: Municipalities directly under the central government, vice-provincial cities, prefecture-level cities, and county-level cities (Guo, 2014). Our panel data contains information on 284 Chinese cities at the prefecture level or above from the 2000-2018 period in China mainland.[8] It includes 4 municipalities, 26 provincial capital cities (11 of them are vice-provincial cities), 5 non-provincial capital but vice-provincial cities (planned cities), and 249 prefecture-level cities. Those 35 above prefecture-level cities are national or provincial centers of Chinese economic, political, and social life (Chen 2015).

[7] In the estimation process, W is row standardized (all nonzero spatial weights are rescaled so that the sum across each row equals 1), and the diagonal of the **W** matrix is zero. Alternatively, we could have normalized the columns, although that would have changed the interpretation of the weights in an undesirable manner. The standardized row elements have the desirable property of reflecting how all other cities impact a given city, but standardizing the column elements reflect the opposite relationship.
[8] Due to Chinese city administrative level adjustment and data availability, the dataset does not include data from the Tibet Autonomous Region, Hong Kong and Macau SAR, Taiwan District, or eight prefecture-level cities in five Provinces. These eight cities are Sansha and Danzhou in Hainan, Tongren and Bijie in Guizhou, Haidong in Qinghai, Zhongwei in Ningxia, and Turpan and Hami in Xinjiang.

We choose the number of industrial above-scale enterprises in each city as the explained variable to describe cities' manufacturing development status.[9] The key explanatory variable, housing price, is proxied by the average selling price of residential houses developed by real estate development enterprises. The data are drawn from the China City Statistical Yearbook (2001-2019), the China Statistical Yearbook for Regional Economy (2001-2014), and the China Real Estate Information Network.

Many regional economics studies indicate that real labor wage and the manufacturing industry agglomeration economy are important factors for regional manufacturing industry development. We take them into account as control variables in our model. We use data on the average earnings of employed people in the urban areas of each city to measure workers' real wages. Referring to Glaeser et al. (1992), we construct a manufacturing specialization economy indicator to proxy for the agglomeration economy, measured as the ratio of the share of employment in the manufacturing industry at the city level to the share of employment at the national level.

$$Sae_{mc} = S_{mc} / S_m \tag{6}$$

where S_{mc} is the share of manufacturing employment that accounts for the total amount of non-agricultural employment in city c, and S_m is the share of manufacturing employment that accounts for the total amount of non-agricultural employment at the national level. Compared to the other cities, a city with a higher Sae_{mc} has a comparative advantage in the manufacturing industry.

[9] China's industrial above-scale firms involve all state-owned and non-state-owned firms whose annual main business income reaches a threshold level. The statistic caliber of the level changed twice during the sampling period. In 1999-2010, the threshold level is 5 million Yuan or more. After 2011, the level increased to 20 million Yuan or more.

Previous studies also find that regional economic situations and traffic infrastructure have important impacts on the development of the manufacturing industry (Holl 2010; Carod et al. 2010). These factors are also crucial for regional housing prices. Thus, we include these control variables in our estimation. We use the per capita regional Gross Domestic Product (GDP) as a proxy for cities' economic development and the area of the city's paved roads at year-end as a proxy for the quality of traffic infrastructure. We also include the city's population density in the estimation model. Data on the control variables are taken from the China City Statistical Yearbook (2001-2019).

In China, the so-called HPR policy not only includes a clear restriction on the number of homes purchased by households, but also is accompanied by a variety of price control policies such as loans restrictions, price limits and sales restrictions. Different cities take different measures to control the rapid rise of house prices according to the specific conditions of the local real estate market. In some cities, such as Beijing, Changsha, and Nanjing, these various measures are carried out simultaneously. However, some cities, such as Wenzhou and Nanning, are controlling the house selling prices and loans, but not in household purchases. The HPR policy mentioned in this article only refers to the policy of explicitly limiting the number of housing units purchased by households, excluding measures such as sales restriction, price restriction, and loan restriction. The variable of *HPR* takes 1 if city *i* has implemented a purchase restriction policy in a certain year, otherwise, it is 0.

Table 1 shows the descriptive statistics for all variables.

Table 1 ▪ Descriptive statistics

	Mean	Standard Deviation.	Minimum	Maximum
Men: Number of manufacturing enterprises	1091.157	1576.737	19	18792
Mlabor: Number of Manufacturing industry workers (10,000 persons)	13.796	23.336	0.06	273.37
Hp: Housing prices (Yuan)	3502.594	3065.951	241.935	54132
HPR: House Purchase Restriction policy	0.061	0.239	0	1
Wage: Worker's wage (Yuan/year)	24694.01	13547.5	3290.7	102487.7
Sae: Specialization agglomeration economy	0.864	0.449	0.021	2.849
Gdppp: GDP per capita (Yuan/person)	24944.62	21403.76	1662.026	180259
Popden: Population density (Person/ sq.meter)	422.111	326.515	4.7	2707
Roadarea: Area of paved road (10,000 sq. meter)	1418.542	2086.471	15	21490

Notes: The total number of observations: 5,396.

We constructed a correlation matrix (Table 2) to check the possibility of multicollinearity. None of the variables included in our models seems to have a high degree of correlation with the other variables in the model. Considering the sample size of this paper, multicollinearity is not a potential threat to the results.

Table 2 ▪ Correlation Matrix of All Independent Variables Considered for the Empirical Model Specification

	Hp	*HPR*	*Sae*	*Wage*	*Gdppp*	*Popden*	*Roadarea*
Hp	1.000						
HPR	0.589	1.000					
Sae	0.196	0.103	1.000				
Wage	0.775	0.393	0.081	1.000			
Gdppp	0.702	0.446	0.347	0.748	1.000		
Popden	0.349	0.226	0.317	0.167	0.242	1.000	
Roadarea	0.629	0.482	0.250	0.500	0.588	0.463	1.000

Estimation Results

Before discussing the estimation results, we must test whether SDM is the best model for our data. Table 3 presents the panel data estimation results of the non-spatial model (OLS), the SAR, the SEM, and the SDM for our panel data, all with the trend and the city (spatial) fixed effects.

The estimation results from different models all point to the existence of positive effects of city house price increase on the local manufacturing industry development. One percent increase in city house prices leads to about 0.04% increase in local manufacturing enterprises. The absolute value of the coefficients of the spatial model is smaller than that of the non-spatial model, indicating that the non-spatial specification would overestimate the effects of house price changes on local manufacturing.

Table 3 ▪ Estimation Results from the OLS, SAR, SEM, and SDM model

Explanatory Variables	OLS	SAR	SEM	SARAR	SDM
ρ		0.529***		0.747***	0.591***
		(0.012)		(0.014)	(0.012)
λ			0.568***	-0.465***	
			(0.013)	(0.034)	
Hp	0.093**	0.044***	0.040***	0.032**	0.041***
	(0.040)	(0.013)	(0.013)	(0.011)	(0.013)
HPR	0.829	0.985***	1.206***	0.749***	0.834***
	(0.841)	(0.279)	(0.279)	(0.246)	(0.284)
*Hp*HPR*	-0.101	-0.118***	-0.144***	-0.090***	-0.105***
	(0.094)	(0.031)	(0.031)	(0.027)	(0.031)
Sae	0.337***	0.240***	0.195***	0.201***	0.185***
	(0.044)	(0.018)	(0.019)	(0.015)	(0.019)
Wage	0.250***	0.127***	0.100***	0.115***	0.089***
	(0.086)	(0.030)	(0.032)	(0.025)	(0.031)
Gdppp	0.475***	0.348***	0.415***	0.236***	0.400***
	(0.063)	(0.019)	(0.021)	(0.017)	(0.022)
Popden	-0.021	-0.015	-0.010	-0.012	-0.016
	(0.034)	(0.021)	(0.023)	(0.017)	(0.023)
Roadarea	0.107***	0.097***	0.090***	0.083***	0.100***
	(0.033)	(0.011)	(0.010)	(0.009)	(0.011)
W*Hp*					0.046**
					(0.020)
W*HPR*					-2.273***
					(0.555)
W*Hp*HPR*					0.250***
					(0.061)
W*Sae*					0.045
					(0.030)
W*Wage*					0.209***
					(0.047)
W*Gdppp*					-0.180***
					(0.031)
W*Popden*					0.029
					(0.041)
W*Roadarea*					0.003
					(0.020)
R^2	0.450	0.493	0.423	0.506	0.540

Notes: (1) The number of observations is 5,396 for each model. (2) Robust standard errors are reported in parentheses. (3) *significant at 10%. **significant at 5%. ***significant at 1%.(3) Maximum Likelihood technique is used in estimating the results of spatial models.

We next use the non-spatial least square method with fixed effects to generate estimates with our panel data, and then apply the Lagrange multiplier (LM) test to verify whether there is a significant spatial lag or spatial error in the residual. The results show that both the spatial lag and the spatial error should be considered in the estimation, which subsequent spatial econometric models confirm. Both the coefficient of the spatial lag of manufacturing firm numbers ρ (in the SAR, SARAR, and SDM model) and the coefficient of the spatial lag of error term λ (in the SEM and SARAR) are significant, indicating substantial spatial dependences among neighboring cities. Therefore, a spatial model—rather than a non-spatial model—is the appropriate model to be used to account for the spatial dependencies. We follow the approach described in LeSage and Pace (2009) and Elhorst (2010a), by beginning with the SDM as a general specification, and test for the alternatives with SAR, SEM, and SDM. The results suggest that the SDM is better than SAR, SEM, and SARAR models. We then perform the Hausman test to judge further whether the panel SDM should adopt the fixed effect or random effect estimation strategy. According to the estimation result of the Hausman test, we finally use the SDM with spatial fixed effects to describe our panel data.

Baseline model estimation results

LeSage and Pace (2009) point out that the point estimate of a spatial model is an incorrect representation of the impact of the explanatory variable on the dependent variable. The partial differential interpretation of the variation of variables in different spatial model settings can be used as a more effective basis for testing the existence of spatial spillover effects. To accurately measure the spatial spillover effects of various variables on manufacturing development, we further disaggregate the marginal (total) effects into direct and indirect effects. Table 5 presents the estimation results from the SDM models ranging from 2000-2018.

The results in Table 4 illustrate three effects: the direct effect (the impact of changes in determinants on manufacturing in a particular city), the indirect or spillover effect (the influence stemming from neighboring cities), and the total effect (the sum of both direct and indirect effects).

Table 4 ▪ Estimation results of panel data Spatial Durbin model with fixed effects

	Direct	Indirect	Total
ρ	0.591***(0.012)		
Hp	0.054***(0.014)	0.160***(0.045)	0.215***(0.051)
HPR	0.488(0.303)	-0.407***(1.214)	-3.580***(1.376)
*Hp**HPR*	-0.068**(0.033)	0.430***(0.133)	0.361**(0.151)
Sae	0.213***(0.019)	0.343***(0.061)	0.557***(0.069)
Wage	0.138***(0.031)	0.595***(0.095)	0.733***(0.106)
Gdppp	0.411***(0.021)	0.122**(0.059)	0.533***(0.063)
Popden	-0.012(0.024)	0.045(0.088)	0.033(0.096)
Roadarea	0.112***(0.012)	0.146***(0.046)	0.258***(0.053)

Notes: (1) Number of observations is 5,396. (2) Robust standard errors are in parentheses. (3) *significant at 10%. ** significant at 5%. ***significant at 1%.

The spatial lag coefficient, ρ, displayed in the first row, is highly significant and suggests that the estimation strategy is appropriate. When the surrounding cities' manufacturing firm numbers rise (fall), the manufacturing firm numbers of the city also tend to rise (fall). For the independent variables, the SDM results divide the total effect into direct and indirect effects. The three types of effects in the model all indicate that at the city level, the housing price changes are positively associated with local manufacturing development. Either the house price rise in a city or in neighboring cities will significantly increase the number of local manufacturing firms. The indirect effects are larger than the direct effects, which indicates that the crowd-in effects mainly stem from the feedback and spillover effects. A possible reason for the crowd-in effect is that increase in housing prices is directly related to the flourishing growth of the real estate sector, which is a strong driving force for the Chinese national economy. The real estate sector has deep intersectoral linkages with the manufacturing industry (Huang et al. 2021; Rogoff and Yang, 2022). Under the input-output framework, Huang et al.(2021) found evidence that real estate intensities were increasing in manufacturing sectors, and an increasing number of real estate products were input into the production process of manufacturing.

House purchase restriction policies (HPR) in China have been a severe way to slow down the rapid house pirce increases and to block investors from engaging in speculation (Du and Zhang, 2015; Sun et al., 2017; Somerville et al., 2020; Zou et al., 2022). The HPR prevents people who reside in the city from purchasing any more than two homes, and those who reside outside of the city can buy at most one home in the city. Somerville et al. (2020) find that the HPR lowered transactions by around 40% relative to cities without any HPR in effect. In Beijing, there was a 17-24% decline in sales prices when there was an HPR in effect (Sun et al., 2017). The HPR policy distorts the housing price and changes the original path of the housing price-manufacturing relationship to a certain extent. The direct effects in Table 5 show that higher house prices lead to higher numbers of manufacturing firms, but when considering the HPR impacts, these policies lead to a lower marginal effect of house price. Specifically, the house price direct crowd-in effect on manufacturing is 0.054 percent when HPR=0 and about -0.014% when HPR =1. Thus, the differential in the marginal effect of house price between the treated (HPR=1) and control (HPR=0) is about 0.07%. For the indirect effects, neighboring cities' HPR policies can benefit the home city's manufacturing.

The estimation results also show evidence that a city's specialization of manufacturing, labors' real wage, economic development, and transportation infrastructure have positive direct and spillover effects. This means that better manufacturing agglomeration economies, higher laborers' real wages, sound economic foundation, and robust transport infrastructure in one city and its neighboring cities can promote the city's manufacturing development. The population density has no significant effects on manufacturing.

Analysis of alternative spatial weights with varying spatial distances

To examine whether the effects of house price changes on the manufacturing industry varies with different spatial distance, we construct a series of distance-band spatial weights. We first calculate the arc distance using the longitude and latitude information of each city, and then construct the spatial weight matrix between any pair of the city *i* and *j* (w_{ij}) based on the following criteria:

$$w_{ij} = \begin{cases} 1 & when\ d_{ij} \leq \varphi \\ 0 & otherwise \end{cases} \tag{7}$$

where φ is a preset critical distance cutoff. [10] Table 5 shows us the estimation results of the SDM based on preset critical distance cutoff φ from 50km to 350km, increased by 50km, respectively.

Table 5 shows that the parameters of the spatial dependence of manufacturing development are estimated to be significantly positive in all distance ranges, which indicates that a city's manufacturing development can be positively affected by its neighboring cities manufacturing development. The greater the preset critical distance to define neighbors is, the stronger the spatial dependence will be. No matter what the preset critical distance is, the direct effect coefficients are all significantly positive, supporting that the rise in a city's housing prices will crowd in local manufacturing. There are positive

[10] The shortest distances between the closet cities in our sample is about 24.5km.

spillover effects in the range above 100km. While for the interaction of house price and HPR, no matter what the preset critical distance is, the direct effect coefficients are all significantly negative, supporting that the house purchase restriction policies lead to a lower marginal effect of house price on manufacturing. The positive spillover effects become significant above 200km. Perhaps the house purchase restrictions and house price interaction only exhibit a positive significant effect when including relatively far distances as “neighbors.” For very close distances, there is not as much feedback associated with the HPR because there is no variation in the HPR when only considering a small distance ring around the target point.

Table 5 ▪ Estimation results of housing price impacts with different critical distance cutoffs

Indep. Variables		Dep. Variable: Number of Manufacturing Entreprises						
φ		50km	100km	150km	200km	250km	300km	350km
ρ		0.153***	0.299***	0.380***	0.517***	0.600***	0.591***	0.609***
		(0.022)	(0.014)	(0.015)	(0.015)	(0.016)	(0.016)	(0.017)
Hp	Direct	0.100***	0.104***	0.085***	0.085***	0.074***	0.055***	0.054***
		(0.015)	(0.015)	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)
	Indirect	0.016	0.127***	0.198***	0.290**	0.214***	0.214***	0.219***
		(0.0131)	(0.022)	(0.034)	(0.051)	(0.071)	(0.071)	(0.069)
	Total	0.117***	0.230***	0.282***	0.376***	0.288***	0.268***	0.235***
		(0.020)	(0.029)	(0.039)	(0.055)	(0.074)	(0.074)	(0.0851)
*Hp*HPR*	Direct	-0.103***	-0.070**	-0.130***	-0.092***	-0.118***	-0.128***	-0.140***
		(0.036)	(0.036)	(0.035)	(0.035)	(0.035)	(0.033)	(0.033)
	Indirect	0.029	0.080	0.134	0.344**	0.649***	0.989***	1.111***
		(0.018)	(0.050)	(0.088)	(0.068)	(0.210)	(0.231)	(0.267)
	Total	-0.074*	0.010	0.004	0.253	0.531**	0.861***	0.971***
		(0.043)	(0.069)	(0.105)	(0.164)	(0.226)	(0.243)	(0.277)
R^2		0.012	0.197	0.097	0.001	0.012	0.006	0.006

Notes: (1) Observations are 5,396 for each model. (2) Standard errors are reported in parentheses. (3) *significant at 10%. **significant at 5%. ***significant at 1%.

Analysis of cities with different characteristics

With the different functions and status of the city, the effects of the city's house price changes may be different. This section mainly focuses on the relations between the center and periphery cities. We divide the sample cities into two categories according to two kinds of classification criteria: the political and economic criterion and the manufacturing criterion. For the first category, we use the cities' political and economic status in China to divide them into political and economic core and periphery cities. As mentioned previously, there are 35 above-prefecture-level major cities in our sample, including 4 municipalities, 26 provincial capital cities, capital cities of the autonomous regions (excluding Lhasa), and 5 planned cities (35 in total). They are China's economic, political, cultural, and social life centers. These 35 major cities have been widely used as analytical samples in previous studies (Zheng et al. 2016; Rogoff and Yang, 2022). We define them as Chinese political and economic core cities (PE core cities) and divide all the cities into two groups: 35 large-sized PE core cities and 249 medium- or small-sized periphery cities. We also categorize all the sample cities as either manufacturing hubs or periphery cities, according to the cities' manufacturing development status. There are no existing classification criteria to help us define the manufacturing hubs and periphery cities. By applying the *K*-Medians clustering algorithm to the manufacturing indicators, the manufacturing enterprise numbers (*Men*), the manufacturing specialization agglomeration economy (*Sae*), and the manufacturing workers in 2018, we define two groups of cities: 62 manufacturing hubs and 222 periphery cities.[11]

[11] Fourteen PE core cities are not manufacturing hubs. They are Taiyuan (Capital of Shanxi), Hohhot (Capital of Inner Mogolia), Changchun (Capital of Jilin), Haerbin (Capital of Heilongjiang), Nanchang (Capital of Jiangxi), Nanning (Capital of Guangxi), Haikou (Capital of Hainan), Guiyang (Capital of

Table 6 shows the mean and median values of variables for two groups of cities. All indicators of the center cities (PE core cities and manufacturing hubs) are larger than their counterpart periphery cities. On average, compared to periphery cities, center cities have more manufacturing firms and workers, higher housing prices and labor wages, greater manufacturing specialization economies, better economic foundations, and transportation infrastructure.

Table 6 ▪ Summary Statistics for PE core cities and periphery cities

Variable	city35=1		city35=0		city62=1		city62=0	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Men	2582.35	1677	881.55	491	3096.71	2454.5	531.05	409
Mlabor	44.207	31.74	9.521	5.86	37.229	23.675	7.251	5.150
Hp	6485.93	5193.48	3083.25	2656.61	5444.05	4235.23	2960.39	2586.37
HPR	0.334	0	0.022	0	0.202	0	0.015	0
Sae	0.963	0.897	0.850	0.764	1.202	1.139	0.769	0.707
Wage	32280.56	29601.58	23627.62	21526.15	29390.14	27133.95	23382.47	21193.63
Gdppp	42072.38	37522.43	22537.11	16907.72	48863.73	38861.5	27618.76	20093
Popden	649.555	585.12	390.141	313.77	724.459	668.225	337.671	264
Roadarea	4715.153	3489	955.163	622	3399.757	2248.5	865.229	576
Obs	665		4731		1178		4218	

Notes: (1) city35=1 represents the 35 political and economic (PE) core cities, and city35=0 represents the other 249 cities. (2) city62=1 represents the 62 manufacturing hub cities, and city62=0 represents the other 222 cities.

Table 7 shows the SDM estimation results for two groups of cities based on equations (2)-(5). It shows that there are significant positive direct effects of housing prices on manufacturing development of both 35 PE core cities and the 249 periphery cities. And

Guizhou), Kunming (Capital of Yunnan), Xi'an (Capital of Shannxi), Lanzhou (Capital of Gansu), Xining (Capital of Qinghai), Yinchuan (Capital of Ningxia), and Urumqi (Capital of Xinjiang).

the ”crowding in” effects of higher housing prices on core cities’ local manufacturing are larger in the core cities than in the peiphery cities. For the indirect effect, we neither find any evidence of spillover effects in the core cities nor in the periphery cities.

Table 7 ▪ Estimation results of housing price impacts among different cites

Indep. Variables	Dep. Variables: Number of Manufacturing Enterprises			
City	city35=1	city35=0	city62=1	city62=0
ρ	0.621***(0.0127)		0.607***(0.012)	
Direct effect	0.072***(0.020)	0.036*** (0.014)	0.098***(0.016)	0.011(0.014)
Indirect effect	0.108(0.076)	0.043(0.048)	0.162***(0.050)	0.029(0.047)
Total effect	0.180**(0.089)	0.079(0.055)	0.260***(0.058)	0.014(0.053)
R^2	0.638		0.682	

Notes: (1) city35=1 represents the 35 PE core cities and city35=0 represents the other 249 cities. (2) city62=1 represents the 62 manufacturing hubs, and city62=0 represents the other 222 cities. (3) The number of observations is 5396 for each model. (3) Standard errors are reported in parentheses. (3) *significant at 10%. **significant at 5%. ***significant at 1%.

The estimation results of manufacturing hubs and their surrounding cities show that cities’ house price increases have significantly better crowding-in direct effects on their manufacturing industries in the 62 manufacturing hubs than in their 222 periphery cities, both with direct and indirect effects. Therefore, the total crowd-in effects of house prices on manufacturing in manufacturing hubs are significantly larger than in peripheral cities. The estimation results show that rising house prices’ promotion effects on local manufacturing are greater in cities with better manufacturing foundations.

Robustness Check

To check the robustness of the findings of the relationship between housing price increases and manufacturing, we take the number of manufacturing laborers as an alternative dependent variable for the number of manufacturing firms, and estimate the equation (1)-(5). The results are shown in Table 8.

The estimation results in Table 8 show that the rise of housing prices in one city can also promote local manufacturing of its neighbors, which indicates that our results are robust.

Table 8 ▪ Estimation results of housing price impacts on manufacturing laborers

	Direct	Indirect	Total
ρ	0.634***(0.018)		
Hp	0.003(0.013)	0.334***(0.078)	0.337***(0.079)
HPR	-1.31***(0.267)	-6.433***(2.238)	-7.744***(2.327)
*Hp*HPR*	0.163***(0.029)	0.720***(0.249)	0.882***(0.258)
Sae	1.429***(0.017)	0.421***(0.112)	1.851***(0.115)
Wage	-0.308***(0.028)	-0.177(0.137)	-0.485***(0.142)
Gdppp	0.039**(0.019)	0.071(0.086)	0.110(0.088)
Popden	0.027(0.0224)	-0.343**(0.173)	-0.316*(0.176)
Roadarea	0.6882***(0.011)	0.082(0.082)	0.150*(0.086)

Notes: (1) Number of observations is 5,396. (2) Robust standard errors are in parentheses. (3) *significant at 10%. ** significant at 5%. ***significant at 1%.

Conclusion

House prices in cities continue to rise across China in recent years. Consequently, various studies have attempted to analyze the impact of this rapid boom on some economic fundamentals. Although some of these studies examine the manufacturing development impact of the growth in housing prices, the findings have been mixed.

In this study, we find that an increase in a city's house price will significantly crowd in local manufacturing firms, which is consistent with the predictions of Alonso (1964) and Muth (1969) for the crowding-in effects of house price rises on manufacturing in the U.S. Also, house purchase restriction policies tend to dampen the crowding-in effect in several specifications.

These findings have important implications for real estate policies in China and potentially elsewhere. First, if a city wants to increase its concentration of manufacturing firms, it should work to enhance house prices. For instance, this could occur via decreasing the supply of land available for new housing. Another way to increase the house prices in a city (and, in turn, raise manufacturing concentration) is to raise demand for local housing, which could be accomplished through housing subsidies or incentives for people to move into the city in question. In addition, since there is some evidence that the house purchase restrictions dampen or offset the crowding-in effects of higher house prices, these purchase restriction policies should be avoided if the goal is to increase manufacturing concentration as much as possible. Finally, there are important feedback and spillover effects between cities that are associated with house price changes, which should be studied in greater detail before implementing the above policy suggestions.

The results of this study can help to explain the coexistence of high house prices and manufacturing industry development in some Chinese cities (e.g., Shenzhen). Although there are differences in land ownership and the land allocation system between China and the U.S., the influences of housing prices on manufacturing are similar.

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