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Exploring the spatial spillover effect of home purchase restrictions on residential land prices based on the difference-in-differences approach: Evidence from 195 Chinese cities

Xian Zheng[a], Xingtao Chen[a], Ziqing Yuan[b,*]

[a] College of Economics, Jinan University, Guangzhou, China
[b] Department of Real Estate and Construction, The University of Hong Kong, China

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ABSTRACT

Since 2008, the sustained and rapid escalation of housing prices has increasingly become an alarming issue in most Chinese cities, to which the government has responded by strengthening its macro-control of the housing marking. The home purchase restrictions (HPR) policy is considered the harshest regulation implemented to cool down the housing market by eliminating housing speculation. This paper investigates the spatial externality of HPR on residential land prices in surrounding unregulated cities from a spatiotemporal perspective. The HPR policy tends to relocate regulation-induced housing demand to neighboring cities without restrictions in place, thereby leading to a rise in residential land demand and prices via inter-city housing purchases. Using the difference-in-differences approach, we reveal that adopting the HPR policy leads to a 10.3 % significant increase in land prices for neighboring cities without purchase restrictions based on parcel-level land transactions in 195 Chinese cities. The causal effects are robust across different specifications. Moreover, spillovers of the HPR policy vary with different land uses and sources. The spatial heterogeneity arises from the structural changes in residential land demand in response to the HPR policy. Finally, this paper emphasizes that policymakers should consider the spatial heterogeneity, dynamic linkages between cities, and the supply side when establishing housing regulations and developing land-use plans.

1. Introduction

The housing boom that has occurred in China over the past two decades has raised concerns regarding the affordability of housing and regional economic development. Most importantly, overstimulated housing markets are more likely to trigger asset bubbles and further threaten macroeconomic development, especially for rapidly developing countries such as China (Dreger and Zhang, 2013; Liu et al., 2018). Housing prices are closely connected to residential land prices in an endogenous dynamic system (Wen and Goodman, 2013). As an essential component of the cost of housing, land prices underlie rising housing prices. Meanwhile, the demand for urban residential land is derived from housing demand (Muth, 2016). Therefore, the long-term equilibrium of land markets can fundamentally determine outcomes in housing markets. Rationalizing land use and residential land allocation are key aspects of sustainable economic and social development (Liu, 2018). In urban China, the imbalanced structure and divergent trends of land markets have been constantly emerging since the economic reforms of 1978. These manifest as inter-regional inequalities and heterogeneities in land-use patterns. Given the importance of the residential land market to the macroeconomy, there is a growing body of literature that investigates the temporal and spatial dynamics of land prices (Cai et al., 2013; Hu et al., 2013; Liu and Lin, 2014; Qin et al., 2016).

To dampen soaring housing prices and address related social issues such as housing affordability and social inequality, governments around the world have implemented policies to suppress speculative demand for

* Corresponding author.
E-mail addresses: bsxzheng@gmail.com (X. Zheng), chenxt9518@163.com (X. Chen), yzq0612@foxmail.com (Z. Yuan).

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local residential properties, including through tax treatment[1] and quota restrictions.[2] In China, this is primarily achieved through the home purchase restrictions (HPR) policy that strictly controls the number of residential properties one can purchase. The multiple homeownership rate of Chinese urban households is more than 20 %, which is significantly higher than the figure for many developed countries (Huang et al., 2020). With limited investment choices, relatively low holding costs, and soaring housing prices, multiple homeownership is regarded as a viable and dominant investment strategy for wealthy households in China. However, stringent housing regulations can directly restrict local housing investment demand and squeeze out speculative demand, leading to spatial spillover effects that extend beyond the regulated areas through household location choice. For example, investors speculating for capital appreciation can alternatively invest in surrounding cities in response to the HPR policy. Moreover, some may also purchase residential properties in neighboring and emerging cities due to their relative affordability in comparison to the cost of buying in large cities. The demand outflows lead to the potential for exogenous housing booms in surrounding areas. After the initial implementation of HPR in certain cities, adjacent cities subsequently show an abnormal upward trend in housing prices, which can be attributed to HPR's spillover effects. As a result, municipal governments in nearby unregulated cities are forced to implement similar HPR policies to suppress the spillover-oriented housing booms that they experience.

When the policy-restricted housing demand is relocated to neighboring localities, this affects the performance of residential land markets in these districts by changing the expectations and behaviors of real estate developers. Developers' expectations differ when they are faced with different demand structures. If developers in surrounding unregulated cities expect that the external housing demand spillover will present opportunities for them to profit in the future, they have the incentive to increase their bids for residential land. Given the rigidity of supply in the land market, there will be an inward shift in residential land prices. Although residential land prices can reflect developers' expectations in response to HPR, how market participants' expectations and responses distort the policy's effect is underresearched.

The spillover effects of HPR may also vary across regions and time. Rapid urbanization and regional economic integration facilitate frequent inter-regional interactions and linkages. The spillover effects of HPR rely on the relative restrictiveness and attractiveness of adjoining regions. HPR was primarily designed to dampen investment demand through administrative regulation. However, demand structures may vary across cities due to remarkable imbalances in segmented local real estate markets. Therefore, housing policies initiated by the central government may be localized differently by municipal governments according to local conditions (Jia et al., 2018; Zhang et al., 2017). Cities dominated by investment housing demand are anticipated to be more sensitive to the HPR policy. Despite the significance of spatial spillovers in real estate markets (DeFusco et al., 2018; Gong et al., 2020; Zhang and Fan, 2019), few studies have systematically analyzed the heterogeneous spillovers of government policy interventions on residential land prices due to data limitations and the complexity of China's land markets.

This paper takes advantage of HPR in China as a plausibly exogenous shock to local investment demand to investigate the externalities of the HPR policy on the land transaction prices of adjacent unregulated cities. Our causal identification is based on the difference-in-differences (DID) method, which is widely employed in policy evaluation to overcome the disadvantages of traditional econometric models (GÖRg and Strobl, 2007; Zheng et al., 2020). It can address the endogeneity and produce casual evidence on HPR's spillovers on land markets. We examine the spatial externalities of HPR on the residential land price dynamics of nearby unregulated cities based on parcel-level land leasing data collected from the *China Land Market* website.[3] The micro-level data allow us to consider geographic location effects within a city to address the omitted variables bias. To address the potential endogeneity arising from inherent city differences, we first control for time-invariant unobserved heterogeneity and time-varying indicators at the city level. We also allow for non-parallel trends between the treatment and control cities by including treatment-specific time fixed effects. We further address the trend differences in land prices by exploiting the difference-in-difference-in-differences (DDD, or "triple difference") method.[4] Additionally, we estimate how the spillover-induced inflation in land prices evolves with time from a dynamic spatiotemporal perspective. Finally, we explore which types or sources of residential land are more sensitive to HPR's spillover effects.

The remainder of this paper is organized as follows. Section 2 summarizes the related literature (categorized into different themes) to identify the potential literature gap existing in the Chinese context. Section 3 describes the data used in the empirical study and the identification strategy for testing the spillovers of HPR. Section 4 presents the baseline results, along with a robustness check. The dynamic effects and heterogeneous effects are also examined in this section, and the economic interpretations of the empirical results are presented. Section 5 presents the conclusion.

2. Related literature

2.1. Government interventions into the housing market

Since welfare-oriented housing allocation systems were replaced by market-oriented housing markets in the 1980s, China's housing prices have surged at an unprecedented rate (Sun et al., 2017). Some high-income investors acquire multiple properties as inflation-resistant investments, and speculation in the real estate market is largely responsible for the rapid growth in housing and land prices. To stabilize the dramatic rise in housing prices and curb speculative demand, the Chinese government has applied counter-cyclical market regulations[5] Specifically, the authorities have taken various measures targeting first- or second-tier cities.[6] For example, buyers are subjected to stricter requirements for accessing mortgages, pay higher interest rates, and must put down larger deposits. Finally, measures are taken to limit directly the number of properties an individual can purchase. The HPR policy is considered the harshest regulation implemented to cool down the Chinese housing market by preventing speculation. The HPR policy issued by the State Council was originally implemented in Beijing on 17 April 2010 and then progressively roll out to 46 cities by July 2010. Following that, some second-tier cities also initiated HPR to curb the surging

[1] For example, non-residential property buyers are subject to higher taxes when acquiring residential properties in Australia, Canada, Singapore, the United Kingdom, and Israel.

[2] The Swiss government limits the number of houses available for investment purposes. New Zealand has also imposed strict restrictions on foreign investment in housing markets.

[3] https://www.landchina.com/.

[4] We employ the DDD approach by introducing industrial land as an additional control group since HPR does not have a direct effect on the industrial land market. Double qualification is required to be categorized into the treatment group.

[5] The State Council issued "Ten National Notices" (effective on 17 April 2010) and "Eight New National Notices" (effective on 26 January 2011) to take administrative measures to restrict speculation in the residential real estate market.

[6] China's central government designed a tier system in the 1980s based on cities' comparative economic, political, and population strengths. According to China's National Bureau of Statistics, the first-tier cities are Beijing, Shanghai, Guangzhou, and Shenzhen; the second-tier cities are provincial capitals, autonomous regional capitals, and other sub-provincial cities (http://www.stats.gov.cn/tjzs/cjwtjd/201308/t20130829_74324.html). Specifically, these cities are listed by tiers in Appendix Table A3.

demand for housing. Despite some slight modifications, in several municipalities, HPR generally prohibits local residents with registered permanent residence (Hukou) from buying more than two residential properties, and non-resident purchasers without Hukou are restricted to buying only one residential property with supporting documents (e.g., a certificate of local tax payments or social security records for a certain period). Subsequently, the State Council issued “Five National Notices” on 20 February 2013, indicating that municipalities should further customize and diversify HPR according to local conditions.

Generally, HPR plausibly achieved the intended goal of immediately reducing housing prices in regulated cities. China’s National Bureau of Statistics reported that the Newly Constructed House Price Index for 70 large and medium-sized cities[7] decreased by 6.5 % in 2011 and continued to fall in early 2012. In Beijing, the trading volume of residential properties[8] in the new home and resale housing markets fell dramatically by 64 % and 65 %, respectively (Wu and Li, 2018). However, adjacent unregulated cities were also greatly influenced by spillover effects because housing investors subject to HPR seek capital gains in peripheral markets with undervalued prices. Shih et al. (2014) find that HPR stimulates the spillover of cash flow from the core to the periphery based on a local housing market equilibrium analysis. Similar patterns were found in some other small cities whose neighboring cities were subject to HPR. Li et al. (2020) suggest that after the first and second rounds of HPR[9] in Beijing, on a quarterly basis, the housing transaction volumes in Tangshan increased by 47 % and 39 %, respectively. Subsequently, with the exception of Beijing, Shanghai, Guangzhou, and Shenzhen, all the HPR-regulated cities withdrew from HPR by the end of 2014. However, given the “retaliatory rebound” of housing prices in 2015, the second round of HPR was intensively implemented in 2016.

Existing research mainly evaluates whether HPR can effectively cool down the housing market by empirically examining HPR’s short-term and long-term effects on curbing housing prices, transaction volume, and speculative activity. Some argue that HPR can effectively dampen speculative investment demand in the short term but that it has limited effects in the long run. For example, Chen et al. (2018) find that while HPR can lower housing prices in the short term, it results in housing prices subsequently appreciating. Li et al. (2017) also find that the removal of HPR may increase housing prices that were previously controlled.

Conversely, some find that HPR cannot effectively curb speculative demand. Zhang and Wang (2015) find that HPR fails to lower housing prices, especially for top-tier cities. Sun et al. (2017) show that HPR cannot exclude some local homeowners from making speculative purchases and even curtails owner-occupied housing demand for non-local households. Glaeser and Luttmer (2003) also argue that HPR impairs rational housing demands and distorts housing market mechanisms, resulting in resource misallocation and the loss of social welfare. Li et al. (2020) reveal that resale housing prices are not significantly lowered by HPR based on residential sales data. Somerville et al. (2020) find little evidence to show that HPR can restrain the growth in housing prices, although HPR has had a salient and diminishing effect in suppressing housing market activity. Jia et al. (2018) find that localized HPR boosted housing prices in Guangzhou, which vastly deviated from the policy’s original goals. Additionally, more recent studies have confirmed the spatial heterogeneity of HPR’s effects on housing prices (Cao et al., 2015; Jia et al., 2018; Li et al., 2020; Sun et al., 2017; Wu and Li, 2018; Zhang and Wang, 2015). For example, Sun et al. (2017) suggest that housing prices are more sensitive to HPR where the housing supply is inelastic. Cao et al. (2015) reveal that HPR’s dampening effect on housing prices is stronger in cities that rely heavily on the real estate industry and land leasing revenues. Overall, there is no consensus among researchers regarding the effectiveness of HPR.

The effectiveness of the government interventions that regulate housing demand, supply, and the land-use regime continues to attract attention from researchers (Han et al., 2020; Hui and Wang, 2014; Tian and Ma, 2009; Wu and Li, 2018). Most of them focus on spatiotemporal price variations in the real estate market and social welfare implications (Lee and Reed, 2014). Some also examine the consequences of land-use regulations from the perspective of supply-side shifts (Brueckner and Singh, 2020; Han et al., 2020; Tan et al., 2020). Although a substantial body of literature focuses on investigating HPR’s effectiveness, little attention has been paid to the spatial connection and contagious effects of government intervention. This paper aims to fill this research gap by assessing how and to what extent HPR affects the transactional dynamics of residential land prices across space and time.

Land prices are equilibrium outcomes in a regional dynamic system where social, economic, legal, and environmental factors interact across space and time (Grigsby, 1986). Fundamentally, the residential land price can be expressed as a function of environment, location, and land attributes based on the hedonic pricing model (Rosen, 1974). Furthermore, some researchers find that the land price is largely determined by market participants’ expectations of future prices and rents (Schmid, 2016). Intuitively, policy effectiveness might be modified by the expectations and strategic adjustments of households in response to policy shocks. Similarly, real estate developers would also adjust their housing supply and bids for residential land according to expectations for the rigidity and duration of the regulation. Developers’ land auction behaviors and local governments’ land supply jointly affect land price dynamics. In China, land ownership is monopolized and overseen by the central government. The land reserve system entitles municipal governments to allocate land-use rights according to the central government’s guidelines. In China’s fiscally decentralized but politically centralized system, local governments tend to maximize land leasing revenues when supplying local land according to a construction land quota (Han and Kung, 2015; Waxman et al., 2020). Real estate developers can acquire land-use rights through a market-oriented land granting scheme (auction, tender, negotiation). Due to the institutional constraints, including a construction land quota and land transfer schemes, the short-term land supply is inelastic (Tan and Beckmann, 2010; Wang et al., 2010; Zhou et al., 2017). These particular institutional arrangements distinguish China’s market from those in developed countries.

In this paper, we fill this research gap by investigating the consequences of HPR for surrounding residential land markets, which can reflect market participants’ responses. The logic behind this is that HPR in overheated cities squeezes out excess investment housing demand, which is forced to spill over into neighboring cities. The developers expecting house prices to appreciate tend to increase the demand for residential land, given the inelastic supply of land. Thus, limits on local purchasing raise the land leasing prices in bordering cities.

2.2. Spatial spillovers of the real estate market

Since cities are becoming increasingly integrated, it is irrational to

[7] China’s National Bureau of Statistics releases the Newly Constructed House Price Index for 70 Large and Medium-Sized Cities on a monthly basis according to housing statistics programs (http://www.stats.gov.cn/tjgz/tzgb/201102/t20110216_57581.html). The Sales Price Indices of Residential Buildings in 70 Large and Medium-Sized Cities can be found in the datasets of the National Bureau of Statistics (http://data.stats.gov.cn/english/tablequery.htm?code=AA0101).

[8] The Total Sale of Commercialized Residential Buildings Sold (100 Million Yuan) for Beijing can be found in the datasets of the National Bureau of Statistics (http://data.stats.gov.cn/english/easyquery.htm?cn=E0103&zb=A051L&reg=110000&sj=2019). Moreover, in 2012, the overall sales of residential buildings went up by 10.9% according to a press release from the National Bureau of Statistics (http://www.stats.gov.cn/english/PressRelease/201301/t20130118_72251.html).

[9] The first round of HPR in Beijing was issued on 30 April 2010. The second round of HPR in Beijing was issued on 30 March 2013.

Table 1
Definition of variables.

Variable	Definition
Dependent variables:	
Ln(price)	= transaction amount divided by land parcel area, namely, the unit transaction price of the land parcel (in log form).
Explanatory variables:	
Residential	= 1 if residential land; = 0 if industrial land; binary variable indicating different land-use types.
Light[a]	= the light intensity of the corresponding grid in the NTL images where the land parcel is located divided by the highest light intensity among all the grids within the particular city; namely, relative light intensity. This variable is used as a proxy for location effects.
DCBD	= the Euclidean distance between the land parcel and the commercial business district (CBD) (km).
DShoppingMall	= the Euclidean distance between the land parcel and its nearest shopping mall (km).
DPark	= the Euclidean distance between the land parcel and the nearest park (km).
DHospital	= the Euclidean distance between the land parcel and the nearest hospital (km).
Auction	= 1 if auction (Paimai) or tender (two-stage auction, Guapai); = 0 if negotiation (Xieyi); binary variable indicating different forms of land leasing.
Ln(area)	= total area of the land parcel (km^2).
Ln(supply)	= city-level total land supply per capita (in log form).
RLSS	= the share of residential land supply in total land supply, namely the land supply structure.
Ratio	=the upper limit of the plot ratio, a ratio of a building's gross floor area to the area of the land parcel upon which it is built.
Ln(POPD)	= city-level population density (in log form).
Ln(GDPPC)	= city-level gross domestic product (GDP) per capita (in log form).

Data sources: China Land Market website (https://www.landchina.com); China City Statistical Yearbook; https://ngdc.noaa.gov/eog/download.html.

[a] We use the Defense Meteorological Satellite Program-Operational Linescan System (DMSP-OLS) nighttime lights time series (https://ngdc.noaa.gov/eog/download.html) to calculate the local relative light intensity as a proxy for geographic location effects and local economic activities, which can indicate a locality's attractiveness to a certain degree. Specifically, we first convert the Night Time Light (NTL) images to 1000 $m \times 1000$ m gridded pieces and project the latitude and longitude of each land parcel on the NTL images to obtain the average visible band digital number (DN) of each land parcel from a corresponding 1000 $m \times 1000$ m gridded piece in the NTL images.

Table 2
Statistics of key variables.

Variable	Observations	Mean	Std. Dev.	Min	Max
Panel A: Residential and industrial land use parcels					
Ln(price)	42,957	6.27	1.15	0.73	10.51
Residential	42,957	0.50	0.50	0.00	1.00
DCBD	42,957	8.65	7.85	0.04	82.75
DShoppingMall	42,957	0.53	1.00	0.01	22.58
DPark	42,957	2.24	3.09	0.01	46.47
DHospital	42,957	0.61	0.94	0.01	17.65
Light	42,957	0.88	0.15	0.00	1.00
ln(area)	42,957	1.37	0.81	0.02	5.91
Auction	42,957	0.13	0.34	0.00	1.00
ln(supply)	42,957	1.37	0.61	0.00	6.12
RSLL	42,957	0.41	0.22	0.00	1.00
Ln(POPD)	42,957	6.65	0.76	3.74	9.51
Ln(GDPPC)	42,957	10.64	0.67	8.19	12.58
Panel B: Residential land use parcels					
Ln(price)	21,297	7.13	0.99	0.73	10.51
DCBD	21,297	8.60	8.32	0.04	82.75
DShoppingMall	21,297	0.46	0.85	0.01	22.58
DPark	21,297	2.05	2.83	0.01	46.47
DHospital	21,297	0.54	0.82	0.01	17.65
Light	21,297	0.90	0.14	0.00	1.00
Ratio	21,297	2.75	1.52	0.23	48.50
ln(area)	21,297	1.37	0.82	0.02	5.42
Auction	21,297	0.21	0.41	0.00	1.00
Panel C: Industrial land use parcels					
Ln(price)	21,660	5.44	0.48	0.83	10.06
DCBD	21,660	8.69	7.36	0.29	81.27
DShoppingMall	21,660	0.61	1.13	0.01	21.11
DPark	21,660	2.43	3.30	0.01	46.39
DHospital	21,660	0.68	1.04	0.01	17.65
Light	21,660	0.87	0.17	0.00	1.00
ln(area)	21,660	1.37	0.79	0.02	5.91
Auction	21,660	0.05	0.22	0.00	1.00

Data sources: China Land Market website (https://www.landchina.com); China City Statistical Yearbook; https://ngdc.noaa.gov/eog/download.html.

consider individual cities as isolated housing markets and ignore geographical interconnections in real estate markets. The existence of regional spillovers and linkages in real estate markets has been empirically proved in the literature (Chen and Chiang, 2020; Costello et al., 2011; Gong et al., 2020; Holmes and Grimes, 2008; Riddel, 2011; Shih et al., 2014; Zhang and Fan, 2019; Zhang and Wang, 2015). The "ripple effect" has been proposed as a way of better understanding the spatially dynamic linkages among local housing prices (Chen and Chiang, 2020; Holmes and Grimes, 2008; Meen, 1999). It implies that changes in local housing prices can spatially spread to adjacent areas, resulting in the convergence of housing prices in the long run. Qian et al. (2019) provide evidence for HPR's spillovers by finding that investors in regulated cities rely heavily on the alternative investment channel in capital markets. Likewise, the land market also manifests significant inter-regional linkages and spillovers. Except for the structural and locational amenities of land parcels in the hedonic model, urban land prices are also closely associated with neighborhood-related factors (Qin et al., 2016). However, how the HPR spillovers that are propelled by inter-city purchases affect the spatiotemporal behavior of residential land prices in neighboring unregulated cities remains underexplored. Theoretically, an increase in investment demand stimulates developers' demand for land in surrounding cities, thereby driving up residential land prices. However, the empirical evidence on these spatial externalities is lacking. We fill the gap by providing causal evidence that spillovers of HPR policy can translate into an economically significant impact on the residential land prices of unregulated cities in close proximity.

At the root of the issue of spillover effects are the economic consequences of non-local housing purchases for real estate markets. Some argue that domestic inter-regional capital flows can exert an influence on the local real estate market (Favilukis and Van Nieuwerburgh, 2017). Given its extreme spatial inequality and rapid urbanization, inter-city housing purchases constitute an important segment of housing investment in urban China (Zhang et al., 2020). Such inter-city capital flows in the housing market usually occur in parallel with multiple homeownership acquisition, household migrations, asset investments, and wealth transfer (Meen, 1999). Most importantly, Zhang et al. (2020) reveal that inter-city housing purchases are vulnerable to being shaped by government policies. However, less is known about how inter-city housing purchases play a role in forming linkages between cities and further affect real estate markets elsewhere. Using micro-panel datasets of land transactions, we scrutinize whether and to what extent inter-city housing purchases driven by excess investment demand affect residential land prices.

This paper contributes to the existing research by going beyond the direct and immediate impacts of HPR policy and focusing on spatial externalities by assessing land price performance as determined by municipal governments and developers' responses to HPR.

3. Identification strategy and data

3.1. Data

The parcel-level land leasing data used in this study are collected from the China Land Market[10] website, which records historical land

[10] https://www.landchina.com/.

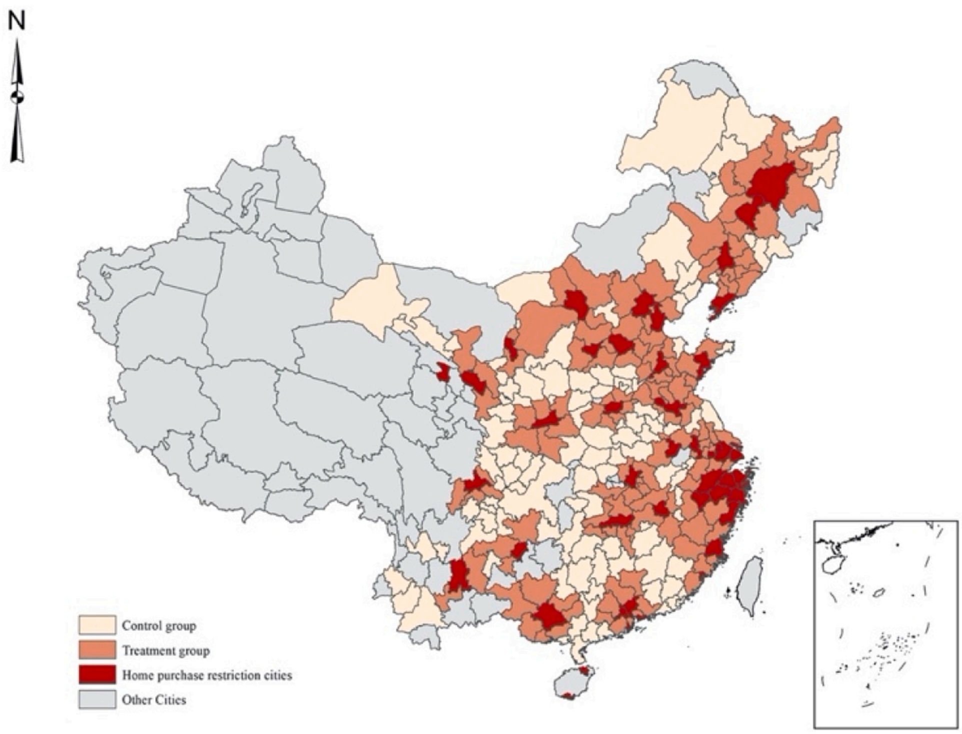

Fig. 1. Geographical distribution of HPR cities and neighboring cities.
Note: This figure illustrates the geographical distribution of cities subject to HPR and their neighboring cities. The red color areas indicate HPR-regulated cities; the orange and light beige areas represent the treatment group (89 cities) and the control group (106 cities), respectively.[15]

transaction data at the city level from 2004. Each land transaction includes rich information on parcel characteristics, such as transaction price, land area, transaction date, address of the land parcel, land-use type (e.g., residential, commercial, and industrial), transaction type (e.g., auction, tender, and negotiation), and the bidder's name. We use the land transaction data for residential and industrial lands from 195 cities (83 treated cities and 112 control cities) spanning 2007–2014.[11] Table 1 provides the definitions of the main variables and Table 2 reports the descriptive statistics for all variables. The descriptive summary of the full sample is presented in panel A of Table 2. The residential land leasing data is used in the baseline identification, while the industrial land leasing data is used for the robustness test. To avoid the biased estimation derived from outliers, we eliminate the observations that the land parcel area is less than 0.02 ha. The information for the residential and industrial land use parcels is presented in panels B and C of Table 2, respectively.

3.2. Difference-in-differences identification strategy

As shown in Fig. 1, 46 Chinese cities[12] adopted the HPR in 2010 and 2011 to curb skyrocketing housing prices and address worsening housing affordability. If the developers in bordering unrestricted cities expect housing demand inflows, then we would expect to see an increase in residential land prices in response to the shift in demand. We identify these spatial spillover effects of the HPR on the land transaction prices of neighboring unregulated cities in DID specifications.

In our DID identification framework, the capital inflow via inter-city purchases stimulated by HPR-induced housing demand is regarded as the treatment. Thus, cities that are bounded by HPR-regulated cities are assigned to the treatment group (i.e., the orange area in Fig. 1), while the treatment group's neighboring cities are viewed as the control group. The specification of our DID model with two-way fixed effects is given as follows:

$$\ln\left(price_{i,j,t}\right) = \beta_0 + \beta_1\left(Treat_j \times Post_{j,t}\right) + \gamma X_{i,t} + \eta_j + \lambda_t + \varphi\left(Treat_j \times t\right) + \varepsilon_{i,j,t} \tag{1}$$

where i, j, and t index land parcel, city, and year, respectively. $\mathrm{Ln}(price)$ is the log price of the land parcel; $Treat_j$ is a treatment indicator that equals one if a land parcel is located in a treatment city (i.e., a city that is adjacent to an HPR-restricted city) and equals zero if it belongs to the control group. $Post_{j,t}$ equals one for the years after HPR's implementation.[13] The interaction term $Treat_j \times Post_{j,t}$ is the DID estimator. The estimated coefficient of primary interest is β_1, which captures the spillover effect of HPR on the land leasing prices of neighboring cities. $X_{i,t}$ is a set of parcel-level and city-level control variables. η_j is the city fixed effect that controls the time-invariant characteristics in a particular city (e.g., natural endowment; location). λ_t is the year fixed effect which controls the common trend of land prices at the national level. Moreover, we include the linear treatment-specific time trend ($Treat_j \times t$) to control for the potential divergence of time trends between the treatment and control groups. $\varepsilon_{i,j,t}$ is the error term.

There remain potential challenges with non-random treatment and inter-city differences. Unobserved patterns in residential land price

[11] We did not include data after 2014 because most HPR cities ended the policy after this date.
[12] Please refer to Table A1 in the Appendix.
[13] In our treatment group, the HPR policy was implemented in different cities in 2010 and 2011. Please refer to Table A1 in the Appendix for details.

Table 3
Results of DID estimations.

	Dependent variable: Ln(price)		
	(1)	(2)	(3)
Treat × Post	0.060*** (0.022)	0.087*** (0.021)	0.084*** (0.021)
Light		0.747*** (0.048)	0.749*** (0.048)
Ratio		0.162*** (0.014)	0.162*** (0.014)
Ln(area)		−0.078*** (0.009)	−0.078*** (0.009)
Auction		0.278*** (0.019)	0.280*** (0.019)
ln(supply)		−0.034** (0.015)	−0.031** (0.015)
RLSS		−0.125*** (0.033)	−0.127*** (0.033)
ln(POPD)			0.089*** (0.034)
ln(GDPPC)			−0.027 (0.041)
City fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Linear treatment trend	Yes	Yes	Yes
Adjusted R^2	0.34	0.42	0.42
Observations	21,297	21,297	21,297

Notes: Table reports coefficients in the baseline model of Eq. (1). Robust standard errors are reported in parentheses. *, **, *** represent significance levels of 10 %, 5%, and 1%, respectively.

dynamics between the treatment and control groups may exist[14]. The systematic and innate differences are likely to be more prominent between HPR-restricted cities and unrestricted cities. However, we mainly focus on spillover effects in our DID identification so that the treatment and control groups are all unregulated cities. Other attributes unrelated to the HPR policy may affect the activities of the land market, such as the share of different land-use types in the supply of land. To rule out the possible impact of the supply side on land prices, we also control for local land supply and the share of residential land supply in total land supply to capture the short-term supply strategy in response to the HPR-induced demand changes.

To further address the violation of the DID parallel trend assumption, we employ a DDD approach by using industrial land leasing data as a control group, since HPR does not have a direct effect on the industrial land market. The causal interpretations of DDD do not require two parallel trends between the treatment and control groups since the bias in the DID estimator will be differenced out by computing the triple difference between two categories (i.e., residential and industrial land). Additionally, DDD can reduce omitted variable bias relative to the DID method (Berck and Villas-Boas, 2016). The specification of the DDD model is given as follows:

$$\begin{aligned}\ln\left(price_{i,j,t}\right) = {} & \beta_0 + \beta_1\left(Treat_j \times Post_{j,t} \times Residential_i\right) + \beta_2\left(Treat_j \times Post_{j,t}\right) \\ & + \beta_3\left(Treat_j \times Residential_i\right) + \beta_4\left(Post_{j,t} \times Residential_i\right) \\ & + \beta_5 Residential_i + \gamma X_{i,t} + \eta_j + \lambda_t + \varphi\left(Treat_j \times t\right) + \varepsilon_{i,j,t},\end{aligned} \tag{2}$$

in which $Residential_i$ represents the land-use type, which takes the value of one for residential land parcels and zero for industrial land parcels. The triple interaction term $Treat_j \times Post_{j,t} \times Residential_i$ is the DDD estimator.

[14] Although we address non-random treatment and inherent differences between cities by relaxing parallel trend assumptions, we cannot fully rule out the differences across local governments in terms of localizing the HPR policy that was initiated by the central government. Future work may include an appropriate proxy to address this problem.

[15] Please refer to Table A2 in the Appendix for details.

Table 4
Robustness check: Alternative measurement of location effect.

	Dependent variable: Ln(price)	
	(1)	(2)
Treat × Post	0.077*** (0.021)	0.075*** (0.021)
DCBD	−0.004*** (0.001)	−0.004*** (0.001)
DShoppingMall	−0.031** (0.012)	−0.031** (0.012)
DPark	−0.020*** (0.002)	−0.020*** (0.002)
DHospital	−0.000 (0.014)	−0.001 (0.014)
Ln(area)	−0.078*** (0.009)	−0.078*** (0.009)
Ratio	0.162*** (0.015)	0.162*** (0.015)
Auction	0.282*** (0.019)	0.283*** (0.019)
ln(supply)	−0.038** (0.015)	−0.035** (0.015)
RLSS	−0.125*** (0.033)	−0.127*** (0.033)
ln(POPD)		0.089*** (0.034)
ln(GDPPC)		−0.013 (0.041)
City fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Linear treatment trend	Yes	Yes
Adjusted R^2	0.42	0.42
Observations	21,297	21,297

Notes: Table reports coefficients in the baseline model of Eq. (1). Robust standard errors are reported in parentheses. *, **, *** represent significance levels of 10 %, 5%, and 1%, respectively.

4. Empirical results

4.1. Basic results

Table 3 presents the DID estimation results for Eq. (1). In column (1), we include the DID term (i.e., $Treat_j \times Post_{j,t}$) and control for the city and year fixed effects. The estimated coefficient of $Treat_j \times Post_{j,t}$ is positive and statistically significant at 1%. The land parcels are highly heterogeneous in terms of locations and amenities. Thus, the estimated spillover effect could be biased in this case. In column (2), we include a set of land parcel-level control variables. The magnitude of the estimated coefficient of interest is slightly lower than the result in column (1) and carries the same sign and significance level. Meanwhile, all the control variables are statistically significant at 1% and carry the expected sign. Land parcels located in the downtown area (higher light intensity) leased via auction-based approaches were transacted with higher unit prices. Hence, the location effects should be taken into consideration when examining the dynamic spatial variations of residential land prices. Our research provides empirical evidence supporting the significance of location-related land price gradients (Zheng and Kahn 2008). In the last column, we further introduce the city-level control variables that reflect the development levels of cities. The results remain robust and show that HPR policy raises the land leasing prices of bordering cities by 10.3 % (i.e., = *exp* (0.098)).

4.2. Robustness checks

In this section, we provide two types of robustness checks to verify whether the estimated spillover effects are sensitive to different specifications.

4.2.1. Using an alternative measurement of location effect

In Table 3, we use relative light intensity to quantify the location effect. Some researchers doubt the ability of relative light intensity to reflect location effects accurately. Therefore, we also use the classic location measurement, distance to the nearest commercial business districts, shopping mall, park, and hospital as alternative measurements of the location effect. We follow the same model specification as in the last two columns of Table 3 while using this set of variables instead of *Light* as location effects. The estimation results in Table 4 show that the coefficients of the DID term remain stable and statistically significant at the 1% level. Overall, the light intensity is a more comprehensive indicator in capturing the socio-economic status and centrality of the area

Table 5
Robustness check: DDD approach.

	Dependent variable: Ln(price)		
	(1)	(2)	(3)
Residential × Treat × Post	0.106*** (0.018)	0.097*** (0.018)	0.095*** (0.018)
Treat × Post	−0.061** (0.029)	−0.044 (0.028)	−0.049* (0.028)
Residential × Post	0.484*** (0.020)	0.513*** (0.020)	0.515*** (0.020)
Residential × Treat	−0.155*** (0.018)	−0.093*** (0.018)	−0.092*** (0.018)
Residential	1.447*** (0.021)	1.331*** (0.021)	1.328*** (0.021)
Light		0.432*** (0.026)	0.433*** (0.026)
Ln(area)		−0.078*** (0.005)	−0.078*** (0.005)
Auction		0.294*** (0.014)	0.295*** (0.014)
ln(supply)		−0.010 (0.010)	−0.011 (0.010)
ln(POPD)			0.109*** (0.027)
ln(GDPPC)			0.037 (0.032)
City fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Linear treatment trend	Yes	Yes	Yes
Adjusted R^2	0.67	0.68	0.68
Observations	42,957	42,957	42,957

Notes: Table reports coefficients in the baseline model of Eq. (2). Robust standard errors are reported in parentheses. *, **, *** represent significance levels of 10 %, 5%, and 1%, respectively.

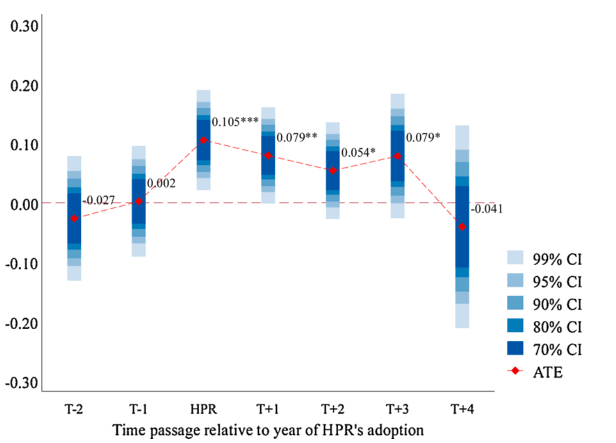

Fig. 2. Dynamic spillover effects of the HPR policy on bordering cities' land prices.
Note: CI indicates confidence interval; ATE indicates average treatment effect; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

in which the land parcel is located.

4.2.2. Triple differences approach

We further include transaction data and employ the DDD approach to verify the spillover effects of the HPR policy. The results in Table 5 show that the interaction terms among *Residential*, *Treat*, and *Post* (the DDD term) are all statistically significant at 1%. The estimated magnitudes are slightly larger than the figure for our benchmark DID model. These results imply that the DID model would at least measure the lower boundary of the spillover effect if there were some unobserved differences between the treatment group and the control group.

4.3. Dynamic effects

The previous results have empirically revealed that the HPR policy

Table 6
Heterogeneous effects: Different land types.

	Dependent variable: Ln(price)	
	(1) Small-apartment land	(2) Other types of land
Treat × Post	0.107*** (0.040)	0.079*** (0.024)
Controls	Yes	Yes
City fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Linear treatment trend	Yes	Yes
Adjusted R^2	0.46	0.45
Observations	6109	15,173

Notes: Robust standard errors are reported in parentheses. *, **, *** represent significance levels of 10 %, 5%, and 1%, respectively.

adopted in a particular city will exert a positive spillover effect on the land prices of adjacent cities. However, whether and how the spillover effects vary over time is still unclear. In this section, we use the following dynamic DID framework to estimate the year-on-year changes in spillover before and after the adoption of the HPR policy:

$$\ln\left(price_{i,j,t}\right) = \beta_0 + \sum_{T=-2}^{4} \beta_T\left(Treat_j \times Year_{j,T}\right) + \gamma X_{i,t} + \eta_j + \lambda_t + \varphi\left(Treat_j \times t\right) + \varepsilon_{i,j,t} \tag{3}$$

where the dummy variable takes the value of one for year T and zero otherwise, and T equals to the difference between the year in which the land transaction took place and the year in which the HPR policy was adopted. The estimated value of β_T represents the time-varying spillover effect of the HPR policy. The estimated coefficients of β_T are illustrated in Fig. 2. The horizontal axis of the figure represents the year before or after the year in which the HPR policy was adopted, while the estimated value of each year is on the vertical axis. The estimated values of β_{-1} and β_{-2} are not statistically different from zero at the 10 % level, which is consistent with the parallel trend assumption of the DID specification. Furthermore, the estimations of β_k become statistically significant at the 1% level for the year in which the HPR policy was adopted (i.e., $T = 0$) and lose significance in the fourth year (i.e., the year 2014) after the policy was implemented.

4.4. Heterogeneous effects

The above results have identified a robust and positive spillover effect of the HPR policy on land leasing prices in neighboring unregulated cities. Next, we explore which types of residential land are more sensitive to external shocks from the policy.

In Table 6, we start by examining whether the spillover effects are heterogeneous across different residential land types: small-apartment land and other types of land. Small-apartment land parcels are designed to provide small-sized apartments (i.e., less than 90 m^2) at a lower total price, while other lands have no restriction on the size or

Table 7
Heterogeneous effects: Different land supply sources.

	Dependent variable: Ln(price)	
	(1) New land supply	(2) Current land supply
Treat × Post	0.106** (0.049)	0.127*** (0.048)
Controls	Yes	Yes
City fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Linear treatment trend	Yes	Yes
Adjusted R^2	0.48	0.43
Observations	7475	7637

Notes: Robust standard errors are reported in parentheses. *, **, *** represent significance levels of 10 %, 5%, and 1%, respectively.

Table 8
Heterogeneous effects: Regional diversity in the spillover effect of HPR.

	Dependent variable: Ln(price)		
	(1) East	(2) Middle	(3) West
Treat × Post	0.087*** (0.030)	0.074** (0.033)	0.346*** (0.078)
Controls	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Linear treatment trend	Yes	Yes	Yes
Adjusted R^2	0.45	0.40	0.41
Observations	10,416	8543	2338

Note: Robust standard errors are reported in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The east sample includes Hebei, Liaoning, Jilin, Heilongjiang, Jiangsu, Zhejiang, Fujian, Shandong, and Guangdong provinces; the middle sample includes Shanxi, Anhui, Guangxi, Jiangxi, Henan, Hubei, and Hunan provinces; the west sample includes Sichuan, Guizhou, Yunnan, Shaanxi, and Gansu provinces.

price of residential apartments. The sub-sample results in Table 6 show that the estimated coefficients of the DID term are all statistically significant at 1%, while the spillover effect on small-apartment land is larger than it is for other types of residential land.

Subsequently, we split the residential land leasing data into two subsamples of construction land source: new land supply and existing land supply. The new residential land supply comes from land-use transformation (i.e., from converting rural or industrial land to residential land use), is generally located in the suburban areas of the treatment cities and is probably closer in proximity to the HPR-regulated cities. We use the same specification as in Table 6 and report the results in Table 7. The estimated spillover effects on the new land supply group and current land supply group are 0.106 and 0.127, respectively. These findings reveal that the current land supply parcels are more likely to be sold at a higher price after the HPR policy has been implemented in neighboring cities. In this sense, HPR's spillovers can shape the residential land demand in nearby cities, thereby affecting the local land supply structure.

We also investigate regional diversity in the spillover effects of HPR following the baseline specification in Table 3, as the economic development in different regions follows different paths with different types of endowments. The sample is divided into east, middle, and west regions. The coefficients on the DID estimator vary among the samples, but the overall patterns and magnitudes are consistent with our baseline results in Table 3. The results in Table 8 indicate that the adoption of the HPR policy leads to a significant increase in land prices for neighboring cities without purchase restrictions in the presence of spatial heterogeneity.

5. Conclusion

This paper explores the spatial spillover effects of the HPR policy on the land transaction prices of surrounding unregulated cities. The results reveal that the HPR policy indirectly increases land prices in adjacent unregulated cities by 10.3 %. Moreover, such spillover effects are heterogeneous according to different land uses and sources. This positive price effect is stronger for residential land designed for small-sized apartments and newly supplied residential lands that have been transformed from other land-use types. This implies that the implementation of the HPR policy has exerted a structural impact on the land demand and supply in China. This process involves market participants' expectations and adjusted behaviors in reaction to the HPR policy. These empirical results help shed light on how inter-city housing purchases driven by HPR's investment demand spillovers cause land price appreciation in nearby unregulated cities.

In general, our empirical results show that inter-regional spillovers in the real estate market are robust and significant for different specifications. This supports the findings of Costello et al. (2011), who reveal the presence of interstate spillovers of non-fundamental components in house prices based on Australian capital city data, and DeFusco et al. (2018) emphasis on the role of spatial spillovers in the temporal and geographical variations of the American housing boom. Moreover, it supports Holly et al. (2011) illustration of the spatiotemporal diffusion of shocks in the dynamic real estate market in the United Kingdom and Gong et al. (2016) indication that shocks to a specific city are propagated spatially to distant cities in China. Overall, our findings are consistent with the previous research on spatial spillover effects in the real estate market, and we provide additional evidence for these spillovers in China's residential land market.

Our findings have implications for policymaking. First, municipal governments should be aware that real estate markets in different cities do not operate in a vacuum; rather, they are always linked through intercity housing purchases. Local housing markets are not only affected by local policy interventions but also by the policies of surrounding cities. Therefore, governments should take spatial spillover and feedback effects into account in their regional policy designs. Second, spillover-induced real estate booms manifested in land prices also reveal that financial investment channels still have room for improvement. Since buying residential property still serves as a major investment vehicle, governments should offer alternative investment assets in order to reduce the reliance on housing assets and diversify investment portfolios. For example, property taxation and related policies can be implemented to increase the holding costs of households owning multiple homes. Third, the obvious heterogeneity of HPR spillover effects should be included in governmental decision-making frameworks. Finally, policymakers should consider local supply constraints when implementing housing policies on the demand side. Otherwise, the demand-side regulations may temporarily suppress overheated housing markets and fail to stabilize the real estate market in the long term. Speculative demand and owner-occupied housing demand are both curtailed by the HPR policy and relocated to surrounding second- and third-tier cities, which may distort the land supply–demand structure in those areas. Therefore, governments should dynamically adjust the residential and industrial land quota in compliance with local housing demand to avoid spatial misallocation.

Table A1
The implementation of Home Purchase Restriction across cities.

City	Effective year	City	Effective year
Tianjin	2010	Nanjing	2010
Shanghai	2010	Wuxi	2011
Guangzhou	2010	Harbin	2011
Fuzhou	2010	Guiyang	2011
Xiamen	2010	Nanning	2011
Ningbo	2010	XiAn	2011
Dalian	2010	Xining	2011
Lanzhou	2010	Yinchuan	2011
Beijing	2010	Chengdu	2011
Shenzhen	2010	Foshan	2011
Zhengzhou	2011	Sanya	2010
Hefei	2011	Suzhou	2010
Changchun	2011	Hangzhou	2010
Wuhan	2011	Wenzhou	2010
Nanchang	2011	Zhoushan	2011
Kunming	2011	Shenyang	2010
Zhuhai	2011	Changsha	2010
Jinhua	2011	Wulumuqi	2011
Haikou	2010	Shaoxing	2011
Jinan	2011	Huhehot	2011
Qingdao	2011	Xuzhou	2011
Shijiazhuang	2011	Taizhou	2011
Taiyuan	2011	Quzhou	2011

CRediT authorship contribution statement

Xian Zheng: Conceptualization, Methodology, Software, Funding acquisition, Supervision, Project administration, Funding acquisition,

Table A2
The treatment group and control group in the baseline specification.

Treatment group	Tangshan, Xingtai, Baoding, Zhangjiakou, Chengde, Cangzhou, Langfang, Hengshui, Yangquan, Shuozhou, Jinzhong, Xinzhou, Lvliang, Anshan, Fushun, Benxi, Dandong, Jinzhou, Yingkou, Fuxin, Liaoyang, Tieling, Songyuan, Jilin, Siping, Daqing, Yichun, Jiamusi, Qitaihe, Mudanjiang, Suihua, Changzhou, Nantong, Lianyungang, Yangzhou, Zhenjiang, Taizhou, Jiaxing, Lishui, Huainan, MaAnshan, Chuzhou, Suzhou (Anhui), Liuan, Xuancheng, Putian, Quanzhou, Zhangzhou, Nanping, Pingxiang, Jiujiang, Yichun, Fuzhou(Jiangxi), Zibo, Zaozhuang, Yantai, Jining, Taian, Rizhao, Laiwu, Linyi, Dezhou, Liaocheng, Binzhou, Heze, Kaifeng, Luoyang, Pingdingshan, Jiaozuo, Xuchang, Huangshi, Ezhou, Xiaogan, Jingzhou, Huanggang, Xianning, Zhuzhou, Xiangtan, Yueyang, Yiyang, Loudi, Shaoguan, Jiangmen, Shiuhing, Huizhou, Qingyuan, Dongguan, Zhongshan, Yunfu, Qinzhou, Guigang, Baise, Laibin, Deyang, Meishan, Ziyang, Zunyi, Anshun, Bijie, Qujing, Yuxi, Xianyang, Hanzhong, Baiyin, Wuwei.
Control group	Qinhuangdao, Handan, Datong, Changzhi, Jincheng, Yuncheng, Linfen, Panjin, Chaoyang, Huludao, Liaoyuan, Tonghua, Baishan, Baicheng, Qiqihar, Jixi, Hegang, Shuangyashan, Huaian, Yancheng, Wuhu, Bengbu, Huaibei, Tongling, Anqing, Fuyang, Haozhou, Chizhou, Longyan, Jingdezhen, Xinyu, Yingtan, JiAn, Dongying, Weihai, Anyang, Hebi, Puyang, Luohe, Sanmenxia, Nanyang, Shangqiu, Xinyang, Zhoukou, Zhumadian, Shiyan, Yichang, Xiangyang, Jinmen, Suizhou, Hengyang, Shaoyang, Changde, Zhangjiajie, Chenzhou, Yonghua, Huaihua, Shantou, Maoming, Heyuan, Yangjiang, Liuzhou, Guilin, Wuzhou, Beihai, Yulin, Hezhou, Luzhou, Zigong, Mianyang, Guangyuan, Suining, Neijiang, Leshan, Nanchong, Yibin, GuangAn, Bazhong, Liupanshui, Tongren, Shaotong, Baoshan, Lijiang, Puer, Tongchuan, Yulin, Tianshui, Zhangye, Pingliang

Table A3
City classification by Tier.

City Tier	City name
First-tier Cities	Beijing, Guangzhou, Shanghai, Shenzhen.
Second-tier Cities (31 cities)	Changchun, Changsha, Chengdu, Chongqing, Dalian, Fuzhou, Haikou, Hangzhou, Harbin Hefei, Hohhot, Jinan, Kunming Nanchang, Nanjing, Nanning, Ningbo, Qingdao, Shenyang Shijiazhuang, Suzhou, Tianjin, Urumqi, Wenzhou, Wuhan, Wuxi, Xiamen, Xian, Xining, Yinchuan, Zhengzhou
Third-tier Cities (66 cities)	Anqing, Anshan, Baoding, Baotou, Bengbu, Changzhou, Chuzhou, Dazhou, Dezhou, Dongguan, Foshan, Fuyang, Heyuan, Huaian, Huangshan, Huizhou, Huludao, Huzhou, Jiangmen, Jiaxing, Jinhua, Jiujiang, Kaifeng, Langfang, Leshan, Lianyungang, Liaocheng, Luoyang, Mianyang, Nanchong, Nantong, Nanyang, Ningde, Panjin, Puyang, Qingyuan, Qinhuangdao, Quanzhou, Rizhao, Shangrao, Shantou, Shanwei, Shaoguan, Shaoxing, Suqian, Taizhou, Tangshan, Wuhu, Xingtai, Xinxiang, Xinyu, Xuancheng, Xuchang, Xuzhou, Yancheng, Yangjiang, Yangzhou, Yiichun, Yingkou, Yuncheng, Zaozhuang, Zhangjiakou, Zhangzhou, Zhaoqing, Zhenjiang, Zhongshan

Investigation. **Xingtao Chen:** Data curation, Visualization. **Ziqing Yuan:** Writing - original draft, Writing - review & editing, Formal analysis, Visualization.

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Appendix A

References

Berck, P., Villas-Boas, S.B., 2016. A note on the triple difference in economic models. Appl. Econ. Lett. 23, 239–242.
Brueckner, J.K., Singh, R., 2020. Stringency of land-use regulation: building heights in US cities. J. Urban Econ. 116, 103239-103239.
Cai, H., Henderson, J.V., Zhang, Q., 2013. China's land market auctions: evidence of corruption? Rand J. Econ. 44, 488–521.
Cao, J., Huang, B., Lai, R.N., 2015. On the effectiveness of housing purchase restriction policy in China: a difference in difference approach. SSRN Electron. J.
Chen, C.F., Chiang, S.H., 2020. Time-varying spillovers among first-tier housing markets in China. Urban Stud. 57, 844–864.
Chen, J.W., Hui, E.C.M., Seiler, M.J., Zhang, H., 2018. Household tenure choice and housing price volatility under a binding home-purchase limit policy constraint. J. Hous. Econ. 41, 124–134.
Costello, G., Fraser, P., Groenewold, N., 2011. House prices, non-fundamental components and interstate spillovers: the Australian experience. J. Bank. Financ. 35, 653–669.
DeFusco, A., Ding, W.J., Ferreira, F., Gyourko, J., 2018. The role of price spillovers in the American housing boom. J. Urban Econ. 108, 72–84.
Dreger, C., Zhang, Y., 2013. Is there a bubble in the Chinese housing market? Urban Policy Res. 31, 27–39.
Favilukis, J., Van Nieuwerburgh, S., 2017. Out-of-town home buyers and city welfare. SSRN Electron. J.
Glaeser, E.L., Luttmer, E.F.P., 2003. The misallocation of housing under rent control. Am. Econ. Rev. 93, 1027–1046.
Gong, Y., Hu, J., Boelhouwer, P.J., 2016. Spatial interrelations of Chinese housing markets: spatial causality, convergence and diffusion. Reg. Sci. Urban Econ. 59, 103–117.
Gong, Y.L., de Haan, J., Boelhouwer, P., 2020. Cross-city spillovers in Chinese housing markets: from a city network perspective. Pap. Reg. Sci.
GÖRg, H., Strobl, E., 2007. The effect of R&D subsidies on private R&D. Economica 74, 215–234.
Grigsby, W., 1986. The Dynamics of Neighborhood Change and Decline.
Han, L., Kung, J.K.-S., 2015. Fiscal incentives and policy choices of local governments: evidence from China. J. Dev. Econ. 116, 89–104.
Han, W.J., Zhang, X.L., Zheng, X., 2020. Land use regulation and urban land value: evidence from China. Land Use Policy 92, 104432-104432.
Holly, S., Hashem Pesaran, M., Yamagata, T., 2011. The spatial and temporal diffusion of house prices in the UK. J. Urban Econ. 69, 2–23.
Holmes, M.J., Grimes, A., 2008. Is There Long-run Convergence among Regional House Prices in the UK? Urban Stud. 45, 1531–1544.
Hu, S.G., Cheng, Q.M., Wang, L., Xu, D.Y., 2013. Modeling land price distribution using multifractal IDW interpolation and fractal filtering method. Landsc. Urban Plan. 110, 25–35.
Huang, Y.Q., Yi, D.C., Clark, W.A.V., 2020. Multiple home ownership in Chinese cities: an institutional and cultural perspective. Cities 97, 102518-102518.
Hui, E.C.M., Wang, Z.Y., 2014. Price anomalies and effectiveness of macro control policies: evidence from Chinese housing markets. Land Use Policy 39, 96–109.
Jia, S.J., Wang, Y.R., Fan, G.Z., 2018. Home-purchase limits and housing prices: evidence from China. J. Real Estate Financ. Econ. 56, 386–409.
Lee, C.L., Reed, R.G., 2014. The relationship between housing market intervention for first-time buyers and house price volatility. Hous. Stud. 29, 1073–1095.
Li, V.J., Cheng, A.W.W., Cheong, T.S., 2017. Home purchase restriction and housing price: a distribution dynamics analysis. Reg. Sci. Urban Econ. 67, 1–10.
Li, Y.Y., Zhu, D.L., Zhao, J.M., Zheng, X.D., Zhang, L.Y., 2020. Effect of the housing purchase restriction policy on the Real Estate Market: evidence from a typical suburb of Beijing. China. Land Use Policy 94, 104528-104528.
Liu, Y.S., 2018. Introduction to land use and rural sustainability in China. Land Use Policy 74, 1–4.
Liu, T., Lin, G.C.S., 2014. New geography of land commodification in Chinese cities: uneven landscape of urban land development under market reforms and globalization. Appl. Geogr. 51, 118–130.
Liu, Y.S., Li, J.T., Yang, Y.Y., 2018. Strategic adjustment of land use policy under the economic transformation. Land Use Policy 74, 5–14.
Meen, G., 1999. Regional house prices and the ripple effect: a new interpretation. Hous. Stud. 14, 733–753.
Muth, R.F., 2016. The derived demand for urban residential land. Urban Stud. 8, 243–254.
Qian, W., Wu, H., Tu, J., Xu, W., 2019. Sticky Expectations in the Housing Market: Evidence From the Housing Purchase Restriction Policy. Working Paper.
Qin, Y., Zhu, H.J., Zhu, R., 2016. Changes in the distribution of land prices in urban China during 2007-2012. Reg. Sci. Urban Econ. 57, 77–90.
Riddel, M., 2011. Are housing bubbles contagious? A case study of Las Vegas and Los Angeles home prices. Land Econ. 87, 126–144.
Rosen, S., 1974. Hedonic prices and implicit markets - product differentiation in pure competition. J. Polit. Econ. 82, 34–55.
Schmid, A.A., 2016. Converting Land from Rural to Urban Uses (Routledge Revivals). Routledge.
Shih, Y.-N., Li, H.-C., Qin, B., 2014. Housing price bubbles and inter-provincial spillover: evidence from China. Habitat Int. 43, 142–151.
Somerville, T., Wang, L., Yang, Y., 2020. Using purchase restrictions to cool housing markets: a within-market analysis. J. Urban Econ. 115.
Sun, W.Z., Zheng, S.Q., Geltner, D.M., Wang, R., 2017. The housing market effects of local home purchase restrictions: evidence from Beijing. J. Real Estate Financ. Econ. 55, 288–312.

Tan, R., Beckmann, V., 2010. Diversity of practical quota systems for farmland preservation: a multicountry comparison and analysis. Environ. Plann. C Gov. Policy 28, 211–224.
Tan, Y., Wang, Z., Zhang, Q.H., 2020. Land-use regulation and the intensive margin of housing supply. J. Urban Econ. 115, 103199-103199.
Tian, L., Ma, W., 2009. Government intervention in city development of China: a tool of land supply. Land Use Policy 26, 599–609.
Wang, H., Tao, R., Wang, L., Su, F., 2010. Farmland preservation and land development rights trading in Zhejiang, China. Habitat Int. 34, 454–463.
Waxman, A., Liang, Y., Li, S., Barwick, P.J., Zhao, M., 2020. Tightening belts to buy a home: consumption responses to rising housing prices in urban China. J. Urban Econ. 115.
Wen, H.Z., Goodman, A.C., 2013. Relationship between urban land price and housing price: evidence from 21 provincial capitals in China. Habitat Int. 40, 9–17.
Wu, Y., Li, Y.N., 2018. Impact of government intervention in the housing market: evidence from the housing purchase restriction policy in China. Appl. Econ. 50, 691–705.
Zhang, D.Y., Fan, G.Z., 2019. Regional spillover and rising connectedness in China's urban housing prices. Reg. Stud. 53, 861–873.
Zhang, H., Wang, X., 2015. Effectiveness of macro-regulation policies on housing prices: a spatial quantile regression approach. Hous. Theory Soc. 33, 1–18.
Zhang, D.Y., Liu, Z.Y., Fan, G.Z., Horsewood, N., 2017. Price bubbles and policy interventions in the Chinese housing market. J. Hous. Built Environ. 32, 133–155.
Zhang, Y.N., Zhu, S.J., Yin, Z.H., Yao, X.M., Wang, Z.Y., 2020. Inter-city housing purchase: a case of China's Yangtze River Delta region. Cities 97, 102491-102491.
Zheng, X., Peng, W., Hu, M., 2020. Airport noise and house prices: a quasi-experimental design study. Land Use Policy 90, 104287.
Zhou, Y., Huang, X., Chen, Y., Zhong, T., Xu, G., He, J., Xu, Y., Meng, H., 2017. The effect of land use planning (2006–2020) on construction land growth in China. Cities 68, 37–47.