JOURNAL OF REGIONAL SCIENCE

JOURNAL OF REGIONAL SCIENCE, VOL. 00, NO. 0, 2013, pp. 1–19

LAND SUPPLY AND CAPITALIZATION OF PUBLIC GOODS IN HOUSING PRICES: EVIDENCE FROM BEIJING*

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ABSTRACT. This paper studies the extent to which spatial heterogeneity in housing prices is affected by housing supply in Beijing's specific context of centralized metropolitan government without local property tax. Taking data sets of residential land leases and private housing sales records from 2006 to 2008 within Beijing's metropolitan area, this paper examines how the capitalization of school quality and subway accessibility in housing prices varies with land availability instrumented by the employment density of state-owned enterprises (SOEs) at the beginning of SOE reform. Results confirm that the capitalization of school quality and subway accessibility is larger in supply-constrained locations.

1. INTRODUCTION

Local public goods, such as public schools, rail access, and environmental quality, are not traded in conventional markets. As a result, willingness to pay for those amenities can only be indirectly derived, but can never be observed directly. Hedonic price analysis (Rosen, 1974) is common approach to uncover the implicit prices of local public goods in the housing market. Numerous studies (such as Lee and Linneman, 1998; Rosen, 2002; Gibbons and Machin, 2005; Berger, Blomquist, and Sabirianova Peter, 2008; Zheng and Kahn, 2008) empirically estimate hedonic equations and derive the implicit prices of various amenities in both developed and developing countries. However, as pointed out by Straszheim (1974), due to market segmentation, it is not always appropriate to assume that the implicit prices of housing attributes remain the same across geographic space. That is, a regional housing market is composed of an interconnected set of many localized submarkets, which have idiosyncratic differences in the structure of supply and/or demand and, consequently, unique schedules of attribute prices (Gregory and Smith, 1990; Carruthers and Clark, 2010).[1] With the tremendous increase in the availability of spatial data and spatial econometric methods since the 1990s, there have been important

*We are grateful to the two anonymous referees and to the participants at the 2012 International Workshop on Regional, Urban, and Spatial Economics in China for useful comments and suggestions. Please direct your correspondence to ruiwang@ucla.edu.

Received: August 2012; revised: April 2013; accepted: April 2013.

[1]Barriers to entry, imperfect information, and/or other restrictions on arbitrage opportunities also contribute to regional housing market segmentation (Carruthers and Clark, 2010).

 DOI: 10.1111/jors.12095

advances to measure this spatial heterogeneity in the implicit prices of local public goods (Can, 1990, 1992; Mulligan, Franklin, and Esparza, 2002; Fik, Ling, and Mulligan, 2003; Bitter, Mulligan, and Dall'erba, 2007).[2]

Beyond spatial econometric studies that describe the spatial heterogeneity of the implicit prices for site amenities, scholars have been motivated to better understand the driving forces behind this heterogeneity. Goodman (1981) argues that heterogeneous demand functions are bound to interact with inelastic short-run supply functions to produce spatially distinct schedules of housing attribute prices. This argument can be linked to the capitalization debate in the local public finance literature that focuses on how the elasticity of housing supply affects the capitalization of local taxes and public service. In his seminal paper, Oates (1969) shows empirically that taxes and public expenditures are capitalized into housing prices. Numerous subsequent empirical studies (e.g., Yinger, 1982, 1995; Ross and Yinger, 1999, pp. 2001–2060; Brasington, 2000) confirm this capitalization effect. However, others (Edel and Sclar, 1974; Henderson, 1980, 1985; Man and Rosentraub, 1998) argue that capitalization does not occur. The two views of capitalization can be reconciled by the elasticity of housing supply (Brasington, 2002). Capitalization happens under the assumption of a fixed housing supply in a fixed number of communities with inflexible boundaries. With a perfectly elastic housing supply, a community can freely expand in response to a demand shock (e.g., an exogenous improvement in local public service). As a result, there is no need for housing prices to change to equalize utility across communities, and thus taxes or public expenditures are not capitalized into housing prices. Hilber and Mayer (2002) and Stadelmann and Billon (2012) present theoretical models to show that the capitalization of taxes and local public goods depends on the elasticity of housing supply. Given a positive shock in the quality of local public service, local markets with less elastic supply of housing experience a larger price increase compared to markets with more elastic housing supply.

A small number of studies have empirically tested the relationship between housing supply (or land availability) and the capitalization of public goods and taxes in the United States and Europe. Using housing sales data from five metropolitan areas in Ohio, Brasington (2002) compares the capitalization of taxes, crime, and school quality into home values in two separate samples of local jurisdictions near the urban center and edge. He finds that the quality of public goods, but not tax, capitalizes at a higher rate near the urban center than at the edge, suggesting the effects of differences in land scarcity. Hilber and Mayer (2009) take Proposition 2½ in Massachusetts as an exogenous spending shock and use a simultaneous equation model to show that capitalization of school spending decreases when a jurisdiction has more developable land. However, neither of the two studies deal with the possible endogeneity in land availability (e.g., the regulatory constraints of land supply), which may be correlated with unobserved factors that affect housing prices. Using a panel data set of representative house prices in 169 local jurisdictions in the Swiss Canton of Zurich from 1998 to 2004, Stadelmann and Billon (2012) estimate reduced-form ordinary least squares (OLS) and instrumental variable

[2]This spatial variation in implicit prices across submarkets facilitates the identification of the demand functions for housing and location attributes for the entire market (Bartik, 1987; Epple, 1987; Black, 1999; Brasington, 2000, 2003; Taylor, 2008). The estimation of such implicit demand functions for site amenities can be regarded as the second stage of the hedonic price analysis (Small and Steimetz, 2012). Our paper does not go into depth on this second-stage estimation because we do not have household information, which is crucial for estimating demand functions. Instead, we focus on the first-stage analysis—examining the role that land availability plays in determining the spatial heterogeneity in implicit prices of site amenities. Our findings can provide useful information for future studies on the second-stage demand function analysis.

(IV) price regressions, in which land availability is instrumented by geographical location. Different from Brasington (2002) and Hilber and Mayer (2009), they find that capitalization of public expenditure does not significantly diminish when more land for construction is available according to local governments. Stadelmann and Billon conclude that available land for construction is a necessary, but not a sufficient, condition for supply to react because housing supply elasticity is also likely to be influenced by land use regulation.[3] In a more elaborated model, taking both geography (slope and water) and endogenous regulatory constraints into consideration, Saiz (2010) analyzes the relationship among land availability, urban growth, housing prices, and regulatory strength of metropolitan areas in the United States and finds elevated housing price appreciation where land is scarce. Saiz does not, however, look into the capitalization of urban amenities.

The existing theory and evidence around housing supply and public goods/taxes remain mostly in the context of decentralized local government systems and public services financed by property tax. This is probably due to most studies being from the United States and other developed countries, which are often more decentralized compared to developing countries (Oates, 1993). In China, where urban governance and public finance systems are significantly different from those in the existing literature, the relationship between supply constraints and the capitalization of public goods and services has not been empirically tested. Chinese cities today have active housing markets, reasonably mobile households, and public land leasehold systems (city government is the sole supplier of land for development).[4] But there is no property tax—public goods and services instead are financed by the general fund of the centralized metropolitan government (Zheng and Kahn, 2013). Nevertheless, distinctive spatial disparities in public goods and housing prices persist even in close-by locations in cities like Beijing. For example, Zheng, Hu, and Wang (2012) find that in adjacent and similar communities, eligibility to enroll in a high-quality primary school brings on average an 8 percent premium to housing prices. It is important to ask, however, whether such a price premium varies across communities. If yes, to what extent is spatial heterogeneity driven by supply constraints?

This study contributes to the existing literature by providing an early piece of evidence on the relationship between housing supply and the capitalization of public goods in the context of centralized metropolitan government without local property tax. Using microdata sets of housing transactions and residential land leasehold records in Beijing, we quantify the impact of land supply on the capitalization effects of public goods in housing prices in the Beijing Metropolitan Area (BMA) between 2006 and 2008. In particular, as in the countries with private land ownership, Chinese local governments' decision to lease land use rights to the market is endogenous to market demand because land sales generate important local revenue. To identify an exogenous variation in land availability across communities in Beijing, we find that the density of state-owned manufacturing employment during the early years of state-owned enterprise (SOE) reform is statistically correlated with the amount of land leased thereafter, but uncorrelated with housing prices. Applying the hedonic regression technique to resale and new housing price data, and controlling for physical and community attributes, this study finds that the capitalization rates of subway accessibility and school quality are greater where land supply is limited by exogenous reasons.

[3]It seems, however, that Stadelmann and Billon's conclusion is not supported by their IV estimates, which agree with their OLS results. Stadelmann and Billon interpret their consistent OLS and IV results as a support for the fact that politically induced variations in housing supply across communities are not significant.

[4]See Henderson (2009) for relevant discussion. Such land leasehold rights provide the purchasers with 70 years for residential use. Since 2004, leaseholds have been, in principle, all sold at public auctions.

The remainder of the paper is organized in six sections. Section 2 provides background information and a simple theoretical model. Section 3 introduces data on housing prices, land lease quantity, and public goods. Section 4 provides preliminary evidence of supply constraints' effect on the capitalization of public goods by comparing Beijing's center versus its edge, similar to Brasington's (2002) analysis of cities in Ohio. Section 5 improves on the center–edge comparison by instrumenting the amount of land leased in different zones in Beijing with an exogenous source of variation in land availability. Section 6 tests the results' robustness against alternative periods in the calculation of the cumulative amount of leased land and spatial autoregressive processes. Finally, section 7 summarizes the paper with policy implications, limitations, and future research needed.

2. BACKGROUND AND ANALYTICAL FRAMEWORK

China has been undergoing rapid urbanization since its economic reform in the late 1970s. China's urbanization rate increased from 19 percent in 1980 to 50 percent in 2010. Beijing, China's capital city, boasts a population of 19.6 million, compared to 8.7 million 30 years ago. Unlike many cities with developed market economies, where employment and urban population have significantly suburbanized (Glaeser and Kahn, 2001), a dominant urban core exists in Beijing (as well as most other Chinese cities) (Zheng and Kahn, 2008; Wang, 2009, 2010, 2011). The BMA is composed of eight districts (*Dongcheng*, *Xicheng*, *Chongwen*, *Xuanwu*, *Chaoyang*, *Haidian*, *Fengtai*, *Shijingshan*) with a total area of about 960 km^2, excluding mountain areas unsuitable for development. Tian'anmen Square, with the surrounding traditional hubs of commercial, cultural, and administrative activities, is considered the city center. In 2004, 43 percent of Beijing's jobs were concentrated within three miles of Tian'anmen Square. The five ring roads circling Tian'anmen Square were built successively from the inside to the outside, demonstrating a monocentric urban structure (see Figure 1).

The administrative system in Beijing has three levels: municipality, district, and street office (*Jiedao*). *Jiedao* is the lowest administrative level. Within the BMA, there are 123 *Jiedaos* with an average size of about 10 km^2 each. Unlike the United States, which has a highly decentralized public goods provision system, the Beijing municipal government provides most of the public infrastructure and services, such as transportation, education, and health care. The *Jiedao* is only responsible for administering basic services such as garbage collection.

The analytical model of this study is similar to those of Hilber and Mayer (2002) and Stadelmann and Billon (2012), but is revised to be appropriate for the institutional context of centrally financed public goods and services in Beijing. Consider a metropolitan area with T communities and N mobile households with identical income (y) and taste. Households choose community i (with public goods g_i) and housing quantity (with unit price p_i) to maximize utility, which is equal across all communities (V^0). The indirect utility function can be expressed as:

$$V(y, p_i, g_i) = V^0. \tag{1}$$

In each community i, housing demand should equal housing supply, expressed as $n_i h_i(p_i) = H_i(p_i)$, where n_i is the number of households in community i, $h_i(p_i)$ is the housing demand function per household, and $H_i(p_i)$ is the housing supply function. Therefore, we obtain $n_i = \frac{H_i(p_i)}{h_i(p_i)}$. All N households should be housed in those T communities, as:

$$\sum_{i=1}^{T} \frac{H_i(p_i)}{h_i(p_i)} = N. \tag{2}$$

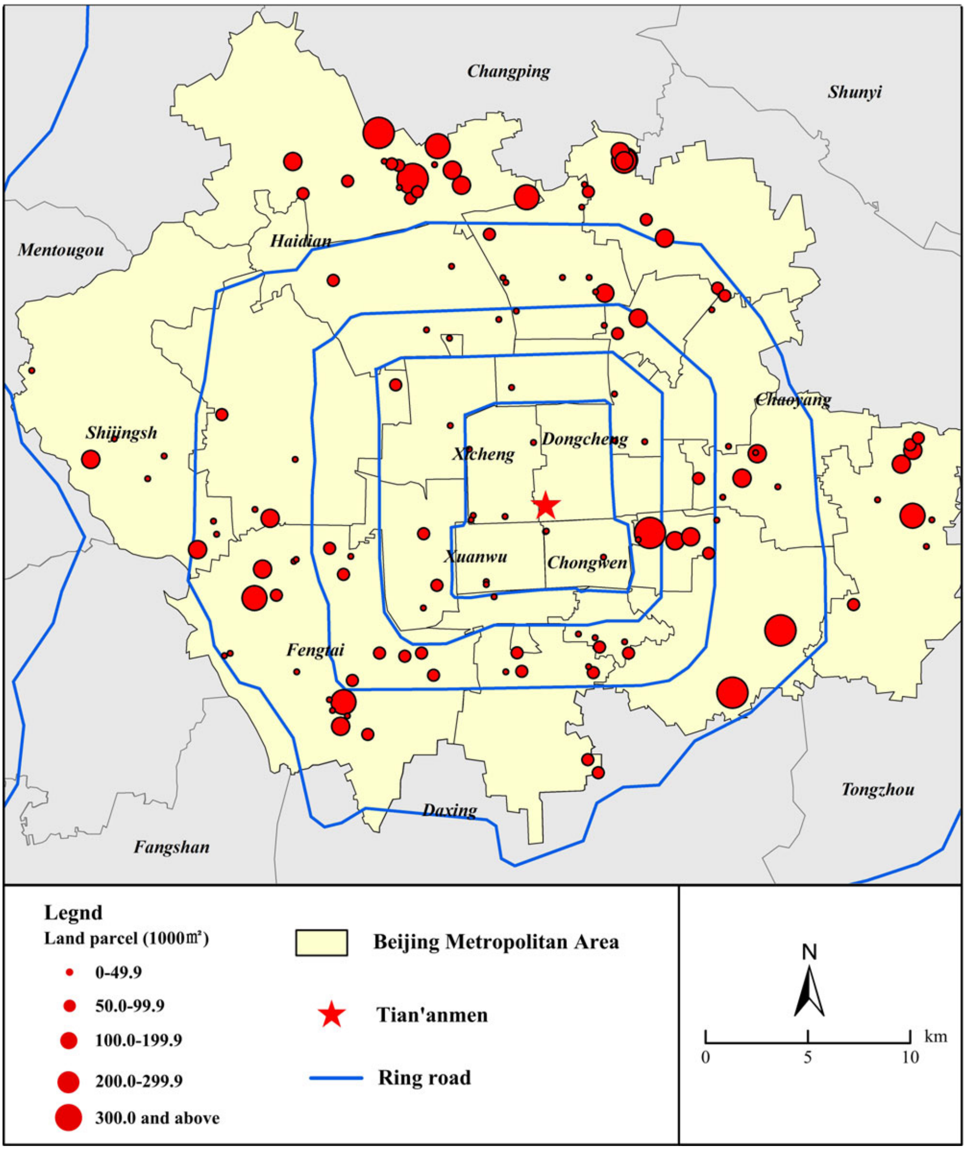

FIGURE 1: Urban Form and the Amount of Leased Land in Beijing (2004–2008).

Equations (1) and (2) are the equilibrium conditions that determine housing price. We focus on the marginal effect of public goods on housing prices. Differentiating Equations (1) and (2) with respect to g_i, we can obtain the expression for the capitalization rate of public goods g_i ($\frac{\partial p_i}{\partial g_i}$):

$$\frac{\partial p_i}{\partial g_i} = \frac{MRS_i \cdot \sum_{j \neq i} \frac{n_j}{p_j}(\eta_j^S - \eta_j^D)h_i}{\frac{n_i}{p_i}(\eta_i^S - \eta_i^D)h_j + \sum_{j \neq i} \frac{n_j}{p_j}(\eta_j^S - \eta_j^D)h_i} = \frac{MRS_i \cdot A}{\frac{n_i}{p_i}(\eta_i^S - \eta_i^D)h_j + A} > 0, \tag{3}$$

where $A = \sum_{j \neq i} \frac{n_j}{p_j}(\eta_j^S - \eta_j^D)h_i$, $\eta_i^S = \frac{\partial H_i}{\partial p_i}\frac{p_i}{H_i}$ is the price elasticity of housing supply, $\eta_i^D = \frac{\partial h_i}{\partial p_i}\frac{p_i}{h_i}$ is the price elasticity of housing demand, and $MRS_i = \frac{\partial V/\partial g_i}{\partial V/\partial y}$ is the marginal rate of substitution between public goods and income. It is clear that $(\eta^S - \eta^D > 0)$ and MRS > 0, which means public goods should be positively capitalized into housing prices. By partially differentiating (3) with respect to η_i^S, we obtain the effect of an increase in housing supply elasticity on capitalization as:

$$\frac{\partial^2 p_i}{\partial g_i \partial \eta_i^S} = -\frac{MRS_i \cdot A \cdot \frac{n_i}{p_i}h_j}{[\frac{n_i}{p_i}(\eta_i^S - \eta_i^D)h_j + A]^2} < 0. \tag{4}$$

Equation (4) predicts that the extent of capitalization depends on the elasticity of housing supply. Namely, higher supply elasticity negatively affects the extent of capitalization of public goods.

We employ a two-stage IV regression strategy to test Equation (4). In the first stage, we use an exogenous variable (the density of state-owned manufacturing employment at the beginning of SOE reform) to explain the spatial variation of the amount of leased residential land by zone in Beijing. In the second stage, we estimate a hedonic price regression with interactions between the instrumented amount of land leased and local public goods. The sign and significance of the interaction terms serve to test the relationship between the rate of capitalization and land availability, which has a reversed relationship with supply elasticity (Saiz, 2010).

3. DATA

We use three transaction data sets in Beijing's land and housing markets. The first data set, obtained from the China Real Estate Index System (a large real estate information company), includes all auctioned residential land parcels from 2004 to 2008, as shown in Figure 1. We define communities within the BMA that both reflect urban spatial structure and encompass enough residential land developments in each community. We follow Zheng, Peiser, and Zhang (2009) to combine three to six adjacent *Jiedao*s with continuous concentrated economic activities into 25 zones as the basic geographic unit of analysis to describe the spatial variation of land supply in Beijing (Figure 1). We use this data set to compute the amount of leased land by zone as the measure of land used for residential development.

We employ two housing transaction data sets, resale housing transactions and new housing complexes, to analyze how land availability affects the capitalization effects of local public goods in both resale and new housing markets. We obtain a large-scale resale housing transaction data set for 2006–2008 from "*WoAiWoJia*" (www.5i5j.com), the second largest broker in Beijing with a market share of about 10 percent. This data set includes all the transactions this broker company engaged in during the study period. After data cleaning, this sample contains 13,188 individual resale transactions in about 2,600 residential complexes across the city (see Figure 2). For each transaction record, we have information regarding the transaction date, exact location, and house physical attributes including unit size (*HSIZE*), housing age (*HAGE*), and level of decoration (*DECO*). The average resale housing unit is 76.9 m^2 in size, 15.3 years old, and the mean house price (*PRICE*) is 10,700 yuan per square meter (2006 price).

The other data set, provided by the China Real Estate Index System, contains all new housing complexes for sale in BMA between 2006 and 2008. It provides the average transaction price and housing attributes by complex. After data cleaning, there are about 1,200 new housing complexes distributed across the BMA (see Figure 3). For each complex, we have information regarding year of sale, exact location, average transaction price, and

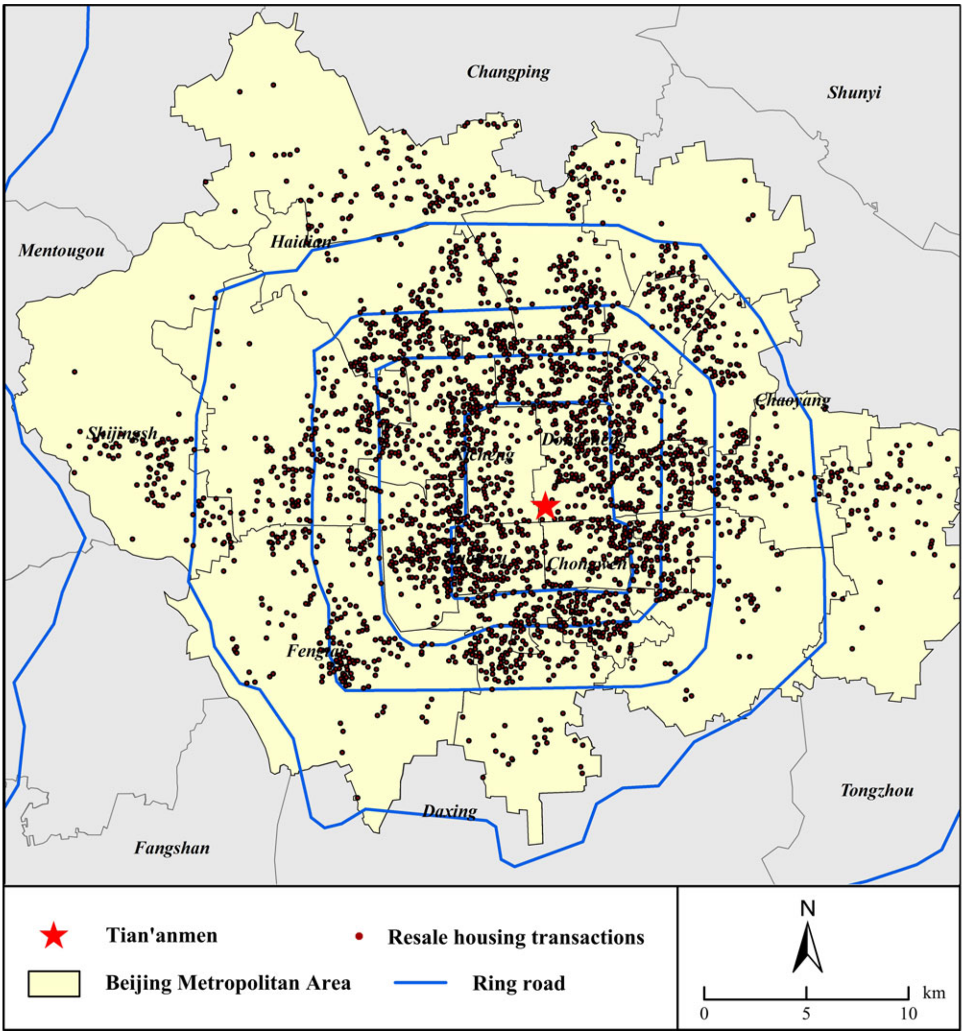

FIGURE 2: Housing Resale Transactions in Beijing (2006–2008).

house physical attributes averaged by complex[5] including average unit size (*AHSIZE*), the complex's total number of floors (*HEIGHT*), and its total floor area (*TOTAL_AREA*). The average new housing unit is 117.58 m^2 in size, and the mean average house price (*APRICE*) is 12,200 yuan per square meter (2006 price).

We consider access to rapid transit stops and the so-called key primary schools as the two most important local public goods affecting housing demand.[6] There are altogether

[5]The information for price and unit size is only for the actual transacted units; the information of those not sold was not registered in the system.

[6]Parks and recreational areas are also believed to contribute to housing value by many studies of housing markets. In results not provided in the paper, we included parks officially designated by the Beijing municipal government in our analysis. However, we do not find that proximity to parks affects home prices in Beijing. We suspect two reasons that may contribute to the insignificance of parks. First, the official

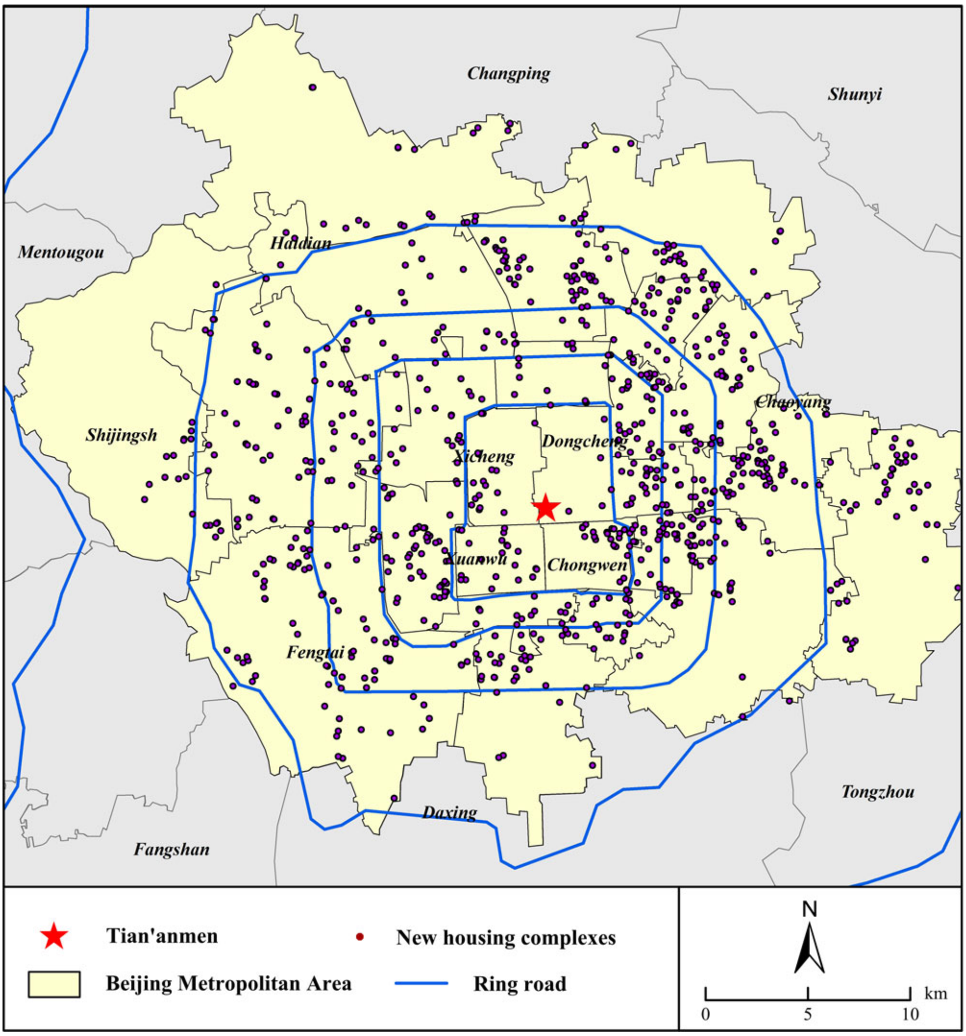

FIGURE 3: New Housing Complexes in Beijing (2006–2008).

40 key public primary schools in Beijing.[7] Unlike secondary schools, enrollment in primary school is based on residential proximity. The 40 key primary schools are widely considered by the residents as superior in quality compared to other schools (Zheng et al., 2012).[8]

list only contains major public parks, excluding many smaller sized community parks/recreational areas. Second, many of the officially designated parks are historical heritages of national importance, serving as major tourist attractions. It is possible that these parks, while bringing certain cultural and environmental amenities to adjacent communities, may also result in congestion, noise, and other disturbances to local neighborhoods.

[7]Almost all children in Beijing go to public schools. Only primary schools accept students based on residential location, whereas middle and high schools enroll students largely by merit.

[8]The 40 key primary schools in Beijing account for a small share (7.3 percent) of all primary schools but remain superior in quality compared to the rest. The quality of these schools obviously varies continuously. However, detailed school quality data, such as spending per student, student–teacher ratio,

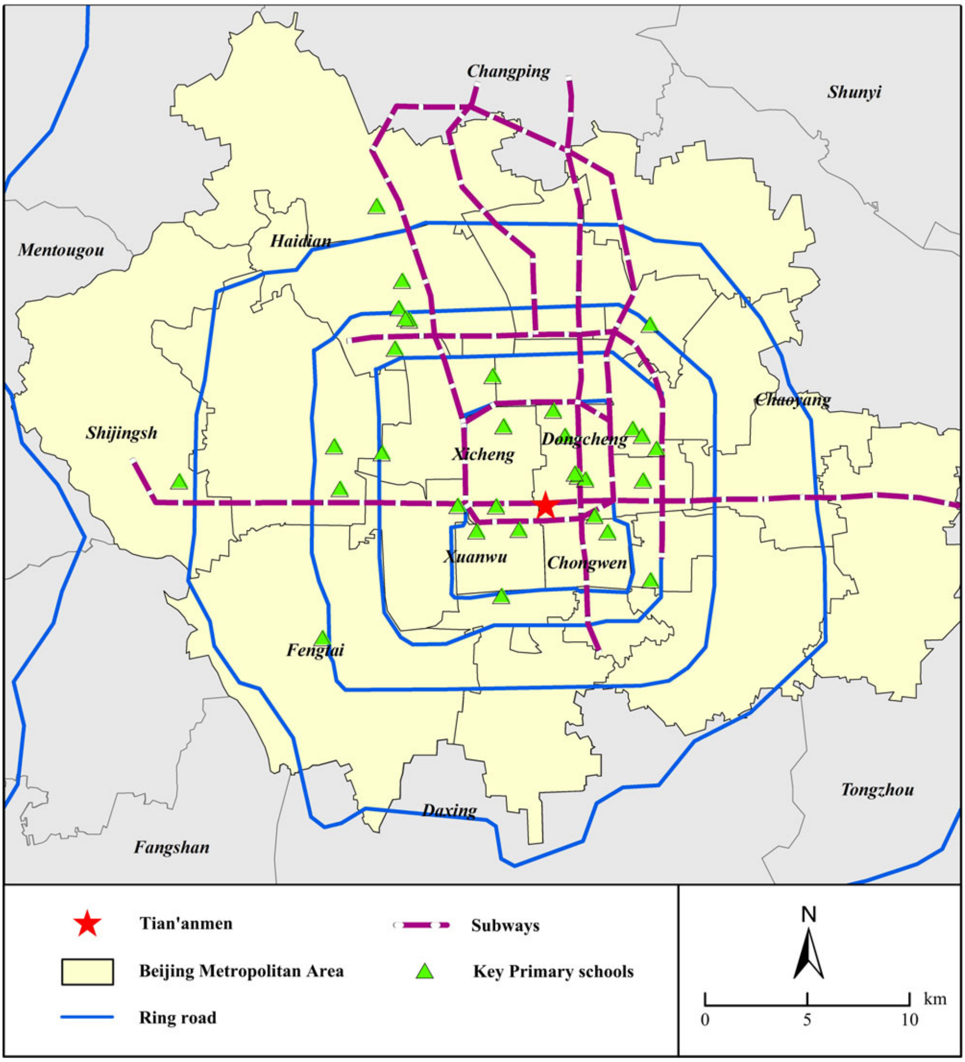

FIGURE 4: Local Public Goods in Beijing.

We calculate the distances of each unit/complex to the closest subway stop (*D_SUBWAY*) and closest key primary school (*D_SCHOOL*). Figure 4 shows the spatial distributions of Beijing's subway lines and key primary schools. We use zone fixed effects to control for other spatially variant amenities. Table 1 reports the summary statistics of all variables.

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or standard exam scores, are not publicly available in Beijing. Nonetheless, there seems to be a consensus among the public about which primary schools are the best based on a list of "key primary schools" designated by the Beijing Municipal Commission of Education as early as the late-1950s. Before the abandonment of the "key primary school" policy in 2000 out of concern for education equality, these schools received more resources from the Beijing Municipal Government. More than 10 years after the official abandonment of the "key primary school" policy, these schools are still considered by most as the best with their legacy of superior quality, thanks to the long-term investment in capital, faculty, and reputation among parents.

TABLE 1: Variable Definitions and Summary Statistics

Variable	Definition	Obs.	Mean	Std. Dev.	Min	Max
Resale housing unit sample						
PRICE	Transaction unit price (yuan/m^2)	13,188	10,672.56	3,022.85	3,133.79	33,186.32
HSIZE	Housing unit size (m^2)	13188	76.88	31.64	20.84	199.90
DECO	Decoration status: 1 = no decoration, 2 = simple decoration, 3 = medium decoration, 4 = full decoration	13,188	3	1.04	1	4
HAGE	Housing age (year)	13,188	15.33	7.36	3	40
D_CBD	Distance to Tian'anmen Square (km)	13,188	8.84	4.33	0.28	25.33
D_SCHOOL	Distance to the closest key primary school (km)	13,188	2.57	1.77	0.01	11.13
D_SUBWAY	Distance to the closest subway stop (km)	13,188	2.45	1.86	0.01	13.52
New housing complex sample						
APRICE	Average transaction unit price of the complex (yuan/m^2)	1,129	12164.35	5634.44	3369.97	45278.21
AHSIZE	Average housing unit size of the complex (m^2)	1,129	117.58	32.72	25.74	195.65
HEIGHT	Total floor number of the complex	1,129	17.46	6.99	4	55
TOTAL_AREA	Total construction area of the complex (m^2)	1,129	117.58	32.72	25.74	195.65
D_CBD	Distance to Tian'anmen Square (km)	1,129	10.18	4.08	1.09	21.92
D_SCHOOL	Distance to the closest key primary school (km)	1,129	3.71	2.54	0.01	10.95
D_SUBWAY	Distance to the closest subway stop (km)	1,129	2.01	1.70	0.02	8.40
Other variables						
LAND_LS	Annual new residential land supply (km^2)	75	0.00166	0.00277	0	0.0138
SOE	SOE employment density of 2,000 (person/km^2)	25	566.31	569.51	48.18	2,023.86

4. EDGE VERSUS CENTER ANALYSIS

Although land sale and land use regulation in Beijing are centrally determined at the metropolitan level, it is reasonable to assume that the implicit assumption of Brasington (2002) holds in Beijing—housing supply is more elastic toward the edge of metropolitan areas where vacant land is physically more available. We follow Brasington's (2002) practice to divide each of the resale and new housing transaction samples into two subsamples. As shown in Figure 2, the zones adjacent to rural areas are defined as edge zones whereas the enclosed zones are defined as center zones. Standard hedonic housing price regressions are performed separately using the subsamples in the following form:

$$\log(PRICE) = \alpha_0 + \alpha_1 X + \alpha_2 \cdot \text{Public goods} + \text{Year and zone fixed effects} + \varepsilon, \tag{5}$$

TABLE 2: Hedonic Price Regressions by Location

	Resale Housing			New Housing		
	Edge Sample Only (1)	Inside Sample Only (2)	Full Sample with Interaction Terms (3)	Edge Sample Only (4)	Inside Sample Only (5)	Full Sample with Interaction Terms (6)
D_CBD	−0.0244***	−0.0179***	−0.0213***	−0.0316***	−0.0565**	−0.0375***
	(−6.70)	(−3.94)	(−7.33)	(−3.37)	(−2.41)	(−4.24)
log(*D_SCHOOL*)	−0.0315**	−0.0368***	−0.0324**	−0.139***	−0.0544	−0.129***
	(−2.28)	(−3.96)	(−2.38)	(−3.53)	(−0.69)	(−3.34)
log(*D_SUBWAY*)	0.00383	−0.0239*	0.00492	0.00658	−0.0664*	0.0129
	(0.44)	(−1.89)	(0.59)	(0.46)	(−1.76)	(0.88)
*INSIDE**log (*D_SCHOOL*)			−0.00314			0.0613
			(−0.20)			(0.74)
*INSIDE**log (*D_SUBWAY*)			−0.0271*			−0.0933***
			(−1.86)			(−2.65)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Zone fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,752	8,436	13,188	770	359	1,129
R^2	0.530	0.501	0.538	0.393	0.373	0.428

Notes: (i) Dependent variable is the logarithm of house price. *t*-statistics are reported in parentheses.
(ii) ***: Significant at the 1 percent level; **: significant at the 5 percent level;*: significant at the 10 percent level. (iii) Control variables for resale housing include *HSIZE, HAGE*, and *DECO*; control variables for new housing include *AHSIZE, HEIGHT*, and *TOTAL_AREA*.
(iv) See Table 1 for variable definitions.
(v) For resale housing units, standard errors are clustered by complex.

where X is a vector of house/complex characteristics and we use zone fixed effects to control for zone-level time-invariant unobservables. For resale housing units, standard errors are clustered by complex. Regression results are reported in Table 2, with columns (1)–(3) for the resale data and columns (4)–(6) for the new housing complexes. Our hedonic model can explain about 50 percent of the housing price variation in resale markets and 40 percent in new housing markets. Columns (1) and (2) report the estimates for the edge and center subsamples of resale homes, respectively. The positive capitalization of a key primary school (negative as distance to school increases) is stronger in the center than on the edge, while the positive capitalization of subway stop proximity is only statistically significant in the center. Column (3) reports the result by combining the center and edge subsamples and introducing interaction terms between *INSIDE* (defined as 1 for center and 0 for edge) and the measures of public goods. Both coefficients of the interaction terms are negative, indicating a stronger capitalization in the center; but only the subway interaction is statistically significant. Results from the new housing data are less clear. Columns (4) and (5) suggest that a subway stop is more strongly capitalized in the center, but the result for a key primary school is contrary to our expectation. For the pooled-sample regression, column (6) confirms that the capitalization rate of a subway stop is larger in the center, while there is no statistically significant difference in the capitalization of a school between the center and the edge.

Our edge-versus-center comparison in Beijing is largely consistent with Brasington (2002). However, as mentioned earlier, this simple split sample methodology cannot differentiate supply side effects from demand side effects and is subject to alternative interpretations such as residential sorting and omitted variables. Therefore, the rest of our analysis focuses on using an exogenous measure of land availability to help identify the effect of supply on the capitalization of public goods.

5. LAND AVAILABILITY AND PUBLIC GOODS CAPITALIZATION: AN IV APPROACH

To improve on the edge-versus-center comparison, we first calculate the amount of land leased for residential development by year and zone. As discussed earlier, the amount of land leased reflects both land availability (supply) and market demand for housing in different communities. As the solution, we use prereform employment density in state-owned manufacturing firms as an exogenous source of variation in urban residential land availability. Due to the industrialization-focused urbanization during the prereform socialist era, state-owned manufacturing enterprises often occupied central and valuable locations in cities (Zheng, Fu, and Liu, 2006). After the reinstatement of the urban land markets in the late-1980s and especially since the SOE reform started in the late-1990s, SOEs, in particular the state-owned manufactures (large land users), have been gradually moved away from their premier locations. The relocation or disassembly of old state-owned manufacturing firms thus became an important source of land for new development. At the end of 1999, the Beijing municipal government announced its plan for manufacturing SOEs' relocation: in three to five years from 2000, 738 manufacturing firms within the fourth ring road would be relocated away.[9] We obtain SOE manufacturing employment numbers at the beginning of 2000 by zone from the Year 2000 China Manufacturing Census, and use the SOE employment density (in logarithm) as a proxy for the available land released from the relocation or disassembly of SOE manufactures. The correlation coefficient between log(*SOE*) and the logarithm of the amount of land leased during 2006–2008 is 0.36 ($P = 0.001$). In the meantime, log(*SOE*)'s correlation with housing price (in logarithm) is very weak (correlation coefficient is –0.02 for resale housing and 0.06 for new housing) and statistically insignificant.[10]

We estimate the following equation:

$$\log(PRICE) = \beta_0 + \beta_1 \log(LAND\_LS) \cdot \text{Public Goods} + \beta_2 X + \text{Year and zone fixed effects} + \xi, \tag{6}$$

[9]See http://house.focus.cn/news/1999-11-03/654.html. According to the plan, the share of industrial land will decrease from 8.74 percent to 7 percent within the fourth ring road.

[10]We also examined the suitability of historical population density as an exogenous source of land supply variation but found its validity to be quite questionable. Historical population density is used as an exogenous indicator for land scarcity in studies such as Glaeser and Ward (2009) and Glaeser, Gyourko, and Saks (2005a, b) because there is less available land to build in already dense areas. We obtain Beijing's historical population density in 1982 by zone from the Third National Census, which predates the birth of modern urban planning in China marked by the "Urban Planning Ordinance" of 1984 and the "Urban Planning Law" of 1989. However, the correlation between historical population density and home prices is quite high—0.40 ($P = 0.00$) for resale housing and 0.21 ($P = 0.07$) for new housing, while the correlation between population density and amount of leased residential land is weak and insignificant (–0.12, $P = 0.29$). Historical population density's low correlation with new residential land, but high correlation with home prices, indicates that historical population density may not be a valid instrument for land supply. It is likely that for Beijing, a city with abundant historical legacies, historical population density may be highly correlated with urban amenities (e.g., cultural environment) that are desirable to home purchasers.

where *LAND_LS* is the zone-level amount of leased residential land (in square kilometers) during a three-year period (current year plus the previous two years),[11] *X* is a vector of home/complex characteristics. For resale housing units, standard errors are clustered by complex. We also control for zone fixed effects and year dummies. Table 3 presents the housing price regression results of Equation (6), with columns (1) and (2) displaying results from analyses of resale housing data, and columns (3) and (4) displaying those of new housing data.

Column (1) shows results of a simple hedonic price regression with interaction terms between the amount of land leased and the accessibility of public goods. Both coefficients of the interaction terms are statistically insignificant. Column (2) reports two-stage least squares (2SLS) regression results by instrumenting log(*LAND_LS*)**Public Goods* with log(*SOE*)**Public Goods*. The coefficients of the interaction terms are both positive as expected (better land availability reduces capitalization of public goods), although only that of key primary schools is statistically significant. Results of the first-stage regression are shown at the bottom of Table 3.[12] The joint *F*-test of the two interaction terms with IV is significant at the 1 percent level, indicating the effectiveness of the instruments. For new housing complexes, in both columns (3) (OLS) and (4) (IV), the capitalization rate of subway proximity is significantly larger where land supply is restricted, while the interaction term of land availability and school proximity has the expected sign but is statistically insignificant, unlike the resale housing result in column (2). This is likely because sometimes newly built housing complexes, even near a key primary school, may not be included in the school's attendance zone due to the limit in capacity (Zheng et al., 2012). Overall, results support that the capitalization rate of a school and subway in housing prices are larger where land supply is restricted.

6. ROBUSTNESS TESTS

To test the robustness of the results discussed earlier, we focus on two potential sources of bias: different periods when calculating the amount of land leased and spatial correlation.[13]

We test the results' robustness to alternative periods (two years and one year) for calculating the cumulative amount of leased residential land. Shown in Table 4, results indicate that measuring land availability within shorter periods tends to produce weaker results. This is understandable for two reasons. First, it typically takes more than one year for developers to turn developable land into housing supply, although many housing sales happen before construction is completed in China. Second, for each individual year in our study period of 2006–2008, the number of leased land parcels is quite small, such that *LAND_LS* equals zero for many zones when measured by the current year's amount of

[11]There are two reasons for using a three-year cumulative amount of leased residential land. First, the amount of leased land in BMA is very small (less than 80 parcels for all 25 zones) each year. Second, it typically takes one to three years for developers to turn developable land into housing supply, which is not necessarily fully constructed.

[12]The Hausman test statistic based on column (1) and column (2) in Table 3 is 95.34 (P = 0.000), suggesting that log(*LAND_LS*)*log(*D_SCHOOL*) and log(*LAND_LS*)*log(*D_SUBWAY*) are indeed endogenous.

[13]In addition, we changed proximity measures of local public goods from continuous measures to dummy variables indicating whether a unit/complex is within 800 m (about a half mile) distance to the closest subway stop and key primary school. This is particularly meaningful for the measurement of school quality due to the cutoff effect at the school attendance zone boundary. The results are consistent with those in Table 3. Regression results are available upon request.

TABLE 3: Hedonic Price Regressions by Land Supply

	Resale Housing		New Housing	
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)
D_CBD	-0.0229^{***}	-0.0211^{**}	-0.0415^{***}	-0.0512^{***}
	(−7.66)	(−2.48)	(−4.42)	(−4.92)
log(*D_SCHOOL*)	-0.0373^{***}	-0.198^{***}	-0.105^{**}	−0.303
	(−3.54)	(−2.85)	(−2.26)	(−1.07)
log(*D_SUBWAY*)	−0.00107	−0.244	-0.0689^{**}	-0.467^{***}
	(−0.10)	(−1.54)	(−2.15)	(−3.19)
log(*LAND_LS*)*log (*D_SCHOOL*)	0.000421	0.0165^{***}	0.000645	0.0176
	(0.46)	(2.72)	(0.42)	(0.66)
log(*LAND_LS*)*log (*D_SUBWAY*)	−0.00133	0.0241	0.00533^{*}	0.0437^{***}
	(−1.50)	(1.40)	(1.95)	(3.10)
Control variables	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Zone fixed effect	Yes	Yes	Yes	Yes
Observations	13,188	13,188	1,129	1,129
R^2	0.538	0.441	0.424	0.306

First-stage regression underlying column (2):
log(*LAND_LS*)*log(*D_SCHOOL*) = −0.0315 × *D_CBD*–8.065 × log(*D_SCHOOL*) + 1.521 × log(*D_SUBWAY*) + 1.792 × log(*SOE*)*log(*D_SCHOOL*) – 0.167 × log(*SOE*)* log(*D_SUBWAY*) + *Control variables* + *Fixed effects*
Joint *F*-test for log(*SOE*)*log(*D_SCHOOL*)and log(*SOE*)*log(*D_SUBWAY*): 5.17***
log(*LAND_LS*)*log(*D_SUBWAY*) = 0.0554 × *D_CBD* + 3.213 × log(*D_SCHOOL*) – 8.617 × log(*D_SUBWAY*) – 0.302 × log(*SOE*)*log(*D_SCHOOL*) + 2.093 × log(*SOE*)*log(*D_SUBWAY*) + *Control variables* + *Fixed effects*
Joint *F*-test for log(*SOE*)*log(*D_SCHOOL*) and log(*SOE*)*log(*D_SUBWAY*): 15.96***

First-stage regression underlying column (4):
log(*LAND_LS*)*log(*D_SCHOOL*) = 0.294 × *D_CBD* – 8.768 × log(*D_SCHOOL*) + 2.056 × log(*D_SUBWAY*) + 2.077 × log(*SOE*)*log(*D_SCHOOL*) – 0.227 × log(*SOE*)*log(*D_SUBWAY*) + *Control variables* + *Fixed effects*
Joint *F*-test for log(*SOE*)*log(*D_SCHOOL*) and log(*SOE*)*log(*D_SUBWAY*): 15.94**
log(*SUPPLY*)*log(*D_SUBWAY*) = 0.0530 × *D_CBD* + 3.086 × log(*D_SCHOOL*) – 3.955 × log(*D_SUBWAY*) – 0.272 × log(*SOE*)*log(*D_SCHOOL*) + 1.593 × log(*SOE*)*log(*D_SUBWAY*) + *Control variables* + *Fixed effects*
Joint *F*-test for log(*SOE*)*log(*D_SCHOOL*) and log(*SOE*)*log(*D_SUBWAY*): 11.30***

Notes: (i) Dependent variable is the logarithm of house price.

(ii) *LAND_LS* is measured by three-year cumulative amount of leased land by zone.

(iii) *t*-statistics are reported in parentheses.

(iv) ***: Significant at the 1 percent level; **: significant at the 5 percent level;*: significant at the 10 percent level.

(v) Instrument variables for log(*LAND_LS*)*log(*D_SCHOOL*) and log(*LAND_LS*)*log(*D_SCHOOL*) are log(*SOE*)*log(*D_SCHOOL*) and log(*SOE*)*log(*D_SUBWAY*).

(vi) Control variables for resale housing include *HSIZE, HAGE*, and *DECO*; control variables for new housing include *AHSIZE, HEIGHT*, and *TOTAL_AREA*.

(vii) For resale housing units, standard errors are clustered by complex.

TABLE 4: Robust Tests of Table 3 Using Alternative Periods for Calculating the Cumulative Amount of Land Leased

	LAND_LS Measured by Current Year's Amount of Leased Land		*LAND_LS* Measured by Two-Year Cumulative Amount of Leased Land	
	Resale Housing (1)	New Housing (2)	Resale Housing (3)	New Housing (8)
D_CBD	−0.0220	−0.0460***	−0.0147**	−0.0484***
	(−1.52)	(−5.84)	(−2.03)	(−4.30)
log(*D_SCHOOL*)	−0.123***	0.0738	−0.179***	−0.244**
	(−3.21)	(0.19)	(−3.61)	(−2.20)
log(*D_SUBWAY*)	−0.0940	0.613*	−0.219*	−0.496
	(−0.56)	(1.84)	(−1.88)	(−1.53)
log(*LAND_LS*)*log (*D_SCHOOL*)	0.0164**	0.00832	0.0167***	0.0723
	(2.24)	(0.16)	(3.03)	(1.26)
log(*LAND_LS*)*log (*D_SUBWAY*)	0.0115	−0.0661*	0.0249*	0.0525
	(0.42)	(−1.77)	(1.71)	(1.54)
Control variables	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Zone fixed effect	Yes	Yes	Yes	Yes
Observations	13.188	1.129	13,188	1,129
R^2	0.538	0.349	0.352	0.350

Notes: (i) Dependent variable is the logarithm of house price.
(ii) *t*-statistics are reported in parentheses.
(iii) ***: Significant at the 1 percent level; **: significant at the 5 percent level; *: significant at the 10 percent level.
(iv) Instrument variables for log(*LAND_LS*)*log(*D_SCHOOL*) and log(*LAND_LS*)*log(*D_SCHOOL*) are log(*SOE*)*log(*D_SCHOOL*) and log(*SOE*)*log(*D_SUBWAY*).
(v) Control variables for resale housing include *HSIZE, HAGE*, and *DECO*; control variables for new housing include *AHSIZE, HEIGHT*, and *TOTAL_AREA*.
(vi) For resale housing units, standard errors are clustered by complex.

leased land. Nevertheless, the two-year period alternative produces results more similar to the 2SLS results in Table 3.

Considerable attention has been given to examining the spatial dependence in estimated hedonic equations (Brasington and Haurin, 2006; Cohen and Coughlin, 2008; Carruthers and Clark, 2010; Bin et al., 2011). Housing prices tend to cluster in space because housing units in a neighborhood share similar location amenities or social demographic characteristics (Anselin and Bera, 1998). To address the well-known fact that omitted spatial dependence can lead to biased estimates, we employ a spatial IV model with a spatial autoregressive process in the dependent variable and disturbances (Drukker, Prucha, and Raciborski, 2011) as shown in Equations (7) and (8):

$$\begin{aligned} \log(PRICE) &= \beta_0 + \beta_1 \log(LAND\_LS) \cdot \text{Public Goods} + \beta_2 X \\ &\quad + \lambda W \log(PRICE) + \text{Year and zone fixed effects} + \mu; \end{aligned} \tag{7}$$

$$\mu = \rho W \mu + \varepsilon, \tag{8}$$

where W is the spatial weighting matrix calculated using the inverse distance between residential complexes; $W \cdot \log(PRICE)$ and $W \cdot \mu$ are the spatially lagged housing prices and disturbances, and λ and ρ are their corresponding scalar parameters. In principle, the

TABLE 5: Housing Price Regressions with Spatial Dependence[14]

	Resale Housing			New Housing		
Spatial Autoregressive Process	Dependent Variable Only (1)	Disturbances Only (2)	Dependent Variable and Disturbances (3)	Dependent Variable Only (4)	Disturbances Only (5)	Dependent Variable and Disturbances (6)
D_CBD	−0.0225***	−0.0229***	−0.0224***	−0.0461***	−0.0513***	−0.0468***
	(−10.71)	(−10.69)	(−10.75)	(−5.59)	(−5.74)	(−5.64)
log(*D_SCHOOL*)	−0.0600***	−0.0753***	−0.0615***	−0.112***	−0.170***	−0.112***
	(−3.73)	(−4.32)	(−7.17)	(−3.30)	(−3.58)	(−3.28)
log(*D_SUBWAY*)	−0.0410***	−0.0426**	−0.0412***	−0.317***	−0.479***	−0.324***
	(−2.64)	(−2.31)	(−2.72)	(−2.87)	(−3.08)	(−2.89)
log(*LAND_LS*)* log (*D_SCHOOL*)	0.00242	0.00414**	0.00643***	0.00103	0.0136	0.00108
	(1.44)	(2.26)	(3.54)	(0.20)	(1.40)	(0.20)
log(*LAND_LS*)* log (*D_SUBWAY*)	0.00220	0.00232	0.00276	0.0294***	0.0453***	0.0302***
	(1.16)	(1.01)	(1.47)	(2.78)	(3.02)	(2.80)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Zone fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,819	3,819	3,819	1,129	1,129	1,129
λ	−0.000937	–	−0.000887*	−0.00450	–	−0.00846
	(−0.59)	–	(−1.84)	(−0.60)	–	(−0.65)
ρ	–	0.0901	−0.361**	–	0.378	0.312
	–	(0.53)	(−2.01)	–	(1.63)	(1.45)

Notes: (i) Dependent variable is the logarithm of house price.

(ii) *t*-statistics are reported in parentheses.

(iii) ***: Significant at the 1 percent level; **: significant at the 5 percent level; *: significant at the 10 percent level.

(iv) Instrument variables for log(*LAND_LS*)*log(*D_SCHOOL*) and log(*LAND_LS*)*log(*D_SCHOOL*) are log(*SOE*)*log(*D_SCHOOL*) and log(*SOE*)*log(*D_SUBWAY*).

(v) Control variables for resale housing include *HSIZE, HAGE*, and *DECO*; control variables for new housing include *AHSIZE, HEIGHT*, and *TOTAL_AREA*.

spatial autoregressive process may exist in housing prices and/or unobservable characteristics that affect housing prices. Because the purpose is to test the robustness of previous results, this paper does not intend to determine the most appropriate assumption about the spatial autoregressive process. Instead, we present results of all three possible spatial autoregressive processes: dependent variable only, disturbance only, and both. Since the sample size of the resale housing data set is too big to efficiently estimate this spatial IV model, we aggregate resale units by residential complex by using the average price per square meter, size, age, and decoration status.[15]

Table 5 reports the results of spatial IV models. Columns (1) through (3) and (4) through (6) correspond to the three processes for the resale and new housing samples, respectively. The results of different spatial autoregressive processes do not differ from one another significantly, and they are also qualitatively consistent with the 2SLS results in Table 3. The coefficients of the interaction terms become smaller in spatial IV models, indicating that models that do not consider spatial interactions may overestimate the differences in capitalization rates across communities with different land supply constraints.

[14]Somewhat surprisingly, the estimated λ and ρ are negative although insignificant in most model specifications. This might be due to the zone fixed effects, which pick up a lot of what normally generates strong positive coefficients on spatial lags and spatial error terms. When we drop the zone fixed effects, the two parameters become positive. Nonetheless, we still prefer to include fixed effects to control for zone-level unobservables.

[15]The average number of resale records per housing complex-year is 3.45.

7. CONCLUSION

Using residential land leasehold and private housing sales data in Beijing, this study confirms the existing theory and evidence from developed countries that housing supply constraint does not just shift up the supply schedule, but also increases the price sensitivity to the quality of local public goods, contributing to high housing price. This study provides one of the earliest pieces of evidence on the relationship between supply constraint and the rate of capitalization in the context of centralized metropolitan government without local property tax. Unlike most existing studies, this study is intrajurisdictional and avoids the potential biases due to differences in regulatory environment. This study also uses proximity/quality instead of fiscal measures of local public goods and tests robustness of results against potential biases induced by spatial correlations.

Our analysis, however, should be viewed with its limitations in mind. The historical employment of state-owned manufacturing firms is a proximate measure of land used by the SOE manufacturers. It may not be perfectly exogenous due to the possible correlation with community attributes such as cultural/historical legacies and/or local population composition. Nonetheless, homeowners in China do not pay residential property tax, while urban public services are financed at the municipal government level. The lack of direct fiscal connection between local property value (associated with household composition) and public spending reduces the omitted variables problem in our housing price hedonics. Our study period is relatively short due to the limitation of data; the designation of the 25 zones can also be deemed as somewhat subjective. Thus, the findings reported here are the results of an initial effort to examine the housing market effects of land supply in a rapidly growing Chinese city, where detailed and reliable data are often hard to obtain. Future studies to corroborate the robustness of our findings through more observations, a longer study period, and alternative ways to define zones would be very useful.

Our findings have some implications for Chinese cities, where local government is responsible for land use decisions and providing local public goods. First, it is clear that land supply affects housing affordability, which is clearly a concern in Beijing, where the past decade or so has seen a rapid increase in property price (Zheng, Kahn, and Liu, 2010). For historical reasons, in many cases, the SOEs and other organizations occupy land at precious locations, which do not contribute much to their productivity. While the internal structure of Chinese cities undergoes a fast transition, Chinese local government should focus on removing the institutional barriers preventing existing state land users with low land use efficiency from moving out of the city center. Second, providing high-quality local public goods, or supplying more land in places with better accessibility to those public goods, will not only increase the welfare of urban households, but also bring in more land leasehold revenues in an era of increasing restrictiveness on urban spatial expansion. Finally, as the spatial variation in housing prices in a metropolitan area is affected by public service levels, where a city chooses to invest in public goods may affect residential sorting and segregation within the metropolitan area. For example, improving public service levels in supply-constrained (often more expensive) areas may further enlarge the housing price gap between those areas and the rest of a city. The result will be that fewer people can afford the areas with improved service, unless housing supply is increased.

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