Spatial Economics Research Centre

SERC DISCUSSION PAPER 116

Does Public Investment Spur the Land Market?: Evidence from Transport Improvement in Beijing

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July 2012

This work is part of the research programme of the independent UK Spatial Economics Research Centre funded by a grant from the Economic and Social Research Council (ESRC), Department for Business, Innovation & Skills (BIS) and the Welsh Assembly Government. The support of the funders is acknowledged. The views expressed are those of the authors and do not represent the views of the funders.

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Acknowledgements
I thank seminar participants at SERC and the European Real Estate Society Conference (2012), and I thank Steve Gibbons, Paul Cheshire, Olmo Silva, Henry Overman, Simona Iammarino, Guanpeng Dong, and Yaping Wang for helpful comments.

Abstract
Over 140 billion CNY (1GBP=10CNY) has been spent between 2000 and 2012 in Beijing on the construction of new rail transit lines. This massive public investment allows me to examine the consequences of transport improvements for land prices near rail stations. Using unique vacant parcel-specific data, I estimate the significant heterogeneity in the capitalization effects of rail transit development for multiple land uses in Beijing urbanised area. The results show that these transport improvements, identified by the parcel-station distance reductions, give rise to sizeable price premiums in the local residential and commercial land markets. Strikingly, the difference between the increase in the value of residential and commercial land parcels are not distributed evenly. These findings lend to support the evidence that public investment has an essential role to play in spurring the spatially targeted land market and provide implications for further land and transport policy making in China.

JEL Classifications: H41, Q51, R41
Keywords: Land prices; transport improvement; Geographical Information System; China

1 Introduction

Since the late 1990s, the explosive growth of public transport investment has been reshaping the face of most Chinese cities. Between 2000 and 2008, the Beijing government invested about 52 billion CNY[1] on the new rail transit constructions, with a subsequent investment of 105 billion CNY by 2012. This massive investment allows me to examine the consequences of the public transport improvement for the price of nearby land parcels.

In this paper I examine how residential and commercial land prices respond to the changes in the parcel-station distance proximities[2]. My purpose is threefold. First, my examination contributes to the small but growing body of literature on valuing rail access based on the difference-in-difference methodology (Ahlfeldt, 2011; Kahn, 2007; Gibbons and Machin, 2005). At its heart it captures the changing nature of geographical links between parcels and rail stations as a result of the rail transit development. This study improves on the previous methods by providing a framework that not only exploits changes in the parcel-station distances that happen when new stations are opened, it also highlights the importance of price changes in planned station areas. My study is also unique in using land parcel data during 1999 and 2009 in the entire urbanised area of Beijing, rather than pre-designed sample areas. To my knowledge, this is the first attempt to evaluate the impact of transport improvement by applying this type of analysis in China. My results, which focus on vacant land prices, document the appreciable economic benefits caused by the increased station proximity effect with the opening and planning of new rail transit lines.

Second, though frequently discussed in lectures, there have been surprisingly few detailed studies that examined the comparative impacts of rail access on both commercial and residential land prices (Debrezion et al., 2007). I employ the

[1] The official exchange rate is around 10 CNY per GBP during my study period.

[2] This valuation does not attempt to examine the impact of mortgage and prepayment risk (Deng and Liu, 2009; Deng et al, 2005) or the impact of overall economic and climate changes on the Chinese real estate market (Zheng et al, 2011). Instead, this study focuses specifically on identifying the new rail transit‟s impact on land prices.

geographical information system (GIS) software to derive proximity measures from the Beijing residential and commercial land use dataset. I define the treatment as parcels that experience the station-distance reductions; and that the outcome distances to the closest station are now less than a certain distance band[3] due to the new rail transit constructions. Such multiple distance-band design allows me to explore the heterogeneous distance decay trends associated with the station-proximity impacts on residential and commercial land prices. Importantly, I also allow the proximity effect of rail stations to depend on employment accessibility, crime rates, educational attainment that believed to indirect influence the value of transport improvement (Gibbons and Machin, 2008; Gibbons, 2004; Bowes and Ihlanfeldt, 2001). Additionally, I control for unobserved spatial characteristics with the local fixed effect. My evidence on new rail transit‟s effects on land prices, suggests that residential and commercial land developers do value the increased station proximity and these valuation varies widely with local socio-demographics over space. Using the entire urbanised area's average effects might therefore mask the value of proximity to stations in particular spatial location by a substantial margin. For example, the value of proximity to new stations falls as crime rates increases and rises with employment accessibility and local residents‟‟median educational attainment level.

Finally, beyond an obvious academic interest, the question of whether rail transit improvement has a substantial affect on land values has tremendous policy implications: showing complementary effects between public investment and private sector investment. Within the "new urbanism" process, transport-oriented development strategies were designed to gentrify previously depressed areas and reduce congestion in central business and residential districts (Knaap et al., 2001). Classic examples of this include Boston‟s Big Dig, Chicago‟s Midway line, Los Angeles‟s Bay Area subway line, Toronto‟s Spadina Subway line and London‟s Jubilee and DLR lines. Given the huge expenditures of transport infrastructures,

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[3] I use the multiple distance bands (0.5km, 1km, 2km, and 4km) to define the treated parcels in order to exploit which distance band has the most significant impact on local prices. See detailed explanation of treatment groups in Section 3.3.

empirical answers are scarce on whether public investments and private investments are complements that spur the emerging land markets of the BRICS countries[4]. My findings offer a limited support for this by demonstrating that the same “game” plays out in Beijing, where public transport investment has been shown to stimulate spatially targeted residential and commercial land markets.

This paper proceeds as follows: Section 2 reviews the literature on the rail access effect on property values. Section 3 describes the institutional settings and data. Section 4 presents the econometric models. Section 5 reports the estimation results. Section 6 concludes.

2 Literature review

The literature relevant to my analysis includes studies that have documented the effects of rail access on urban property prices with respect to different methodologies, motivations and property types. Findings from each of these dimensions are briefly summarized in this section.

First, after conducting a broad literature search, I find existing empirical approaches on valuing rail access can be grouped into two broad types. The first approach is a straightforward cross-sectional analysis, in which property price is regressed on accessibility to stations at one specific time whilst controlling for other attributes. Over the past 30 years, a large number of studies have contributed to improving the model specification and the ways in which the values of transport access are capitalised into land values. Recent examples includes Grass (1992), Cheshire and Sheppard (1995), Vessali (1996), Coffman and Gregson (1998), Landis and Zhang (2000), Bowes and Ihlanfeldt (2001), and Debrezion et al (2011). However, there are some problems underlie this approach. One relates to the omitted variable issue; admittedly, no matter how many control variables can be included in the regression, there are still unobserved characteristics that might be correlated with transport access and land values. Since the affected station areas are relatively small,

[4] BRICS countries refer to the top five developing countries as Brazil, Russia, India, China and South Africa.

failure to account for correlated local contextual effects separately would bias the estimated value of the proximity to stations. The second problem associated with this approach is that it cannot take into account the changing nature of rail access, especially when new stations are built. Unlike permanent green spaces and park amenities, the state and local governments have continued to make investments in building public transport infrastructures especially in the developing countries. These new rail transit lines have fundamentally reshaped the evolution of the urban transport network over time and have changed the closest distance from stations to land parcels whilst leaving others unaffected. Thus the estimating results should conceal significant variation in transport access and economic outcomes over time.

Alternatively, the difference-in-difference approach, moved on to use cross-sectional time series data to look at the changes in land values before and after a new rail transit line is in service. By comparing the distance changes in rail access over time, this approach can mitigate many of the problems with the pure cross-sectional applications. Most existing studies, employing before-and-after comparisons, have focused on examining the property price effects of new rail transit lines in North American cities. See, for example, Davis (1970) on the San Fancisco Bay Area subway line, Bajic (1983) on new subway lines in Toronto or McMillen and McDonald (2004) on Chicago Midway Rapid Transit Line. Recent studies, though less common, have exploited changes in the distances between properties and stations as a result of new stations opened and estimated such impacts on property prices (Gibbons and Machin, 2005; Kahn, 2007; Ahlfeldt, 2011). For example, Gibbons and Machin (2005) developed a precise framework for capturing the changes in distances between houses and tube stations in London when the Jubilee line and Docklands Light Railway (DLR) opened in the late 1990s. They highlighted the fact that difference-in-difference regression estimates can better avoid the biases inherent in pure cross-sectional empirical work. Following Gibbon‟s and Machin (2005)‟s study, Ahlfeldt (2011) reexamined the property price effects of transport network extensions in London using extended housing price data. In particular, he emphasized the importance of employment accessibility on the adjustment of property prices. Kahn (2007) documented the significant heterogeneity in the effects of rail transit expansions across the 14 large US cities. He found that the average housing prices of communities that experienced increased proximity to new stations rise significantly compared to communities that have never experienced improved access to stations. My methods are closest to this approach type, but I improve on previous methods by considering explicit changes in the distances between parcels and stations that occur when new stations are opened and planning to opening as a result of urban transport improvement.

Second, the literature on the effects of rail access on property values includes two motivation categories: tests of present effects, the most common, have focused on examining the relationship between the proximity to the existed stations and land values. Earlier studies, such as Dewees (1976), found that the economic benefits of living close to subway stations were capitalised into property values. Recent research has drawn more attention to the external effects associated with rail stations. For example, Bowes and Ihlanfeldt (2001) found that the proximity effect of rail transit on property prices vary substantially in Chicago, according to different neighborhood characteristics, local public goods qualities and other location-specific features. RICS (2002) conducted a detailed review of more than 150 empirical studies on the relationship of land values and public transport in the North American cities, and found largely support for the positive impact of transport access on land values. Tests of planning/anticipation effect with respect to the impact of planned station accessibility on property values, have been less common. Using housing price data from 1969 to 1976 in the Washington D.C, Damm et al. (1980) found that property values near future Metro station areas increased significantly. McDonald and Osuji (1995) looked into the anticipation effect of the Midway line in Chicago and found that there was a 17% premium on residential land values within half a mile of station locations, even before the new transit line opened. Henneberry (1998), however, found that housing prices decreased a little after launching the transport infrastructure plan, largely because of the anticipated construction nuisance. Knaap et al. (2001) found that the plans for rail transit investments have positive effects on land values around designed station sites. Overall, the combined empirical findings show that the expectations of transport improvements, whether positive or negative, can be reflected in property price changes before the new transit opening. Indeed, this planned transit‟s impact actually serves as an effective means of coordinating public investments in transportation infrastructure with private investments in the real estate market. Thus the economic welfare analysis of such planning effect has important practical relevance.

A third literature dimension lies in the different types of real property markets. While a large number of studies have focused on examining the residential property market, there have been few studies combined both residential and commercial properties in empirical analysis. Some empirical studies have shown that the affected areas of the rail access effects are larger for residential properties, whereas the effect of proximity to rail stations on commercial properties is concentrated at nearby areas (Debrezion et al., 2007; Cervero and Duncan, 2001). This finding is consistent with the expectation that station areas---by gathering large amount of population flow, will attract commercial establishments and thus have greater price premiums for commercial properties at a closer distance range.

By zooming into the urban China literature, it is not easy to find empirical studies on valuing rail access despite the rapid transport infrastructure changes. Research on this issue has been limited by the lack of systemic micro-level land parcel data and related local socio-demographics data. Recent excellent works, however, include Zheng and Kahn (2008), Wang (2009), and Wu, Gyourko and Deng (2011), among others. For example, Zheng and Kahn (2008) reported the significant impact of the established subway stations access on land and housing prices in Beijing. However, existing empirical studies in China have only focused on the residential property market; nothing is known about the commercial land market. In addition, they don‟t capture the increased station access effects as a result of the transport improvement. A further problem is that these studies do not account for the indirect effects between the station access and local socio-demographic characteristics. Thus their resulting estimates are likely to be biased. It is likely, for example, that the welfare benefits derived from proximity to new stations would decrease when located in high crime rate areas.

Empirically, the implications of empirical studies are often difficult to compare because of the heterogeneous local contextual characteristics through which the new transit‟s impact is thought to operate. I am implicitly assuming that the impact of increased station access on land prices occurred only when parcel-station distance changes due to the transport improvement. The next sections spell out the detailed data and econometric models.

3 Data and Institutional Settings

The focus of this section lies on introducing the land development and transport infrastructure supply within a unique transitional economy context. To better understand this, it is necessary to provide a brief introduction to the centralized urban governance structure in Beijing. The Beijing municipal administrative system has three levels: Beijing municipality, district and zone (*jiedao*, it will be referred to as zone thereafter in this study). While the Beijing metropolitan area consists of eighteen districts, this study mainly focuses on the eight urbanised districts (*Dongcheng, Xicheng, Xunwu, Chongwen, Chaoyang, Fengtai, Shijingshan, and Haidian*) because the other districts are predominately rural areas. There are five "ring roads (Nos. 2–6)" circled around the central business district (CBD) from the central city to the suburbs (see circle lines in Figure 1 below). The Beijing urbanised area is mostly within the No. 6 ring road, which covers about 1368 km^2. Existing empirical studies have shown that the Beijing urbanised area is still quite mono-centric with respect to the spatial distribution of population density, as well as land and housing prices (Zheng and Kahn, 2008).

Within the Beijing‟s urbanised area, 135 *jiedaos* (zones) exist as the fundamental administrative organization and census unit (the average size of each *jiedao* is about 10 km^2). However, unlike in the US, land supply and public infrastructure construction are highly centralized and controlled by the Beijing municipal government. The zones (*jiedaos*) are only responsible for street cleaning and do not have control over public infrastructure construction and service provision. Thus the zone area functions as a basic geographical unit for data collection and analysis, not as a political unit using local revenue to provide public services. Zones are intended to be similar areas with respect to general socio-demographic characteristics. Ideally, I should find a geographical space that can yield perfectly homogeneity in the characteristics of each location. However, in all urban China studies, researchers face the challenging of the large size of the basic geographic zone (*jiedao*). While I am well aware that there could comprise heterogeneous characteristics within zones, the availability of local public goods and other socio-demographics still share greater common characteristics within zones than across zones. Thus the findings reported here can be viewed as the best possible evidence in this fast developing country, where micro-geographical data is very difficult to obtain. Future works to strengthen the robustness of my findings would be helpful.

I divide this section into three parts. The first part introduces the land parcel data and related micro-geographical data. The second part discusses the transport infrastructure improvement in Beijing. The third part presents the details about the treatments and do balancing test to see if the treatment groups and control groups were matched in terms of pre-treatment demographic and other characteristics.

3.1 Data

The Chinese urban land market is a booming market with vigorous reforms and rapid growth over the past twenty years[5]. Since the 1978 Reform and Opening-up policy in China, tremendous changes had happened in this "magic" economy, from a central-planned economy towards a market-oriented economy. Within this context, a land market was reborn in the recent two decades. In 1988, the Chinese

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[5] See Wu, Gyourko and Deng (2011) for a recent evaluation of major Chinese cities" land market.

Constitution---which had prohibited land transfers before, was amended to permit land leasing rights (70 years for residential land use and 40 years for commercial land use) while retaining land ownership. In 1990, the State Council formally affirmed such dramatic transformation of the land use system from free allocation toward a leasehold system. By 1992, local governments in Beijing and Shanghai had begun to practice the land leasing policy, and it quickly spread to other cities in China.

In Beijing, the Municipal Land Resource Authority is responsible for the land allocations and sales of leasehold right, first through negotiation between developers and governments (during 1992 and 1998), then through partly negotiation and partly competitively open auction (during 1999 and 2003), and through the full competitively open auction way since 2004. See Zhu (2005), Cheshire (2007) and Cai, Henderson and Zhang (2009) for more details on the Chinese land market reform policies. From the Beijing Municipal Land Resource Authority, I have collected all the vacant residential and commercial land parcels[6] during 1999 and 2009 within the study area. I have excluded uncompleted land transaction data and the land parcels that were obtained through negotiation because the strong institutional forces could reduce the market price effectiveness (Zheng and Kahn, 2008). The final sample size is 2343 and 1341 parcels[7] for residential and commercial land uses respectively.

In this study, the unit of analysis for the hedonic price regressions is a land parcel. Using the Geographical Information System (GIS) software, I have geocoded all the parcels. In order to measure transport infrastructure changes, I map the rail transit network before and after 2003 and calculated the distance from land parcels to the nearest station using the GIS techniques. To implement the transport improvement analysis, I group the parcel-level residential and commercial land parcel data into

[6] The land supply is exogenous with the public transport planning since it is made independently by Beijing Municipal Land Resource Authority.

[7] To mitigate the inflation effect, I have adjusted the land prices by using the CPI index reported by the Beijing Statistical Year Book 1999-2010. All monetary figures are constant in 2009 CNY *yuan*. Also, I have trimmed the land price distribution by only keeping parcels in each year whose price is between the 5th and 95th percentiles of the whole sample price distribution.

three time periods: before 2003 ($1999 \leq \text{year} < 2003$); during 2003 and 2008 ($2003 \leq \text{year} < 2008$); after 2008 ($\text{year} \geq 2008$).

Geographical information on other localised characteristics is taken from a variety of sources for the use of controllable variables in the regression models. The local public goods were built long ago in the central-planning economy and seldom change their locations after they are built. Thus, one advantage of using these local public goods as a set of controllable variables is that the location of public goods (such as schools, parks) is exogenously determined in Beijing. Meanwhile, Chinese homeowners do not need to pay property tax. Rail transit infrastructure and other local public goods, are financed by the Beijing Municipal Government. Thus the capitalization effects of local public goods should be more significant than places with property taxes (Gyourko et al., 1999), since land developers implicitly buy the local public goods when bidding for land parcels. School location and quality comes from the Beijing Municipal Committee of Education. The location of bus stops and expressways are used as proxies for the competing commuting modes, and is obtained by a web-based search from the Beijing Municipal Committee of Transport. Additional GIS data on the sites of rivers, parks and green spaces is taken from the Beijing Water Authority and Beijing Municipal Garden Bureau respectively. Air quality is measured by the air pollution index (API) published the Beijing Municipal Environmental Protection Bureau[8]. Crime rates for the number of violent crimes taking place in each zone are obtained from the Beijing Public Security and Safety Bureau (BPSSB). The 2000 City Population Census reports the detailed local socio-demographic characteristics such as the zonal population density, resident median education attainment levels, public housing rent ratio, and the percentage of old housings built before 1949. The 2001 City Employment Census provides

[8] The Beijing Municipal Environmental Protection Bureau reports daily API by different monitoring station. Instead of including the all-year round data, I only use the spring quarter data because it is the worst air quality season in Beijing. Thus it can reduce the overall noise for the potential impact of air quality on the land market. Following on the conventional way to create the appropriate metric, I assign the average API values of the daily maxima at the monitoring stations to the each parcel using the ordinary Kriging method (Anselin and Le Gallo, 2006).

employment accessibility[9] estimates. Table 1 gives the descriptive statistics of variables involved in the modeling analysis.

3.2 Transport infrastructure improvement

To meet the rapid urbanization process and increasing commuting demand, the Beijing government has invested a huge amount of money into rail transit development during 2000 and 2012. The full set of new rail transit lines data is detailed in Table 2[10]. This table highlights that the constructions of rail transit lines differ with respect to their starting time[11] and completion date[12]. This table also provides differential figures of each line with respect to the construction cost, track length, and station numbers. Figure 1 shows the sketch map of the Beijing rail transit network before and after the completion of these new rail transit lines. Despite such differences, these new lines share several common characters: First, they are all

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[9] I use the gravity model to calculate the employment accessibility with respect to each land parcel. The formula can be expressed as: $\text{Employment Accessibility}_i = \sum_k \exp(-\delta * \text{distance}_{ik}) * \text{subcenter}_k$. Where δ is the distance decay parameter over geographical area. The parameter value that provides the best fit would eventually be selected (d=2 in this case). subcenter_k represents the total job number in the employment sub-center *k* in Beijing, which is identified by the pilot study of Ding et al (2010) based on the non-parametric methods proposed by McMillen (2001).

[10] The Beijing Municipal Committee of Transport's official website http://www.bjjtw.gov.cn/ contains informative details of subway lines in Beijing. This study does not include the subway lines to be completed after 2012, because of the large uncertainties involved with the proposed timetable. As a robustness check, I do test the anticipation effects for subway lines (Line 14 and 16) that had been announced but the exact completion time would be no early than 2015. The coefficients of these estimates are not reported. The insignificant estimating results confirm the prior expectation.

[11] I am unable to test the announcement effect separately because the announcement time of these lines is generally before my study period.

[12] It should be noted that Line 5 was temporarily opened at October 2007, but fully opened at the beginning of 2008. Line 4 was temporarily opened at December 2008, and fully opened at February 2009. To facilitate the interpretation, I treat both of them opened at 2008. Additionally, as a robustness check and to help reduce the estimation bias, I extend the land parcel sample by including parcels sold during the last quarter of 2007. The results are virtually similar.

intended to reduce congestion and meet the rapid growth of the commuting demand in the central city. For instance, a recent internal report by Beijing Municipal Commission of Urban Planning has clarified that subway line 6 and line 7 are constructed to handle the ridership growth of subway line 1 and the road congestion around the CBD areas. Second, they aim to strengthen the connections between the central city and suburbs from different spatial directions. Practically, the rail transit construction can be regarded as a fundamental policy lever to gentrify the less-desirable areas. Due to the unbalanced planning history in Beijing, the central and northern city regions are more developed than the western and southern city regions. Thus most of the new subway lines focus on linking the central city with previous depressed city parts, especially those emerging super-"bedroom" residential communities in the suburbs (such as *Tiantongyuan, Yizhuang, Daxing,* and *Tongzhou*). To facilitate the 2008 Beijing Olympics, new transport infrastructures are also extended to the Olympic Park area. Given the importance of the political economy behind the placed-based investment on rail transit lines, there is a danger of mixing up the Olympics effect and other trends with the station-distance reduction effect. Below, I will control the interactions of time trends with distance to CBD, distance to Olympic Park, and distance to those emerging "bedroom" communities ($\textit{Distance to New Residential Area}_i$) that can affirm the robustness of the increased station proximity outcomes for treated parcels.

In this study I use the opening of two lines in 2003, four lines in 2008, and eight planned lines opening after 2009 (to be completed before 2012) as my transport improvement evaluation. Ideally, I could single out the effects of each of these new lines and even go further by measuring each new station‟s effect individually[13]. Yet in

[13] Below, I will test the effect of new simple stations, new cross stations, and new simple-to-cross stations (stations that were converted from simple stops into junctions with the building of new lines) separately.

reality, I simplify the estimation framework by treating them as three nested events (stations open after 2003, after 2008 and after 2009 respectively) to better understand the opening effect and net planning effect of new rail station access in Beijing.

3.3 Balancing test for "*treated*" and "*control*" places

The main interest of this part is to answer two questions: what is the treatment?; and whether treatment groups and control groups are balanced in terms of observable pre-treatment demographic characteristics?

To be clear from the outset, a residential or commercial land parcel will be assigned to a treatment group if:

Criteria 1: It experienced the station-distance reductions with the stations opening after 2003;

Criteria 2: And if the outcome distance to the closest station opening after 2003 is now less than 0.5km, 1km, 2km, 4km respectively, it will be assigned to the corresponding treatment group of $(0.5km\_station \geq 2003)$, $(1km\_station \geq 2003)$, $(2km\_station \geq 2003)$, $(4km\_station \geq 2003)$.

Accordingly, my control groups are parcels that have never been experienced distance reductions to the stations opening after 2003 and that the outcome distances to the closet stations are beyond the distance bands (0.5km, 1km, 2km, 4km respectively).

I impose the second criteria because I want to avoid the estimating noise from the parcels that became closer to a station, but still remain a long distance away from the new station[14]. Notably, the choice of a 2 km threshold is based on most existing

[14] It is certainly true that land parcels located more than 4 km away from a new station might also benefit from

empirical literature as well as a reasonable walking distance to a station (about 20 minutes). Figures 2-3 show the spatial distributions of treated residential and commercial land parcels respectively that are now within 2km from a new station. From the GIS map it can be seen a clear spatial differentiation pattern among parcels in the treatment groups of $(station \geq 2009)$, $(station \geq 2008)$ and $(station \geq 2003)$, which gives some confidences that my results are not sensitive to the potential spillover effects within-groups. Below, I will examine the spillover effects both within and across groups in the robustness check section of this paper.

However, instead of using the fixed distance band such as 2km, this study considers the multiple distance bands (0.5km, 1km, 2km, 4km) to select the treated parcels. As described by Gibbons and Machin (2005), the ideal application of a difference-in-difference design would compare the treatment effects using alternative parcel-station distance bands. This comparison would hold everything the same in the model specification and any changes in land prices would be attributable to the difference in the selection of distance bands. As such, I am able to test the marginal effects of each distance band relative to the larger one.

Following the same selection principles, I further create the treatment groups when a parcel has been experienced the station-distance reductions with the stations opening after 2008/2009; and the outcome distance to the closest station opening after 2008/2009 is now less than 0.5km, 1km, 2km, 4km respectively. Of necessity, the treatment groups of $(station \geq 2009)$ are nested within the corresponding treatment

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the opening and planning of such a station. In this study I implicit assume that a 4-kilometer ball around the station is sufficient for defining the impact of rail access at station areas---not at remote places.

groups of $(station \geq 2008)$, and the treatment groups of $(station \geq 2008)$ are nested within the corresponding treatment group of $(station \geq 2003)$.

As an initial step towards valuing rail access in the land market, it is worthwhile to do the balancing test to see if treated places would be significantly different from the untreated places in terms of the observable demographic characteristics[15]. Thus I estimate a set of regression models using residential and commercial land parcel sample in Table 3-4. The dependent variable is the log of initial prices for land parcels sold during 1999 and 2002, educational attainment, public housing rent ratio, population density, old building percentage, employment accessibility, and distance to the CBD respectively. The main independent variables are the treatment groups.

Ideally, in terms of the perfect treatment-control balancing, it would be expected to see that the estimated coefficients for the treatment groups are not statistically significant. As can be seen from Table 3, the treated and control places are not significantly different with respect to their initial residential land prices, population density, old building percentage and public housing rent ratio. However, places with higher educational attainment level are more likely to be treated with rail access under all treatment scenarios (within 4km). Perhaps more informative are the last two columns, which report the results of employment accessibility and distance to the CBD. Lower employment accessibility areas are more likely to be treated with rail access under all treatment scenarios (within 2km and 4km). Moreover, places that located further away from the CBD are more likely to be treated with rail access to

[15] Due to the lack of census panel data, this study has not attempted to measure demographics dynamics in treated places relative to observationally identical control places as a result of transport improvement.

stations after 2003 and 2008 (within 2km and 4km). I do the same test for commercial land parcel sample in Table 4. It shows a balanced pattern for treated and control places in terms of their initial commercial land prices, educational attainment, population density, old building percentage and public housing rent ratio. Though the magnitudes are very small, places with lower employment accessibility are more likely to be treated with rail access under all treatment scenarios (within 2km and 4km). All else equal, places that located further away from the CBD are more likely to be treated with rail access to planned stations opening after 2009 (within 2km and 4km). It is certainly the case that some other pre-treatment characteristics would be unbalanced between treated and control places. Nonetheless, the headline result in Table 3-4 suggests that there is limited difference for the treatment groups and control groups in terms of key observable pre-treatment demographics and related spatial characteristics. In the empirical analysis, of course, I include the fixed effect, time trends and a bunch of location-specific factors to adjust further for differences in characteristics, in the regression estimates reported in Section 5.

4 Models

Using a rich geo-coded dataset, this study estimates the effects of increased station proximity on residential and commercial land prices in Beijing. My transport improvement model builds on the hedonic spirit that is widely used in the evaluation of amenities values[16]. The baseline equation for my analysis is expressed as follows[17]:

$$Ln\Pr ice_{ilt} = \beta_0 + \beta_j \sum_{j=1}^{3} Lndist_{it} + \beta_t \sum_{t=1}^{3} Y_t + \beta_k X_{ilk} + f_l + \varepsilon \qquad (1)$$

Where $Price_{ilt}$ represents the price of vacant residential or commercial land parcel i located at area l in the period t; $dist_{it}$ is the distance to the nearest station; X_{ilk}

[16] See the seminal work by Rosen (1974), and see Sheppard (1999), Hilber (2011) and Gibbons et al. (2011) for a recent hedonic review.

[17] By having a number of choices regarding the functional form of the hedonic analysis (such as linear, semi-log, etc), a better fit is achieved for the available data and variables. In this study, I have tried estimating flexible-form models with Box–Cox transformation but could not reject a strong log–log relationship between land prices and key explanatory variables.

is a matrix of land structural and localised characteristics; Y_t presents the time trend effects; f_l indicates the local fixed effect, measured by each parcel's location coordinates (x,y) and its spatial variations (x^2,y^2, xy); ε is a random error term[18]. Other Greek letters are parameters to be estimated.

This traditional cross-sectional approach is highly successful at capturing long-run relationships between land prices and rail access, but may not recover the impact of increased station proximity on local prices before and after a change in transport improvement policy. To explicitly account for this, I adopt a conceptually more attractive approach. By focusing on what happens after the transport improvement, in places affected and unaffected by the change, I can more reliably assess the new rail transit's impact[19].

To achieve this, I need data on land price changes and rail station access changes. In contrast to the systemic repeated sales data and limited transport infrastructure changes in the developed countries, it is easy to observe an opposite scenario in China: an emerging land market system since the 1990s and the rapid urban rail transit development. The first data requirement is met by using a 1999-2009 cross-sectional land parcel transaction data. One limitation here is that I do not have access to repeated observations for the same parcel over time and therefore cannot apply panel-data methods to control for fixed-over-time omitted variables. However, this paper does provide an extremely rich set of parcel and location characteristics allowing me to mitigate the problems induced in the regressions by unobservable variables (Ferrer-i-Carbonell and Frijters, 2004). But this approach is not effective for eliminating changes in location characteristics as a result of changes in parcel–station distance. For example, if the crime rates declined disproportionately in places treated with a new rail station for exogenous reasons, the econometrician does not see this but the households do. Thus I would observe the land price premium and would attribute

[18] Standard errors are clustered at the zone level to allow for heteroscedasticity and spatial and temporal correlation in the error structure within zones.

[19] Gibbons and Machin (2005) have shown that the cross-sectional estimates, which tend to overstate the benefits of rail access, are generally larger than the estimates from the transport improvement models.

this to the effect of increased station access when in reality it actually accounts for the omitted amenity values (increased local safety). I implicitly assume that the error term is uncorrelated with the explanatory variables, and those time-varying unobserved factors do not spill over space. I will also provide sensitivity analysis to test the robustness of the results.

The second data requirement is easier to meet because of the recent dramatic changes in public transport infrastructures in Beijing. The supply of new rail transit stations increased over time---two subway lines were opened in 2003, four lines were opened around 2008 and another eight lines were planned to open after 2009. These improvements will lead to the increased proximity to stations for a series of subset of land parcels in my data set after 2003, after 2008, and after 2009 respectively. This means that I can, in principle, estimate the increased station proximity effect in the multi-nested treatment scenarios[20]. The outcome regression equation becomes:

$$Ln\Pr ice_{iljt} = \beta_0 + \beta_1 \sum_{j=1}^{3} Treatment_j + \beta_t \sum_{t=1}^{3} Period_t + \sum_{j=1}^{3}\sum_{t=1}^{3} \beta_{jt} Treatment_j * Period_t + \beta_k X_{ilk} + f_l + \varepsilon \quad (2)$$

In this equation, $Treatment_j$ refers to a specific treatment group (e.g. $(station \geq 2003)$, $(station \geq 2008)$, $(station \geq 2009)$). $Period_t$ is a set of "policy-on" time dummy variables ($(1999 \leq year < 2003)$, $(2003 \leq year < 2008)$, $(year \geq 2008)$). The coefficients β_{jt} then show the various treatment effects ($Treatment_j * Period_t$) in different periods[21].

I seek to test for heterogeneous new rail transit‟s impacts on Beijing‟s land market along several dimensions. It is anticipated that these estimates are significantly

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[20] In the presence of nested treatment groups, my study‟s estimates provide new insights about each treatment effect conditional on the subsequent treatment scenarios. One major concern is to test whether there are spillover effects among treatment groups when adding all of them into one model specification. As a robustness check, I have tried to add each treatment group subsequently in different model specifications, but the difference between their coefficients won't tell anything about the spillover effect because the sum up value of the treatment coefficients remains the same as when adding all of them into one model specification. To further test this, I will explicitly exploit spatial spillover effects within and across residential/commercial treatment groups in Section 5.2.

[21] β_{j1} represent a set of baseline categories ($Treatment_j * Period_1$) that are omitted in the estimating result tables.

positive in corresponding periods. For example, the interactions between $(station \geq 2003 * 2003 \leq year < 2008)$ and $(station \geq 2008 * year \geq 2008)$ should be significantly positive and show the opening effect[22] for stations in 2003 and in 2008 respectively. A second dimension is captured by estimates of $(station \geq 2003 * year \geq 2008)$ and $(station \geq 2008 * 2003 \leq year < 2008)$. These two coefficients allow me to test post-opening effect for stations in 2003 and pre-opening effect for station in 2008 respectively. Their expected signs largely depend on the price growth trends during 2003 and 2008 versus after 2008. If the price growth trends after 2008 are greater than that during 2003 and 2008, then their estimates would be less positive and insignificant. A third dimension is to examine the net planning effect[23] for stations opening after 2009 relating to different land market periods like $(station \geq 2009 * 2003 \leq year < 2008)$ and $(station \geq 2009 * year \geq 2008)$. As indicated by recent empirical findings (Knaap et al, 2001), it is reasonable to expect that there would be positive signs associated with the planning effect of new stations.

Notably, land prices are affected by rail access not just in terms of direct effects from its structural and location-specific characteristics, but also indirect (interaction) effects between transport accessibility and those social, economic, and location-specific characteristics. For example, stations located near highways that could offer retail services and other amenities provide additional value for land developers, whereas increasing proximity to station areas with high crime levels would decrease the transport accessibility affect on land values (Gibbons and Machin, 2008; Gibbons, 2004). To help identify such interaction effects, the model specification can be written as:

[22] Here and thereafter, the opening effect means the estimated amenity benefits from the distance reductions to land parcels that are now within 0.5km, 1km, 2km, 4km respectively from newly-opened stations in 2003/2008.

[23] Here and thereafter, the net planning effect means the estimated amenity benefits from the distance reductions to land parcels that are now within 0.5km, 1km, 2km, 4km respectively from stations opening after 2009. It includes a combination of the potential negative construction effect and the positive anticipation effect for planned stations.

$$\mathrm{Ln}Price_{\mathrm{iljt}} = \beta_0 + \beta_j \sum_{j=1}^{3} Treatment_j + \beta_t \sum_{t=1}^{3} Period_t + \sum_{j=1}^{3} \sum_{t=1}^{3} (\beta_{jt} + \beta_k' X_{ilk})\, Treatment_j * Period_t + \beta_k X_{ilk} + f_l + \varepsilon \quad (3)$$

5 Results

5.1 Baseline regression estimates

In this section the results obtained from estimating the model described in Eq.(2) using residential and commercial land parcel data are discussed in turn. In discussing the regression estimates in Table 5-6, I focus primarily on significant heterogeneity in the effects of increased station proximity on local residential and commercial land prices. In light of recent urban transport improvement literature, the implicit assumptions underlying the interpretation of these estimates are as follows: (i) the measured effects of increased station-distance proximity on land prices happen only through parcel-station distance changes result from new rail transit constructions and expansions; (ii) unobserved characteristics and trends, such as land supply constraints and overall economic climate do not vary greatly; and (iii) the measures for localised characteristics included in the models can effectively explain the impact of transport access on the land market.

Column (1) in both tables shows estimates that include parcel unit fixed effects, proximity effects for parcels that are beyond the distance bands (0.5km, 1km, 2km, 4km thereafter), treatment dummies, general time effects[24], but no additional controls. As for the first treatment group $(station \geq 2003)$, the opening effect of stations in 2003 on the residential land prices is found insignificant when treated with the 0.5km distance band, but turns to be significantly positive when using wider distance bands

[24] To further control the spatial-temporal effect, I include interactions between time trends and parcels in each treatment group that only meet the first treatment selection criteria---parcels that experienced distance reductions to the closet stations(Treatment Criteria 1*Trends); and interactions between time trends and parcels in each treatment group that only meet the second treatment selection criteria---the parcel-station distance is now within the distance bands(Treatment Criteria 2*Trends).

(1km, 2km, 4km). Parcels that are now within 2km from a station have a significantly higher price premium compared to other distance bands. These results suggest that residential land parcels that are very close to stations are affected by negative externalities, but those at an intermediate spatial range are beyond the negative externality effects and benefit from the increased station proximity provided by new stations in 2003. There are no statistically significant post-opening impacts from distance reductions to parcels that are beyond 0.5km, 1km, 2km, and 4km spatial contours from new stations in 2003.

When I compare the estimated coefficients on the second treatment group $(station \geq 2008)$, the results are qualitatively similar to those reported in the first treatment group $(station \geq 2003)$. As for the quantitative magnitudes, the price premium paid for being closer to a station opening in 2008 is larger than that of newly-opened station in 2003. This is expected because many new stations were opened in 2008, resulting in obvious parcel-station distance reductions. The pre-opening effects for stations in 2008 are positively significant when treated with the 1km, 2km and 4km distance-bands[25].

Continuing to discuss the results in Column (1), I next focus on the estimated results for the third treatment group $(station \geq 2009)$. This treatment group highlights the net planning effects for stations opening after 2009. As expected, I find that prices rose significantly in areas affected by planned stations opening after 2009 when treated with both of the $(2003 \leq year < 2008)$ period and the $(year \geq 2008)$ period. When comparing the quantitative nature between different time periods and among different distance bands, the price premiums are greater linked with the 2km distance band, and are much larger during the period after 2008 than that of during 2003 and 2008. This result confirms the possibility that the under-constructed rail transit plans are observed by the developers and increasingly capitalized into land

[25] Note that the treatment dummies have insignificant signs in tables 5-6. These results, to some extent, can help explain the pre-opening effect of station in 2008 is not caused by the price-growing trends in the treated places.

prices when closing to their completion times.

Notably, for mega-cities like Beijing, part of the increased station proximity effects could be attributed to the overall spatial effects, like differences in price trends in the central city and suburbs. In Column (2), I estimate the same specification but augmented with a set of spatial measures by allowing the interaction between the time trend and distance to CBD, and by allowing for time trends interacted with the distance to the Olympic park, and the distance to several important emerging "bedroom" communities (*Tiantongyuan, Yizhuang, Daxing,* and *Tongzhou*)[26]. The rationale behind this is that, during the time period I study, there was a boom in land price growth in Beijing, especially in some hot areas like the central city. This is confirmed by the significantly negative coefficient on the distance to CBD and its interactive terms with the time trend in Table 5. But the key finding here is that whilst the price growth trend effect matters, the increased station proximity effects are still robust and contribute to significantly higher residential land prices.

In Columns (3) and (4), I control for a wide range of land structural and location-specific characteristics (documented in Table 1). About 45% of the variation in the log of residential land prices respectively is explained by my transport improvement models. This compares favorably to previous hedonic literature in China. In addition, estimated treatment effect coefficients exhibit reasonable stability over alternative model specifications. After controlling for the full set of localised characteristics and adjusting for different temporal-spatial trends in column (4), I find that the opening effects of station in 2003, on average, are valued at around 0.61%, 1.96%, 1.25% of residential land prices at affected areas (within 1km, 2km, 4km respectively). The opening effects of station in 2008, on average, are valued at about 3.75%, 4.20%, 2.02% of the prices of affected residential land parcels (within 1km, 2km, 4km respectively). The positive and significant signs associated with the pre-opening effect for station in 2008 show that the potential increased station

[26] The estimated coefficients of these interaction terms are not reported. The results remain robust by controlling the interactions between time trends and distance-to-stations.

proximity effect is captialised into local land prices (within 1km, 2km and 4km). In terms of the net planning effect, prices rise by about 0.23%, 0.58%, 0.48% on average when treated with the time period during 2003 and 2008 (using 1km, 2km, 4km distance band respectively); and prices rise by around 3.01%, 3.79%, 3.51% on average when treated with the time period after 2008 (using 1km, 2km, 4km distance band respectively). The insignificant signs of the increased station proximity effect within 0.5km imply the negative externalities such as noise and congestion effects that reduce the capitalisation effect for parcels that are too close to the new stations.

Switching to the commercial land parcel sample in Table 6, I find quite similar qualitative patterns in comparison to the results reported in Table 5, expect for estimating results using the 0.5 km distance band. In contrast to the residential land parcels‟ result, there are significantly positive impact from the opening effect of station in 2003 and 2008 on commercial land prices within 0.5km. This finding is in line with the expectation that when comparing to the residential land values, commercial land values accrue greater benefit at a closer distance range from a station------by gathering large population flows and demand for commercial activities.

As for the quantitative nature, I find that station proximity impacts on commercial land prices are slightly lower than those on residential land prices. This is not surprising given that the parcel sample of the commercial land market is relatively thinner than that of the residential land market. Strikingly, I also find that these station proximity impacts generally decay with distance in a non-linear trend. For example, the effect of increased proximity to stations on residential land parcels that are now within 2km from new stations is larger than other distance bands‟ results; while the most affected places for commercial land parcels are those that are now within 1km from new stations (see Table 5-6 for details). To further explore whether the observed differences in proximity impacts on residential and commercial land prices are statistically significant, the Chow statistical test (Chow, 1960) is conducted[27]. The null hypotheses are: the set of coefficients for the treatment effects on the commercial parcels and the corresponding set of coefficients for the treatment effects on the residential parcels are not significantly different from each other. An interesting finding is that, the null hypotheses are rejected at the 5% significance level for those statistically significant treatment effects reported in Table 5-6. This clear evidence demonstrates the heterogeneous station proximity impacts across residential and commercial land markets[28].

5.2 Robustness checks

To test the robustness of main findings, I now examine how sensitive the baseline results presented in Table 5-6 are across different subsamples and across analogous econometric specifications.

The first sensitivity analysis is to adjust spatial selections in the land parcel sample. Because Beijing urbanised area is so large, it may have a large influence on the baseline estimates. I therefore, in model specifications of Table 7 report results that only include the land parcel sample located within the central city (within the 3rd ring road) and within the inner suburb (within the 5th ring road) subsequently[29]. The results, reported in Columns 1-4 of Table 7, mirror that of the baseline estimates in terms of qualitative nature. But the estimated coefficients of treatment effects within the central city have lower magnitudes than those within the inner suburbs, indicating that the proximity impacts are not distributed evenly over space.

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27 Full results are available from the author upon request.

28 In addition to the non-linear distance decay trend, there is also some statistical justification in supporting the heterogeneous proximity impacts when interacted with localised characteristics.

29 Recall that the full sample refers to the spatial range within the 6th ring road of Beijing.

Second, I consider a further robustness issue related to the impact on effective proximity of new lines on existing stations. With the rapid rail transit development in Beijing, it is noteworthy that some new lines convert what were simple stops into new cross-stations. Accordingly, I have re-assigned the new station sample into three sub-categories[30]: new simple stations, new cross stations, and new simple-to-cross stations. The results shown in Table 8[31] are generally robust relative to the main treatment effect estimates in Table 5-6. One thing to note is that, the positive impact of distance reductions to the new simple-to-cross stations (within 2km) on commercial land prices are greater than that of the new simple and cross stations. Another interesting finding is that, residential land prices rose slightly higher when treated to a new simple station compared to new cross stations and simple-to-cross stations. One possible explanation is that it more deeply reflects the differential effects of increased proximity to stations valued by the land developers. Certainly, new simple-to-cross stations are more likely to gather a larger number of population flows and greater demand for retail establishment than purely new cross stations and simple stations. Thus proximity to a new simple-to-cross station is of higher value to commercial land prices than other types of new stations. But residential land prices are more sensitive to the increased negative externalities such as crime and noise emitted by the junction stations, and therefore the effect of proximity to a new simple station benefits more on residential land values.

[30] In the preliminary estimation process, I have divided new station status into underground and over-ground stations, but their results are not statistically significant.

[31] To avoid redundancy, I focus on results using the 2 km distance band in Table 8. Although not shown in the table, the results in other distance bands are also robust.

Next, I consider whether there are significant spillover effects within and across residential/commercial treatment groups[32]. Such test helps to gauge the robustness of the results more fully[33]. As for the within-group spillover effects, I focused on examining whether the parcels in the subsequent treatment group affect the increased station proximity effect on parcels in the prior treatment group. Two steps are involved in measuring the spillover effect from the $Treatment_{j+1}$ onto the $Treatment_j$: first, to calculate the distance between parcels that belong to the $Treatment_j$ (but not belong to the $Treatment_{j+1}$) and parcels in $Treatment_{j+1}$; and second, to make interactions between this distance variable and its corresponding treatment effect ($Treatment_j*Year_t$). The results in Columns 1-2 of Table 9[34] show that the estimated spillover effect coefficients are small in magnitudes and insignificant for both residential and commercial parcel sample. Another natural question is to ask whether the new rail transit‟s effect on residential land parcels is affected by adjacent commercial land parcels. To this end, the cross-group spillover effect measures are calculated through the interactions of the distance between all treated commercial land parcels[35] and residential land parcels in each treatment group. Estimates from column (3) in Table 9 show that most of the residential treatment effect variables are reassuringly quite robust to the potential spillover impacts from nearby commercial land parcels. The only two exceptions are associated with the treated residential land parcels receiving distance reductions to stations after 2009. However, the small

[32] There are two steps involved in measuring the spillover effect from the $Treatment_{j+1}$ onto the $Treatment_j$: the first step is to calculate the distance in kilometer between parcels that belong to the $Treatment_j$ (but not belong to the $Treatment_{j+1}$) and parcels in $Treatment_{j+1}$; and second, to make interactions between this distance variable and its corresponding treatment effect ($Treatment_j*Year_t$). To test the spillover effect from commercial parcels to residential parcels, I have proposed a straightforward measurement through the interactions of the distance between treated commercial parcels and treated residential parcels with each residential treatment effect.

[33] In light of recent literature, this method is very effective to identify the spillover effects in the land market (Irwin and Bockstael, 2001).

[34] I report only the model using the 2km distance band scenario. There are no statistically significant spillover effects within groups when using the 0.5km, 1km, and 4km distance bands.

[35] Note that I have also interacted the residential land parcels in each treatment group with all commercial land parcels. Because the estimating results are not significant, they were dropped from the table. Plus, there are also no statistically significant cross-group spillover impacts when using the interactions of the residential land parcels in $Treatment_j$ with its distance to the commercial land parcels in either $Treatment_j$ or $Treatment_{j+1}$.

magnitudes of their coefficients affirm the possibility that residential land parcels gain weakly positive spillover effects from adjacent commercial land parcels[36].

Finally, reliance on estimates of amenity benefits for the average sample effect in a metropolitan area would mask rail access values to parcels in particular places. Thus I develop a heterogeneous model of transport improvement, estimated by using Eq.(3) to help recover the relationships between local socio-demographics and the rail access effects. As an additional robustness check, I now turn to the model with interactions in Table 10[37]. The interactions between treatment effect variables and local residents" median educational attainment level show that residential land price premiums are valued greater for being close to a station in high- than in low-educational attainment areas. Assuming that residents" incomes are positively correlated with their educational attainment level in Beijing[38], this result implies that the greater commuting time savings provided by transport development enhance the rail access value for well-educated residents. Meanwhile, the commercial land prices are found to be valued higher when treated in high- than in low--educational attainment places, possibly because the larger consumption capability for well-educated residents gentrifies the value they attach to rail access.

The interactions of treatment effect variables with crime rates show that in places

[36] The cross-group spillover effects do not have a significant sign when treated with the 0.5km distance band, but have slightly negative and significant impacts associated with the treated residential land parcels that are now within 1km or 4km from a planned station after 2009.

[37] These estimates do not rely on the within-zone changes induced by the transport improvement. The results are not statistically significant to the inclusion of the interactions between treatment effect variables and other location-specific variables listed in the Table 1. Also, I interacted the treatment effect variables with dummies indicating whether the nearest station is underground or over-ground, however, there were no statistically significant signs of these interactions, so they were dropped from the final models.

[38] There is no available information about local residents" income in the urban China census data. Yet in reality, this assumption is consistent with the actual observations in Bejing.

within 0.5km of a station, an increase in crime results in less residential and commercial land prices, however, the coefficients are very small in magnitude. There are no statistically significant impacts when treated with residential and commercial land parcels that are within 1km, 2km, and 4km distance contours of a station. The results suggest that the interactive impact of increased station proximity and crime is not strong on both residential and commercial land markets, but clearly the negative effect is dominant close to the station.

Finally, the treatment effect variables and employment accessibility interactions show that the effect of increased station proximity is more valuable in places with higher- than lower-employment accessibility. When reading the results of residential and commercial land parcel samples, their estimated coefficients on this interaction variable have sort of negative „„price gradients" across space. This lends support to the idea that the employment accessibility is valued higher closer in, even though many localised characteristics are controlled for with other measures.

These results suggest that the effects of proximity to stations on land prices depend on a parcel's location and localised characteristics. Beyond these interaction variables, what other local amenities and disamenities that might have significant complementarities with rail stations were overlooked? The list could be very long, including climate, social capital, architectural factors, and other forces of local heterogeneity that are unlikely to be observed by the econometrician. I certainly do not claim that my models are perfect. However, at the minimum, my result sheds light on the importance of valuing rail access, not just in terms of controlling its structural characteristics, but how those characteristics interact with local socio-demographics.

Overall, the earlier results plus all of the sensitivity analyses establish that the baseline regression estimates of station proximity effects are remarkably robust in terms of qualitative nature. Nevertheless, when one is reading the estimation results, it is necessary to keep in mind that the data limits my transport improvement analysis to changes that occurred within about 3 years of the new rail transit development[39]. Estimates based on the transport improvement models might underestimate the whole effect of transport accessibility when the price-lag adjustment process is long before or after the opening of new lines[40], or might overestimate the benefits if negative externalities at station areas evolve with the improved transport accessibility. In practice, it should be recognised that land developers usually don"t like to bear the great financial risk relating to the long-run benefits from the transport improvements. Thus it is reasonable to expect that the timing of price adjustment should be occurred closely to the completion time of the new rail transit lines.

6 Conclusions

Beijing has recently made heavy public investments in upgrading its rail transit networks. The investments have created a large number of land parcels that are now closing to new stations. Using rich vacant residential and commercial land parcel data, I examined whether land prices in such treated parcels changed after the geographical distances to the nearest station were reduced, relative to observationally control parcels. The empirical answer is mostly yes.

My results yield three important insights that have not been fully considered in the previous literature. First, residential and commercial land parcels receiving increased proximity to both newly opened stations and planned stations (that have been under-constructed) experienced appreciable price premiums, though the relative benefits are different in magnitudes. I further reported that the qualitative pattern of estimation results is remarkably robust across a set of stringent sensitivity analyses. Altogether, these empirical findings add to a growing body of literature by demonstrating that public investment in rail transit infrastructure and private sector

[39] Recall that the transport improvement estimates are obtained from price differentials among three time periods: 1999-2003, 2004-2007 and 2008-2009.

[40] See McDonald and Osuji (1995) and McMillen and McDonald (2004) for a detailed discussion.

investment in land development have complementary effects that spur the spatially targeted land market in Beijing.

Second, the rail access effects on residential and commercial land prices, identified by distance reductions induced by the transport improvement, show substantial variations over space. Broadly speaking, the increased station proximity effects on residential and commercial land prices play out differently at different distance ranges from a station, but clearly there is no significant evidence of the capitalisation effects when residential land parcels located nearby stations (within 0.5km). Specifically, the estimated values of increased station proximity vary widely with local socio-demographics. For example, in places that have higher employment accessibility, the amenity value of proximity to new stations is valued much higher than average. Thus my evidence strongly demonstrates that when simply using the sample mean effects, it is likely to underestimate or overestimate the amenity value of rail access in particular geographical locations.

Finally, my results have wide policy implications for further public transport investment and land use planning. The empirical evidence suggests that the impact of transport improvement is observed by land developers and capitalised into residential and commercial land prices. Accordingly, the urban spatial structure is likely to change due to such transportation-oriented development strategies. For example, in order to offset higher land prices, developers are more likely to build high-density constructions in station areas. The public investment in rail transit expansions would also gentrify the commercial activities at station areas and increase metropolitan public transport revenues in the long term. For such strategies to succeed, planners need to create market interventions that discourage low-density land development (such as the town-house) and encourage high-density development. This can be done by using zoning, building floor-area-ratio controls, or other forms of land use planning constraints. Of course, transport-oriented development is not purely a "free lunch". For example, the rural farmers are likely to be displaced from lands with increased values. In order to offset the rising rents, low-income workers are pushed further out to the remote suburbs and bear longer commuting distances to workplaces. Evidence on station-distance proximity effect on people‟s happiness, identified through residence-station distance changes induced by transport improvements, is unclear and will require future research. These implications provide a rationale for local government to go beyond the real estate consequences, and consider effective policy levers to maximize the subjective well-beings associated with public investment in rail transit expansions.

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Table list

Table.1 Descriptive statistics of variables

Variables	Definition	Residential land sample Mean/ (Std.Dev)	Commercial land sample Mean/ (Std.Dev)
Dependent Variable			
Land Price	Ln (Land parcels' leasing price per square meter (CNY/sq.meter))	7.45(1.08)	7.76(1.42)
Locational-specific Variables			
CBD	Ln (Distance between a land parcel and CBD (meters))	9.03 (0.64)	8.85(0.75)
Land parcel size	Ln (The area of a land parcel (m^2))	9.06 (1.34)	7.59(1.78)
Park	Ln (Distance to the nearest park (meters))	7.77 (0.72)	7.61(0.81)
River	Indicator of proximity to rivers (<500 meter)	0.18 (0.38)	0.11(0.31)
Air quality	Indicator of Air pollution index to each parcel	1.93 (0.87)	1.99(0.88)
Bus	Ln (Distance to the nearest bus stop (meters))	6.03(0.82)	6.12 (1.06)
Expressways	Ln (Distance to the nearest expressway (meters))	6.43(1.14)	6.36 (0.98)
School	Ln (Distance to the nearest middle school*school rank)	25.01 (5.68)	24.34(6.34)
Employment Accessibility	Indicator of employment accessibility to each parcel	0.04(0.05)	0.06(0.07)
Population Density	Population density in each zone (1,000 people per km^2)	2.37 (3.35)	2.76(4.35)
Old Building	Ratio of buildings built before 1949 in each zone (%)	0.03(0.09)	0.07(0.14)
Education Attainment	Median resident educational attainment in each zone:1=middle school or lower;2=high school;3=university;4=post graduate	1.715(0.508)	1.91(0.46)
Crime	Number of crimes per 1000 people in each zone	5.335(6.655)	4.08(5.15)
Public Housing	Percentage of people renting public housing in each zone	0.31(0.20)	0.33(0.21)

Table.2 New Rail Transit Construction in the urbanised area of Beijing

Line	Start by (year)	Open by (year)	Cost (CNY billions)	Length (kilometer)	Station (number)
13	2000	2003	6.6	40.5	16
Batong	2001	2003	3.4	19	13
4	2004	2008	15.2	28	24
5	2003	2008	11.9	27.6	23
10A	2004	2008	12.8	24.6	22
8A	2005	2008	2.5	15.8	4
Daxing	2008	2010	6.0	22	12
Yizhuang	2008	2011	11.0	23.2	14
8B	2009	2012	10.1	17	11
6	2007	2012	18.2	39	30
7	2009	2012	15.1	24	21
9	2007	2012	8.8	16.4	13
10B	2007	2012	18.5	32.9	23
15A	2009	2012	18.1	20.2	13

Notes.---The information on the rail transit lines that have not been completed yet may be changed. See the updated information on the Beijing Municipal Committee of Transport's official website http://www.bjjtw.gov.cn/

Table.3 Balancing test results based on residential land parcel sample

	Land Price	Education Attainment	Public housing	Population density	Old Building	Employment Accessibility	Distance to CBD
0.5km_($station \geq 2003$)	0.023	0.086	-0.021	0.255	0.013	-0.001	-0.044
	(0.291)	(1.365)	(-1.235)	(0.823)	(1.182)	(-0.333)	(-1.343)
0.5km_($station \geq 2008$)	-0.011	0.122	0.027	-0.141	-0.012	0.003	0.040
	(-0.129)	(1.371)	(1.421)	(-0.429)	(-1.338)	(1.500)	(1.143)
0.5km_($station \geq 2009$)	0.054	0.029	-0.001	-0.327	-0.010	0.001	-0.021
	(0.635)	(0.592)	(-0.048)	(-0.991)	(-1.250)	(0.503)	(-0.603)
1km_($station \geq 2003$)	0.009	0.139	0.005	1.082	-0.005	0.003	0.021
	(0.083)	(1.495)	(0.208)	(1.497)	(-0.556)	(1.502)	(0.467)
1km_($station \geq 2008$)	0.161	0.123	0.028	-1.188	0.006	-0.004	-0.071
	(1.626)	(2.158)	(1.273)	(-1.344)	(0.667)	(-1.333)	(-1.392)
1km_($station \geq 2009$)	-0.104	0.009	-0.009	0.093	0.012	-0.002	0.004
	(-1.268)	(0.196)	(-0.501)	(0.292)	(1.200)	(-1.010)	(0.121)
2km_($station \geq 2003$)	0.173	0.013	-0.038	-0.972	0.015	-0.013	0.197
	(0.935)	(0.121)	(-0.950)	(-1.358)	(0.938)	(-3.250)	(2.592)
2km_($station \geq 2008$)	-0.235	0.163	-0.005	1.398	-0.039	-0.024	0.232
	(-1.343)	(1.598)	(-0.132)	(1.431)	(-1.560)	(-6.001)	(3.222)
2km_($station \geq 2009$)	-0.072	0.019	-0.019	0.198	-0.010	-0.004	0.037
	(-1.075)	(0.487)	(-1.267)	(0.759)	(-1.429)	(-2.021)	(1.370)
4km_($station \geq 2003$)	-0.316	0.312	-0.027	1.640	-0.053	-0.027	0.491
	(-1.430)	(2.403)	(-0.551)	(1.534)	(-1.359)	(-4.513)	(5.337)
4km_($station \geq 2008$)	0.083	0.419	-0.015	1.035	0.026	-0.004	0.157
	(0.483)	(4.190)	(-0.395)	(1.549)	(1.368)	(-2.008)	(2.211)
4km_($station \geq 2009$)	0.111	0.429	-0.039	-1.602	0.016	-0.019	0.078
	(0.631)	(4.206)	(-1.083)	(-1.689)	(1.067)	(-4.508)	(1.083)
Constant	0.304	1.011	-0.402	-3.016	-0.106	-0.272	8.680
	(0.749)	(4.284)	(-4.568)	(-2.811)	(-3.029)	(-6.727)	(5.667)
Fixed effects (Parcel location coordinates)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1054	1054	1054	1054	1054	1054	1054
Adjusted R-squared	0.416	0.34	0.207	0.222	0.153	0.577	0.698

Notes.---Each column reports estimates of the balancing tests from a separate regression. The dependent variable for each regression is listed in the first row of the table (initial residential land prices, educational attainment, public housing rent ratio, population density, old building percentage, employment accessibility, distance to CBD), as described in the text. The data sample is used residential land parcels sold during 1999 and 2002. t-statistics in parentheses, clustered on zone unit.

Table.4 Balancing test results based on commercial land parcel sample

	Land Price	Education Attainment	Public housing	Population density	Old Building	Employment Accessibility	Distance to CBD
0.5km_($station \geq 2003$)	-0.252	0.126	0.009	-1.001	0.039	-0.003	-0.132
	(-1.120)	(1.370)	(0.265)	(-1.053)	(1.393)	(-0.750)	(-1.361)
0.5km_($station \geq 2008$)	0.381	0.082	0.048	1.781	-0.022	0.002	0.191
	(1.371)	(0.719)	(1.143)	(1.516)	(-0.846)	(0.401)	(1.619)
0.5km_($station \geq 2009$)	0.009	0.145	-0.015	1.605	-0.009	0.002	-0.021
	(0.032)	(1.261)	(-0.349)	(1.354)	(-0.346)	(0.400)	(-0.219)
1km_($station \geq 2003$)	0.455	0.126	-0.037	2.871	0.003	0.009	-0.015
	(1.458)	(0.977)	(-0.805)	(1.670)	(0.103)	(1.501)	(-0.139)
1km_($station \geq 2008$)	0.073	0.006	0.018	-2.567	-0.016	0.011	-0.112
	(0.213)	(0.043)	(0.346)	(-1.389)	(-0.503)	(1.222)	(-0.949)
1km_($station \geq 2009$)	-0.083	0.039	0.086	-0.899	0.035	-0.002	-0.054
	(-0.219)	(0.250)	(1.509)	(-0.562)	(0.971)	(-0.333)	(-0.412)
2km_($station \geq 2003$)	0.323	0.242	-0.028	-1.373	0.057	-0.023	0.143
	(0.441)	(0.804)	(-0.252)	(-0.454)	(0.838)	(-1.769)	(0.565)
2km_($station \geq 2008$)	-0.312	0.117	0.097	3.737	-0.143	-0.056	0.305
	(-0.429)	(0.391)	(0.875)	(1.217)	(-1.607)	(-4.308)	(1.215)
2km_($station \geq 2009$)	0.681	0.303	-0.145	-4.506	0.081	-0.039	0.813
	(0.799)	(0.866)	(-1.124)	(-1.253)	(1.025)	(-2.610)	(2.765)
4km_($station \geq 2003$)	-0.976	0.317	0.003	1.519	-0.112	-0.036	0.297
	(-1.310)	(1.036)	(0.027)	(0.483)	(-1.623)	(-2.769)	(1.156)
4km_($station \geq 2008$)	-0.229	0.121	-0.116	-3.978	0.136	-0.043	-0.179
	(-0.318)	(0.409)	(-1.064)	(-1.310)	(1.563)	(-3.308)	(-0.722)
4km_($station \geq 2009$)	-0.592	0.261	0.051	5.043	-0.096	-0.039	0.852
	(-0.743)	(0.796)	(0.423)	(1.499)	(-1.280)	(-2.786)	(3.098)
Constant	1.357	0.428	-0.536	-5.312	-0.263	-0.190	7.061
	(1.182)	(0.909)	(-3.045)	(-2.006)	(-2.430)	(-9.048)	(-10.823)
Fixed effects (Parcel location coordinates)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	466	466	466	466	466	466	466
Adjusted R-squared	0.277	0.278	0.199	0.278	0.148	0.538	0.682

Notes.---Each column reports estimates of the balancing tests from a separate regression. The dependent variable for each regression is listed in the first row of the table (initial commercial land prices, educational attainment, public housing rent ratio, population density, old building percentage, employment accessibility, distance to CBD), as described in the text. The data sample is used commercial land parcels sold during 1999 and 2002. t-statistics in parentheses, clustered on zone unit.

Table.5 Regression estimates of new rail transit's effect on residential land parcel sample

Distance band	Variables	Model 1	Model 2	Model 3	Model 4
0.5 km	$(station \geq 2003) * (2008 > year \geq 2003)$	-0.014	-0.011	-0.012	-0.006
		(-0.115)	(-0.089)	(-0.103)	(-0.051)
	$(station \geq 2003) * (year \geq 2008)$	-0.185	-0.162	-0.151	-0.137
		(-0.387)	(-0.336)	(-0.330)	(-0.297)
	$(station \geq 2008) * (2008 > year \geq 2003)$	0.116	0.105	0.094	0.083
		(0.678)	(0.618)	(0.573)	(0.509)
	$(station \geq 2008) * (year \geq 2008)$	0.811	0.765	0.661	0.619
		(1.542)	(1.457)	(1.317)	(1.231)
	$(station \geq 2009) * (2008 > year \geq 2003)$	0.117	0.115	0.071	0.053
		(0.713)	(0.706)	(0.452)	(0.340)
	$(station \geq 2009) * (year \geq 2008)$	0.382	0.323	0.249	0.213
		(0.737)	(0.620)	(0.504)	(0.428)
1 km	$(station \geq 2003) * (2008 > year \geq 2003)$	0.664	0.642	0.621	0.611
		(1.829)	(1.778)	(1.876)	(1.746)
	$(station \geq 2003) * (year \geq 2008)$	0.383	0.196	0.183	0.199
		(0.834)	(0.422)	(0.416)	(0.449)
	$(station \geq 2008) * (2008 > year \geq 2003)$	0.653	0.592	0.584	0.575
		(0.351)	(0.333)	(0.312)	(0.319)
	$(station \geq 2008) * (year \geq 2008)$	4.532	4.218	3.992	3.750
		(4.263)	(3.957)	(3.580)	(3.378)
	$(station \geq 2009) * (2008 > year \geq 2003)$	0.298	0.256	0.242	0.239
		(1.776)	(1.631)	(1.779)	(2.025)
	$(station \geq 2009) * (year \geq 2008)$	3.276	3.134	3.188	3.009
		(2.884)	(2.796)	(3.107)	(3.067)
2 km	$(station \geq 2003) * (2008 > year \geq 2003)$	2.337	2.148	2.026	1.968
		(2.452)	(2.201)	(2.034)	(1.977)
	$(station \geq 2003) * (year \geq 2008)$	1.121	1.799	1.206	1.053
		(1.045)	(1.598)	(1.193)	(1.020)
	$(station \geq 2008) * (2008 > year \geq 2003)$	1.695	1.675	1.509	1.281
		(2.042)	(2.204)	(2.219)	(2.100)
	$(station \geq 2008) * (year \geq 2008)$	4.661	4.427	4.221	4.206
		(4.099)	(3.900)	(3.765)	(3.862)
	$(station \geq 2009) * (2008 > year \geq 2003)$	0.699	0.634	0.601	0.584
		(3.344)	(3.268)	(3.284)	(3.281)
	$(station \geq 2009) * (year \geq 2008)$	4.206	4.052	4.001	3.799
		(3.456)	(3.289)	(3.143)	(2.954)
4 km	$(station \geq 2003) * (2008 > year \geq 2003)$	1.664	1.459	1.361	1.259
		(2.956)	(2.727)	(2.638)	(2.596)
	$(station \geq 2003) * (year \geq 2008)$	1.992	1.750	1.518	1.332
		(1.515)	(1.345)	(1.248)	(1.213)
	$(station \geq 2008) * (2008 > year \geq 2003)$	1.449	1.225	0.912	0.941
		(1.723)	(1.690)	(1.737)	(1.860)
	$(station \geq 2008) * (year \geq 2008)$	2.589	2.297	2.129	2.023
		(2.631)	(2.441)	(2.234)	(2.168)

	(1)	(2)	(3)	(4)
$(station \geq 2009) * (2008 > year \geq 2003)$	0.538	0.496	0.485	0.481
	(1.724)	(1.664)	(1.792)	(1.979)
$(station \geq 2009) * (year \geq 2008)$	4.179	4.156	4.043	3.511
	(4.053)	(4.194)	(4.092)	(4.388)
Distance to CBD*Trends	No	Yes	No	Yes
Distance to Stations>0.5/1/2/4KM	Yes	Yes	Yes	Yes
Parcel Characteristics	No	No	Yes	Yes
Treatment dummies	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Treatment Criteria 1*Trends	Yes	Yes	Yes	Yes
Treatment Criteria 2*Trends	Yes	Yes	Yes	Yes
Distance to OlympicPark*Trends	No	Yes	No	Yes
Distance to New Residential Area$_i$*Trends	No	Yes	No	Yes
Station-distance*Trends	No	Yes	No	Yes
Fixed effects (Parcel location coordinates)	Yes	Yes	Yes	Yes
Location-specific characteristics	No	No	Yes	Yes
Observations	2,343	2,343	2,343	2,343
Adjusted R-squared	0.384	0.393	0.437	0.456

Notes.---Dependent variable is log residential land price. Data is the disaggregated parcel-level data for three periods: pre-2003, 2003-2007 and after. The baseline omitted category is $Treatment_j*Period_1$(pre-2003). Regressions include control variables detailed in Table 1. t-statistics in parentheses, clustered on zone unit.

Table.6 Regression estimates of new rail transit's effect on commercial land parcel sample

Distance band	Variables	Model 1	Model 2	Model 3	Model 4
0.5 km	$(station \geq 2003) * (2008 > year \geq 2003)$	0.669	0.615	0.571	0.535
		(1.962)	(1.825)	(1.757)	(1.720)
	$(station \geq 2003) * (year \geq 2008)$	0.336	0.531	0.277	0.513
		(0.723)	(1.137)	(0.602)	(1.108)
	$(station \geq 2008) * (2008 > year \geq 2003)$	0.431	0.442	0.415	0.382
		(1.014)	(1.046)	(1.007)	(0.905)
	$(station \geq 2008) * (year \geq 2008)$	1.057	1.042	0.987	0.958
		(1.752)	(1.734)	(1.648)	(1.666)
	$(station \geq 2009) * (2008 > year \geq 2003)$	0.231	0.207	0.158	0.149
		(0.542)	(0.489)	(0.375)	(0.356)
	$(station \geq 2009) * (year \geq 2008)$	0.364	0.281	0.223	0.181
		(0.599)	(0.464)	(0.370)	(0.301)
1 km	$(station \geq 2003) * (2008 > year \geq 2003)$	0.889	0.763	0.662	0.625
		(2.102)	(2.079)	(2.181)	(2.097)
	$(station \geq 2003) * (year \geq 2008)$	0.805	0.621	0.556	0.511
		(1.214)	(0.944)	(0.832)	(0.768)
	$(station \geq 2008) * (2008 > year \geq 2003)$	1.605	1.469	1.185	0.871
		(2.439)	(2.652)	(2.319)	(1.919)
	$(station \geq 2008) * (year \geq 2008)$	2.788	2.376	1.828	1.663
		(3.584)	(3.337)	(2.653)	(3.035)
	$(station \geq 2009) * (2008 > year \geq 2003)$	0.795	0.668	0.622	0.582
		(1.944)	(1.663)	(1.709)	(1.921)
	$(station \geq 2009) * (year \geq 2008)$	1.463	1.298	1.165	1.081
		(1.701)	(1.728)	(1.686)	(1.941)
2 km	$(station \geq 2003) * (2008 > year \geq 2003)$	0.736	0.687	0.675	0.622
		(1.669)	(1.789)	(1.843)	(1.891)
	$(station \geq 2003) * (year \geq 2008)$	0.753	0.501	0.499	0.389
		(0.506)	(0.334)	(0.341)	(0.268)
	$(station \geq 2008) * (2008 > year \geq 2003)$	1.359	1.135	0.986	0.766
		(1.810)	(1.736)	(1.680)	(1.662)
	$(station \geq 2008) * (year \geq 2008)$	1.913	1.616	1.567	1.449
		(2.142)	(1.973)	(2.040)	(2.153)
	$(station \geq 2009) * (2008 > year \geq 2003)$	0.706	0.616	0.588	0.516
		(1.709)	(1.735)	(1.861)	(1.823)
	$(station \geq 2009) * (year \geq 2008)$	1.493	1.346	1.211	1.014
		(1.868)	(1.775)	(1.670)	(1.684)
4 km	$(station \geq 2003) * (2008 > year \geq 2003)$	0.646	0.627	0.552	0.396
		(1.755)	(1.923)	(1.890)	(1.692)
	$(station \geq 2003) * (year \geq 2008)$	1.268	1.007	0.939	0.604
		(0.856)	(0.679)	(0.644)	(0.586)
	$(station \geq 2008) * (2008 > year \geq 2003)$	1.251	1.208	1.024	0.876
		(1.700)	(1.808)	(1.769)	(1.708)
	$(station \geq 2008) * (year \geq 2008)$	2.494	2.111	1.988	1.834

	(2.269)	(2.359)	(2.513)	(2.327)
$(station \geq 2009) * (2008 > year \geq 2003)$	0.885	0.756	0.688	0.582
	(1.667)	(1.662)	(1.707)	(1.813)
$(station \geq 2009) * (year \geq 2008)$	1.651	1.489	1.439	1.322
	(1.705)	(1.686)	(1.725)	(1.737)
Distance to CBD*Trends	No	Yes	No	Yes
Distance to Stations>0.5/1/2/4KM	Yes	Yes	Yes	Yes
Parcel Characteristics	No	No	Yes	Yes
Treatment dummies	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Treatment Criteria 1*Trends	Yes	Yes	Yes	Yes
Treatment Criteria 2*Trends	Yes	Yes	Yes	Yes
Distance to OlympicPark*Trends	No	Yes	No	Yes
Distance to New Residential Area$_i$*Trends	No	Yes	No	Yes
Station-distance*Trends	No	Yes	No	Yes
Fixed effects (Parcel location coordinates)	Yes	Yes	Yes	Yes
Location-specific characteristics	No	No	Yes	Yes
Observations	1,341	1,341	1,341	1,341
Adjusted R-squared	0.297	0.331	0.365	0.388

Notes.---Dependent variable is log commercial land price. See notes to Table 5 for additional details.

Table.7 Regression estimates of new rail transit's effect on selected sample, sensitivity analysis

Distance band	Variables	Residential land parcel sample		Commercial land parcel sample	
		(1)	(2)	(3)	(4)
0.5 km	$(station \geq 2003) * (2008 > year \geq 2003)$	-0.012	-0.003	0.287	0.541
		(-0.064)	(-0.021)	(0.663)	(1.663)
	$(station \geq 2003) * (year \geq 2008)$	-0.095	-0.121	0.324	0.411
		(-0.135)	(-0.138)	(0.573)	(0.853)
	$(station \geq 2008) * (2008 > year \geq 2003)$	0.041	0.072	0.262	0.357
		(0.214)	(0.483)	(0.483)	(0.828)
	$(station \geq 2008) * (year \geq 2008)$	0.307	0.556	1.352	1.021
		(0.506)	(0.981)	(2.067)	(1.916)
	$(station \geq 2009) * (2008 > year \geq 2003)$	0.038	0.041	0.034	0.108
		(0.251)	(0.287)	(0.058)	(0.242)
	$(station \geq 2009) * (year \geq 2008)$	0.162	0.184	0.066	0.102
		(0.241)	(0.332)	(0.094)	(0.160)
1 km	$(station \geq 2003) * (2008 > year \geq 2003)$	0.565	0.597	0.568	0.592
		(1.652)	(1.860)	(1.656)	(1.935)
	$(station \geq 2003) * (year \geq 2008)$	0.093	0.135	0.377	0.425
		(0.178)	(0.288)	(0.475)	(0.613)
	$(station \geq 2008) * (2008 > year \geq 2003)$	0.328	0.551	0.798	0.889
		(0.818)	(1.662)	(1.659)	(1.912)
	$(station \geq 2008) * (year \geq 2008)$	2.851	3.031	1.392	1.556
		(2.021)	(2.403)	(1.891)	(2.542)
	$(station \geq 2009) * (2008 > year \geq 2003)$	0.216	0.225	0.501	0.614
		(1.649)	(1.844)	(1.176)	(1.878)
	$(station \geq 2009) * (year \geq 2008)$	1.949	2.352	0.981	1.016
		(1.633)	(2.277)	(1.657)	(1.648)
2 km	$(station \geq 2003) * (2008 > year \geq 2003)$	1.763	1.835	0.579	0.605
		(1.676)	(1.829)	(1.662)	(1.790)
	$(station \geq 2003) * (year \geq 2008)$	0.825	1.027	0.172	0.225
		(0.621)	(0.973)	(0.089)	(0.142)
	$(station \geq 2008) * (2008 > year \geq 2003)$	1.146	1.162	0.628	0.791
		(1.654)	(1.793)	(1.244)	(1.750)
	$(station \geq 2008) * (year \geq 2008)$	2.202	2.911	1.185	1.295
		(1.661)	(2.281)	(1.676)	(1.986)
	$(station \geq 2009) * (2008 > year \geq 2003)$	0.456	0.512	0.578	0.603
		(2.151)	(2.653)	(1.656)	(2.003)
	$(station \geq 2009) * (year \geq 2008)$	2.271	2.862	1.552	1.068
		(1.706)	(2.273)	(1.685)	(1.687)
4 km	$(station \geq 2003) * (2008 > year \geq 2003)$	0.981	1.148	0.278	0.423
		(1.654)	(2.199)	(0.921)	(1.652)
	$(station \geq 2003) * (year \geq 2008)$	0.967	1.201	0.212	0.278
		(0.729)	(1.055)	(0.113)	(0.168)

	(1)	(2)	(3)	(4)
$(station \geq 2008) * (2008 > year \geq 2003)$	0.695	0.852	0.732	0.813
	(1.221)	(1.661)	(1.386)	(1.886)
$(station \geq 2008) * (year \geq 2008)$	1.793	1.916	1.663	1.735
	(1.732)	(1.912)	(1.691)	(2.070)
$(station \geq 2009) * (2008 > year \geq 2003)$	0.381	0.458	0.481	0.545
	(1.180)	(1.665)	(1.033)	(1.548)
$(station \geq 2009) * (year \geq 2008)$	1.889	2.878	1.026	1.211
	(2.373)	(4.389)	(1.177)	(1.821)
Distance to CBD*Trends	Yes	Yes	Yes	Yes
Distance to Stations>0.5/1/2/4KM	Yes	Yes	Yes	Yes
Parcel Characteristics	Yes	Yes	Yes	Yes
Treatment dummies	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Treatment Criteria 1*Trends	Yes	Yes	Yes	Yes
Treatment Criteria 2*Trends	Yes	Yes	Yes	Yes
Distance to Olympic Park*Trends	Yes	Yes	Yes	Yes
Distance to New Residential Area$_i$*Trends	Yes	Yes	Yes	Yes
Station-distance*Trends	Yes	Yes	Yes	Yes
Fixed effects (Parcel location coordinates)	Yes	Yes	Yes	Yes
Location-specific characteristics	Yes	Yes	Yes	Yes
Observations	1181	1826	707	1036
Adjusted R-squared	0.389	0.431	0.322	0.346

Notes.---The dependent variable is the log of land prices. This table reports the estimates of treatment effects from two spatially selected data sample. Specifications 1-2 are based on the residential land parcel sample within the central city and inner suburb respectively. Specifications 3-4 are based on the commercial land parcel sample within the central city and inner suburb respectively. t-statistics in parentheses, clustered on zone unit.

Table.8 Regression estimates of effective proximity impacts of new lines, sensitivity analysis

Station sample	Variables	Residential land parcel sample (1)	(2)	Commercial land parcel sample (3)	(4)
Cross_station	$(station \geq 2003) * (2008 > year \geq 2003)$	0.258	0.251	0.819	0.694
		(1.870)	(1.832)	(1.777)	(1.689)
	$(station \geq 2003) * (year \geq 2008)$	0.066	0.086	0.649	0.531
		(0.402)	(0.534)	(0.994)	(0.800)
	$(station \geq 2008) * (2008 > year \geq 2003)$	0.915	0.863	1.242	0.988
		(1.743)	(1.672)	(2.168)	(1.743)
	$(station \geq 2008) * (year \geq 2008)$	3.321	3.179	1.684	1.297
		(2.232)	(2.267)	(2.190)	(1.671)
	$(station \geq 2009) * (2008 > year \geq 2003)$	0.454	0.444	-0.829	-0.794
		(2.009)	(1.991)	1.946	1.873
	$(station \geq 2009) * (year \geq 2008)$	2.544	2.282	1.904	1.907
		(1.889)	(1.715)	(2.159)	(2.172)
Simple_station	$(station \geq 2003) * (2008 > year \geq 2003)$	1.738	1.069	0.598	0.585
		(3.201)	(2.056)	(1.718)	(1.671)
	$(station \geq 2003) * (year \geq 2008)$	0.140	0.101	0.318	0.311
		(0.893)	(0.669)	(0.779)	(0.766)
	$(station \geq 2008) * (2008 > year \geq 2003)$	1.662	1.528	0.660	0.636
		(2.537)	(2.344)	(1.875)	(1.797)
	$(station \geq 2008) * (year \geq 2008)$	4.807	4.044	0.951	0.916
		(3.371)	(2.799)	(1.645)	(1.699)
	$(station \geq 2009) * (2008 > year \geq 2003)$	0.719	0.683	0.383	0.406
		(1.858)	(1.798)	(1.079)	(1.150)
	$(station \geq 2009) * (year \geq 2008)$	4.693	4.455	1.342	1.511
		(4.245)	(3.942)	(1.525)	(1.670)
Simple_to_Cross station	$(station \geq 2003) * (2008 > year \geq 2003)$	1.197	0.992	1.131	1.035
		(2.196)	(1.830)	(1.827)	(1.677)
	$(station \geq 2003) * (year \geq 2008)$	1.609	1.449	0.768	0.533
		(0.753)	(0.679)	(1.180)	(0.811)
	$(station \geq 2008) * (2008 > year \geq 2003)$	0.875	0.864	1.437	1.403
		(1.953)	(1.942)	(2.123)	(2.091)
	$(station \geq 2008) * (year \geq 2008)$	4.158	3.849	2.305	2.070
		(3.194)	(2.988)	(2.333)	(2.151)
	$(station \geq 2009) * (2008 > year \geq 2003)$	0.634	0.612	1.003	0.870
		(2.120)	(2.054)	(1.990)	(1.723)
	$(station \geq 2009) * (year \geq 2008)$	3.832	2.901	1.360	1.286
		(3.840)	(2.994)	(1.843)	(1.752)
Distance to CBD*Trends		No	Yes	No	Yes
Distance to Stations>0.5/1/2/4KM		Yes	Yes	Yes	Yes
Parcel Characteristics		Yes	Yes	Yes	Yes
Treatment dummies		Yes	Yes	Yes	Yes
Time dummies		Yes	Yes	Yes	Yes

Treatment Criteria 1*Trends	Yes	Yes	Yes	Yes
Treatment Criteria 2*Trends	Yes	Yes	Yes	Yes
Distance to Olympic Park*Trends	No	Yes	No	Yes
Distance to New Residential Area$_i$*Trends	No	Yes	No	Yes
Station-distance*Trends	No	Yes	No	Yes
Fixed effects (Parcel location coordinates)	Yes	Yes	Yes	Yes
Location-specific characteristics	Yes	Yes	Yes	Yes
Observations	2343	2343	1341	1341
Adjusted R-squared	0.423	0.441	0.311	0.334

Notes.---The dependent variable is the log of land prices. This table reports the estimates of treatment effects from two separate data sample. Specifications 1-2 are based on the residential land parcel sample. Specifications 3-4 are based on the commercial land parcel sample. The sample sizes are the same as in Table 5-6. All specifications are based on treated parcels that experienced distance reductions and the outcome distance to the nearest stations are now within the 2km distance band. t-statistics in parentheses, clustered on zone unit.

Table.9 Regression estimates of spillover effects, sensitivity analysis

Variables	Residential	Commercial	Cross
$Dist*(station \geq 2003)*(2008 > year \geq 2003)$	0.011	0.020	-0.021
	(1.222)	(0.153)	(0.375)
$Dist*(station \geq 2003)*(year \geq 2008)$	0.033	0.080	-0.095
	(1.031)	(0.320)	(0.429)
$Dist*(station \geq 2008)*(2008 > year \geq 2003)$	0.020	0.010	-0.024
	(1.001)	(0.250)	(0.381)
$Dist*(station \geq 2008)*(year \geq 2008)$	0.040	0.010	-0.029
	(0.801)	(0.166)	(1.223)
$Dist*(station \geq 2009)*(2008 > year \geq 2003)$	0.040	0.010	-0.011
	(1.000)	(0.250)	(1.911)
$Dist*(station \geq 2009)*(year \geq 2008)$	-0.080	0.010	-0.021
	(-1.143)	(0.142)	(2.131)
Distance to CBD*Trends	Yes	Yes	Yes
Distance to Stations>0.5/1/2/4KM	Yes	Yes	Yes
Parcel Characteristics	Yes	Yes	Yes
Treatment dummies	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes
Treatment Criteria 1*Trends	Yes	Yes	Yes
Treatment Criteria 2*Trends	Yes	Yes	Yes
Distance to Olympic Park*Trends	Yes	Yes	Yes
Distance to New Residential Area$_i$*Trends	Yes	Yes	Yes
Station-distance*Trends	Yes	Yes	Yes
Fixed effects (Parcel location coordinates)	Yes	Yes	Yes
Location-specific characteristics	Yes	Yes	Yes
Observations	2343	1341	2343
Adjusted R-squared	0.428	0.278	0.439

Notes.---This table reports the estimates of spillover effects from two separate data sample. The within-group spillover effects estimates are shown on model specification 1 and 2 based on residential and commercial land parcel sample respectively. The sample sizes are the same as in Table 5-6. Estimates of cross-group spillover effects from commercial parcels to residential parcels are shown on column 3. In specifications 1-2, *Dist* represents a series of distance (in kilometer) interactions between parcels in the subsequent treatment group and parcels in the prior treatment group, as described more details in the text. In specification 3, *Dist* means the interactions of the distance (in kilometer) between treated commercial parcels and treated residential parcels with each residential treatment effect. All specifications are based on treated parcels that experienced distance reductions and the outcome distance to the nearest stations are now within the 2km distance band. t-statistics in parentheses, clustered on zone unit.

Table.10 Regression estimates of interaction effects, sensitivity analysis

Distance band	Variables	Residential land parcel sample			Commercial land parcel sample		
		Educational attainment	Employment accessibility	Crime	Educational attainment	Employment accessibility	Crime
0.5km	$(station \geq 2003) * (2008 > year \geq 2003)$	0.003	0.011	-0.076	0.143	0.038	-0.059
		(0.044)	(0.408)	(2.235)	(0.177)	(0.975)	(-2.565)
	$(station \geq 2003) * (year \geq 2008)$	-0.273	0.154	-0.256	0.154	0.077	-0.135
		(-1.079)	(0.526)	(-1.939)	(0.726)	(0.681)	(-0.912)
	$(station \geq 2008) * (2008 > year \geq 2003)$	0.044	0.059	-0.096	0.034	0.039	-0.079
		(0.611)	(1.475)	(-3.01)	(0.213)	(0.848)	(-1.491)
	$(station \geq 2008) * (year \geq 2008)$	0.222	0.138	-0.244	0.362	0.325	-0.287
		(1.187)	(0.484)	(-2.103)	(1.716)	(1.593)	(-2.009)
	$(station \geq 2009) * (2008 > year \geq 2003)$	0.052	0.023	-0.005	0.058	0.054	-0.009
		(0.788)	(0.639)	(-0.278)	(0.503)	(1.176)	(-0.221)
	$(station \geq 2009) * (year \geq 2008)$	0.087	0.028	-0.013	0.096	0.001	-0.443
		(0.323)	(0.092)	(-0.157)	(0.382)	(0.007)	(-3.852)
1km	$(station \geq 2003) * (2008 > year \geq 2003)$	0.138	0.064	-0.007	0.296	0.085	-0.016
		(1.816)	(1.685)	(-0.121)	(2.176)	(1.667)	(-0.262)
	$(station \geq 2003) * (year \geq 2008)$	0.937	0.239	-0.201	0.054	0.293	-0.225
		(1.583)	(1.067)	(-1.142)	(0.185)	(1.296)	(-1.271)
	$(station \geq 2008) * (2008 > year \geq 2003)$	0.191	0.005	-0.026	0.197	0.058	-0.009
		(1.073)	(0.172)	(-0.473)	(1.225)	(0.925)	(-0.148)
	$(station \geq 2008) * (year \geq 2008)$	2.071	4.837	-0.782	2.268	2.676	-0.036
		(3.277)	(2.072)	(-1.367)	(2.187)	(1.988)	(-0.165)
	$(station \geq 2009) * (2008 > year \geq 2003)$	0.032	0.028	-0.016	0.131	0.075	-0.053
		(0.481)	(0.622)	(-0.941)	(0.824)	(1.019)	(-1.104)
	$(station \geq 2009) * (year \geq 2008)$	0.148	1.156	-0.063	2.082	0.966	-0.145
		(0.534)	(1.883)	(-0.488)	(2.511)	(1.845)	(-0.879)

	$(station \geq 2003) * (2008 > year \geq 2003)$	2.114	0.105	-0.004	0.266	0.378	-0.166
		(4.161)	(2.283)	(-0.058)	(1.750)	(1.979)	(-0.933)
	$(station \geq 2003) * (year \geq 2008)$	0.191	0.325	-0.292	0.292	0.712	-0.809
		(1.073)	(1.109)	(-0.598)	(0.861)	(0.698)	(-0.967)
	$(station \geq 2008) * (2008 > year \geq 2003)$	0.281	0.026	-0.028	0.208	0.942	-0.322
2km		(1.965)	(0.116)	(-0.444)	(0.504)	(0.661)	(-0.578)
	$(station \geq 2008) * (year \geq 2008)$	3.007	4.660	-0.353	1.751	2.115	-2.793
		(1.755)	(2.149)	(-1.587)	(1.689)	(1.779)	(-1.623)
	$(station \geq 2009) * (2008 > year \geq 2003)$	0.068	0.022	-0.012	0.568	1.213	-0.211
		(1.243)	(0.688)	(-0.800)	(1.303)	(0.719)	(-1.148)
	$(station \geq 2009) * (year \geq 2008)$	2.382	2.521	-0.061	1.979	1.185	-0.389
		(4.436)	(2.942)	(-0.457)	(2.213)	(1.787)	(-1.154)
	$(station \geq 2003) * (2008 > year \geq 2003)$	0.462	0.646	-0.039	0.332	0.236	-0.163
		(3.756)	(1.737)	(-0.582)	(1.677)	(2.165)	(-0.896)
	$(station \geq 2003) * (year \geq 2008)$	0.672	0.316	-0.202	0.311	0.642	-2.751
		(1.566)	(1.295)	(-1.270)	(0.816)	(0.633)	(-1.597)
	$(station \geq 2008) * (2008 > year \geq 2003)$	0.186	0.070	-0.027	0.356	0.901	-0.935
4km		(1.420)	(0.731)	(-0.519)	(0.866)	(0.632)	(-0.962)
	$(station \geq 2008) * (year \geq 2008)$	0.969	3.046	-0.218	1.071	1.439	-1.782
		(2.612)	(1.765)	(-0.965)	(2.052)	(2.129)	(-1.129)
	$(station \geq 2009) * (2008 > year \geq 2003)$	0.039	0.044	-0.012	0.255	1.162	-0.144
		(0.283)	(0.201)	(-0.185)	(0.593)	(0.689)	(-1.321)
	$(station \geq 2009) * (year \geq 2008)$	2.064	1.636	-0.106	0.654	3.395	-0.456
		(4.291)	(3.752)	(-0.404)	(2.003)	(2.066)	(-0.889)
	Observations		2343			1341	

Notes.---This matrix table can be viewed as two parts with respect to the residential and commercial land parcel sample respectively. The sample sizes are the same as in Table 5-6. Each part reports the estimates of the interactions between treatment effect variables and educational attainment, employment accessibility, crime rates from one single regression. The regressions shown in the table also include a full set of controls like column 4 in Table 5-6. t-statistics in parentheses, clustered on zone unit.

Figure list

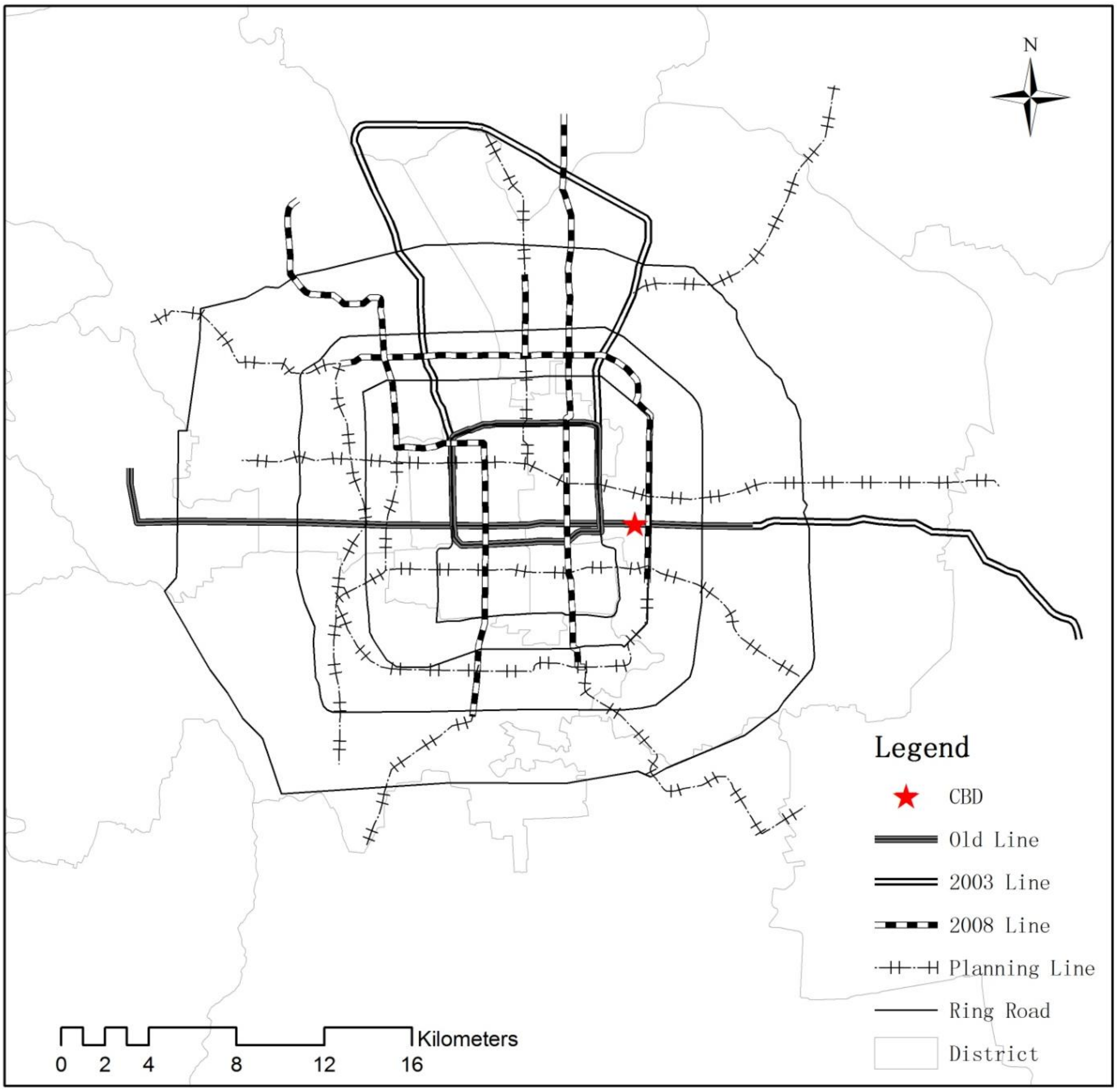

Figure 1. Rail Transit Network in the Beijing urbanised area

Notes.---Old lines were opened before 2003; 2003 lines were opened in 2003; 2008 lines were opened in 2008; Planned lines will open after 2009. See detailed explanation in Section 3.2.

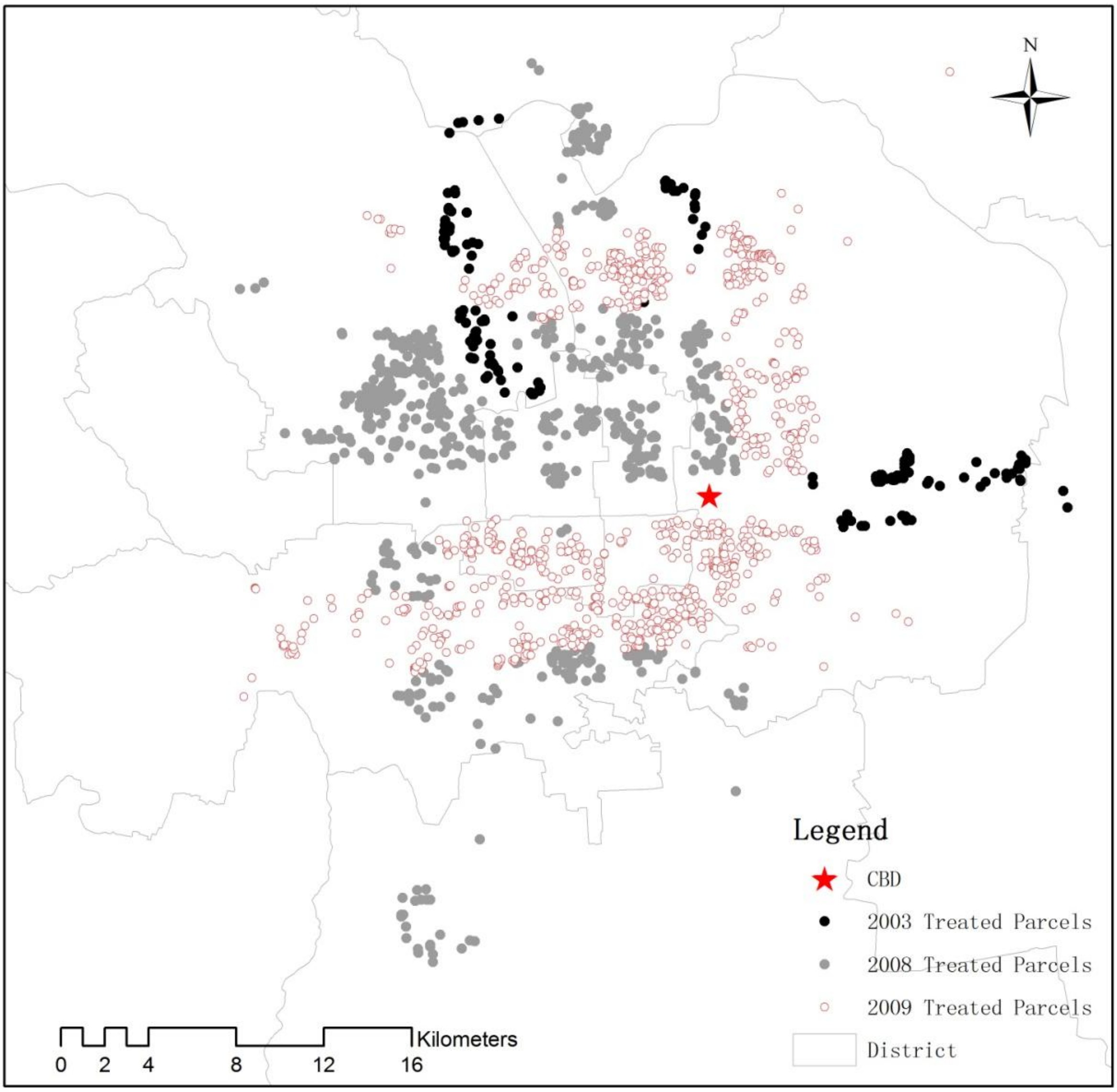

Figure 2. Spatial distribution of treated residential land parcels

Notes.---"2009 Treated Parcels" refer to the parcels in the $Treatment_3$ (station ≥ 2009); In comparison to the $Treatment_3$, "2008 Treated Parcels" are the additional parcels that belong to the $Treatment_2$ (station ≥ 2008). In comparison to the $Treatment_2$, "2003 Treated Parcels" are the additional parcels that belong to the $Treatment_1$ (station ≥ 2003). All treated parcels are selected using the 2km distance band.

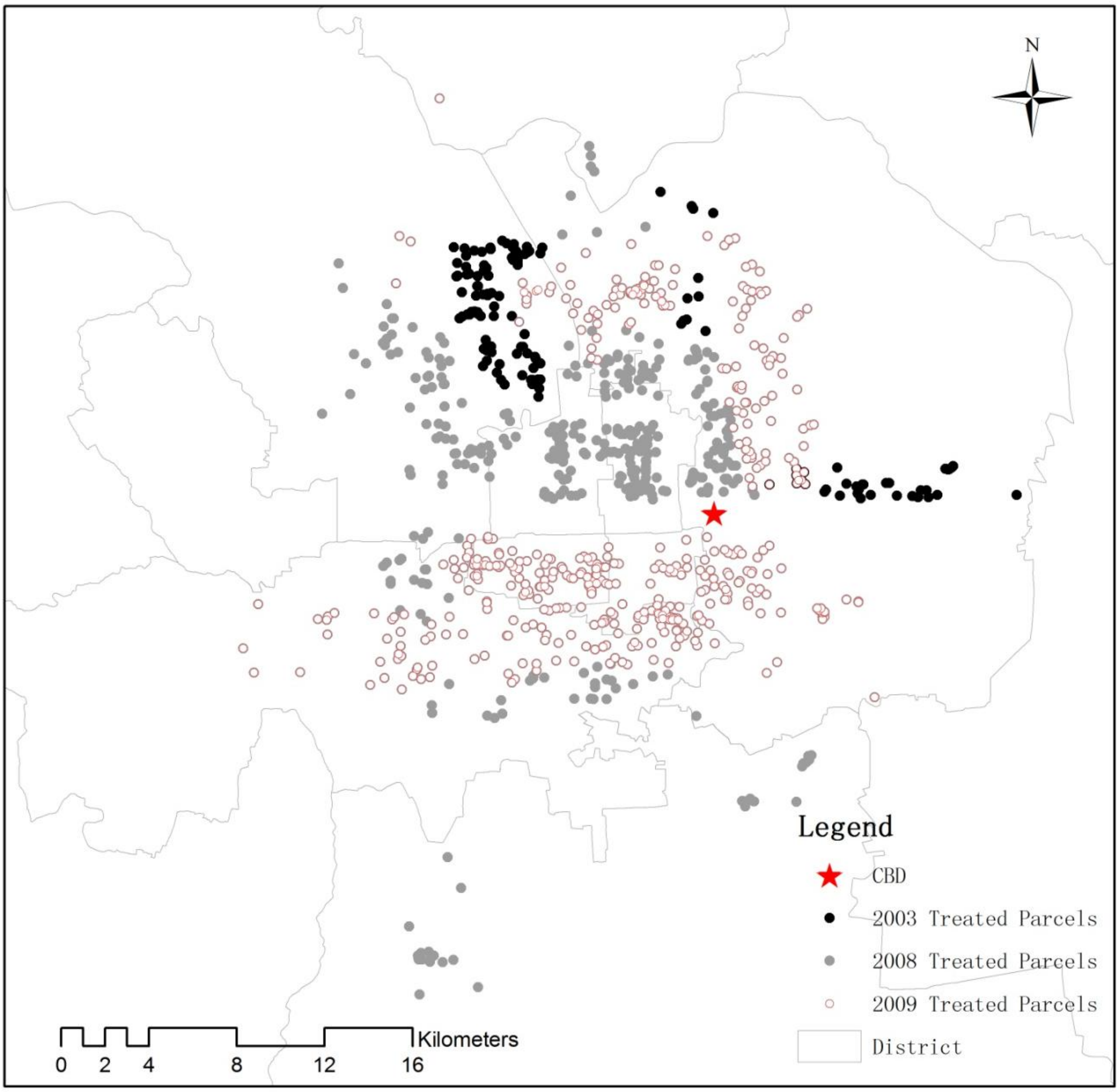

Figure 3. Spatial distribution of treated commercial land parcels

See notes to Figure 2 for details.

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SERC is an independent research centre funded by the Economic and Social Research Council (ESRC), Department for Business Innovation and Skills (BIS) and the Welsh Assembly Government.