The Capitalization of Subway Access in Home Value:

A Repeat-Rentals Model with Supply Constraints

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Abstract: Urban rail transit enhances accessibility of the communities it serves and contributes to the value of local real property. The majority of the literature on the capitalization of urban rail transit in nearby property value presents cross-sectional evidence, which is particularly vulnerable to estimate bias caused by unobservable neighborhood differences. Moreover, this empirical literature has failed to answer an important theoretical question on the existence and extent of local amenity capitalization – why would property value appreciate if supply is elastic? The answer to this question may help explain the mixed existing evidence on the capitalization effect of rail transit. This study addresses the above research gaps using data from Beijing, where nearly 400 kilometers of new subway lines were constructed during the past decade. Taking Beijing's unprecedented expansion of mass rapid transit infrastructure as a natural experiment, we investigate how property value reacts to changes in the service level of rail transit using a large dataset of repeat rental transaction records. Repeat-transactions estimates of improved proximity to subway stations on home value suggest that as a housing unit's distance to closest subway station is reduced by 10 percent, its rental value appreciates by 0.2%. This effect is below 30 percent of that estimated using the traditional hedonic method, indicating significant bias caused by omitted variables in the cross-sectional estimates. Moreover, significant spatial variation in the extent of capitalization exists within Beijing. Using the unique history of state-owned enterprise relocation to instrument the variation in land supply, we find that the capitalization of subway proximity in home value is significantly weaker where land supply is more elastic. The findings of this study provide insights for estimating benefits and distributional effects of urban infrastructure projects, and have important policy implications for the spatial planning and property value-based finance of urban infrastructure in Chinese cities.

Key words: subway; home value; repeat rentals; land supply; Beijing

1 INTRODUCTION

Urban rail transit enhances accessibility of the communities it serves and contributes to the value of local real property. In his seminal work, Oats (1969) theorizes that in a spatial equilibrium with mobile land users, rents for real estate, and the derived rents of land, vary by location within a city so as to exactly offset the value that property users place on the advantage of different locations. A large number of studies have emerged on the property value capitalization of local (dis)amenities and taxes, and many, but not all found evidence in support of capitalization. Transportation infrastructure, as a specific category of local public good, has some distinct characteristics (e.g., proximity rather than jurisdictional boundary matters) and has been studied by both spatial and real estate economists and transportation scholars.

The majority of the literature on the capitalization of urban rail transit in nearby property value presents cross-sectional evidence, which is particularly vulnerable to estimate bias caused by unobservable neighborhood differences. For example, subway routes may be planned where there is a larger potential of property value growth (so that government may collect more property tax or public land leasehold revenue), which leads to a sample selection problem. Among the small number of studies that take the natural experimental approach, almost all rely on a before-after analysis of single transit projects and most use property sales data. Such analyses are often subject to the problems of few data points and the difficulty to identify the true before-project property value due to anticipation. This study combines a natural experiment of multiple subway lines and repeat-rentals data of a much higher transaction frequency compared to resale data in order to obtain results that are more robust in terms of sample size, spatial coverage, and the identification of cleaner before-project property value.

Beijing saw nearly 400 kilometers of new subway lines constructed during the past decade. Taking this unprecedented city-wide expansion of mass rapid transit infrastructure, we investigate how property value reacts to changes in the service level of rail transit using a large dataset of repeat rental transaction records. Repeat-transactions estimates of improved proximity to subway stations on home values suggest that as a housing unit’s distance to closest subway station is reduced by 10 percent, its rental value appreciates by 0.2 percent. This effect is below 30 percent of that estimated using the traditional hedonic method, indicating significant bias caused by omitted variables in the cross-sectional estimates.

Moreover, the empirical literature has yet to respond to an important theoretical debate on the existence and extent of local amenity capitalization – why would property value appreciate if supply is elastic? Recent development in urban economics suggests that different empirical findings regarding local amenity capitalization can be reconciled by the elasticity of housing supply (Brasington, 2002). As formally derived by Hilber and Mayer (2002), given a positive shock in the quality of local public service, local markets with less elastic supply of housing experience a larger price increase compared to markets with more elastic housing supply. This study tests this theory in the case of urban rail transit. Taking advantage of the unique history of state-owned enterprise relocation, we conduct an instrumental variable (IV) regression and find that the capitalization of subway proximity in home value is significantly weaker where land supply is more elastic.

This study makes two major contributions. First, being one of the earliest repeat transactions analyses in the transportation literature, it furthers the fiscal analysis of urban transportation projects in terms of theory and evidence. Financial feasibility is crucial when cities consider transportation investments such as building additional subway lines. How a new subway line will affect the value of residential properties and the sales revenue of commercial properties is central to the projection of local fiscal revenue. It is also one of the earliest rigorous analyses in China, where urban infrastructure and property markets expand at unprecedented speeds. As Chinese cities experiment property tax schemes, policy makers interested in value capture could benefit from more reliable estimates of how improvements in subway coverage may affect home value and how such effects vary spatially. Second, studying the capitalization of transit infrastructure and its relationship with housing market condition can directly inform the evaluation of project distributional effect. The prevailing method of transportation project evaluation is able to estimate the spatial and socio-demographic heterogeneities in travel time savings (usually as a short-term static estimate), but is short on the incidence of the public spending. This is because renters' savings in travel time could be partially or even fully offset by the increase in rent. The perspective of home (rental) value capitalization will provide a tool for distributional analysis, especially for the renters.

The rest of this paper is organized as follows. Section Two reviews the literature. Section Three and Four describe the analytical models and data. Section Five presents the results, followed by conclusions in Section Six.

2 LITERATURE REVIEW

There is an extensive literature on the property value capitalization of urban rail transit investment, mostly from the US and other industrialized countries. This literature is primarily empirical, relating property value to distance from a rail station. An incomplete count suggests at least 50 studies on this topic since the 1970s (Duncan 2011), with more than a dozen literature reviews (Bartholomew and Ewing 2011). The vast majority of studies have found positive price premiums of properties closer to rail transit stations. Cervero et al. (2004) review studies completed since 1993, showing homes within a quarter to half mile of rail stations are 6.4 to 45 percent more expensive than otherwise similar homes further away. A meta-analysis of 57 studies by Debrezion et al. (2007) suggests that proximity to a transit station is worth 2.4 percent of home value every 250 meters closer. Of course, not all studies identify positive price premiums of rail transit proximity. Some have shown insignificant effects of capitalization (e.g., Gatzlaff and Smith, 1993; Ryan, 2005), and some even find negative effects (e.g. Nelson 1992), primarily attributed to the nuisances (e.g. noise and congestion) brought by nearby transit facilities (especially bus and at-grade rail).

The dominant approach to infer the value people put on urban rail transit, among other local (dis)amenities, is the hedonic (implicit) price method. In his seminal paper, Rosen (1974) explains how market transactions can reveal buyers' willingness to pay for the characteristics of a differentiated product, which has hence provided the theoretical basis for developing revealed preference estimates of the value people put on local public goods and externalities. The majority of such revealed preference estimates, however, are based on a direct comparison of different properties. The recent development in the economic theory and methods of program evaluation (Imbens and Wooldridge, 2009), however, has clearly pointed out the methodological weakness of the prevailing cross-sectional hedonic method. Many public goods are endogenously determined through the housing market in ways that are likely to induce correlation between local amenity, housing characteristics, and unobserved neighborhood attributes, creating a problem for the ordinary linear squares (OLS) estimation of the capitalization effect. For example, households may sort themselves into different neighborhoods based on their preference over transit proximity, which leads to missing variable bias when comparing neighborhoods near and far from transit stations. Such an endogenous choice could also happen during the government planning of transit routes.

A recent wave of empirical research has sought to improve the credibility of hedonic estimates by refining conventional research designs to mitigate confounding by omitted variables. The leading strategy uses temporal variations in panel data (including multi-year panel and before-after comparison) to identify how exogenous shocks to public goods are capitalized into property values. Recent examples on rail transit include studies focusing on aggregate market impacts (Gatzlaff and Smith 1993, Baum-Snow and Kahn 2000) and those analyzing effects on individual properties (e.g. McMillen and McDonald 2004; Gibbons and Machin 2005; Dubé et al. 2013). In general, these studies still find positive capitalization of rail transit in home value, although the magnitudes of effects seem to be on the small side of the overall literature on rail transit capitalization reviewed by Cervero et al. (2004) and Debrezion et al. (2007). However, many of the existing panel studies using property-level data rely on before-after comparison of property sales. The usual scarcity of sales of any given residential property means most, if not all, before-after analyses based on housing sales are still cross-sectional in nature, as there would be so few repeat sales. Some estimates using true longitudinal sale records of homes (e.g., McMillen and McDonald 2004) may be critiqued as based on a non-representative sample of housing units that are particularly subject to frequent changes of ownership.

The factors often suspected responsible for the significant variation in estimated capitalization effects (sometimes coming from studies of the same city or even same project) include nuisance effects, transit service level, traffic congestion on alternative road routes, and neighborhood income (Bartholomew and Ewing 2011; Nelson 1992). However, there has never been a discussion of the linkage between capitalization and the condition of the housing market in the transportation literature. Due to market segmentation within a city, it is not always appropriate to assume that the implicit prices of housing attributes remain the same across geographic space (Straszheim 1974). That is, a regional housing market is composed of an interconnected set of many localized submarkets which have idiosyncratic differences in the structure of supply and/or demand and, consequently, unique schedules of attribute prices (Michaels and Smith, 1990; Carruthers and Clark, 2010). In particular, one may consider the capitalization, as implied by Oates (1969), happens under the assumption of a fixed housing supply in a fixed number of communities with inflexible boundaries (Brasington, 2002). As illustrated by the theoretical models of Hilber and Mayer (2002) and Stadelmann and Billon (2012), the capitalization of taxes and local public goods depends on the elasticity of housing supply. With a perfectly elastic housing supply, a community can freely expand in response to a demand shock (e.g., an exogenous improvement in local public service). As a result, there is no need for housing prices to change to equalize utility across communities, and thus taxes or public expenditures are not capitalized into housing prices. This argument has been empirically supported by evidence found on the capitalization of taxes, crime, and school quality into home values (Brasington, 2002; Hilber and Mayer 2009), but has not been tested in the literature on transportation infrastructure capitalization and program evaluation. Nevertheless, existing evidence suggests the argument's validity. Two broad points stand out in Bartholomew and Ewing's (2011) literature review. First, the closer a station is to the central business district (CBD), the larger the effect of proximity to the station. Second, the extent of capitalization seems to co-vary with development densities—as one rises, so does the other. Both make sense when the supply elasticity–capitalization connection exists, because housing supply tends to be less elastic when it is closer to the CBD or when the existing density is high.

3 MODEL

To estimate the capitalization effect of an increase in subway accessibility on property value we begin with the traditional hedonic price function:

$$\ln VALUE_i = \text{Constant} + \lambda \cdot \ln D\_SUB_i + \mathrm{A} \cdot X_i + \mathrm{B} \cdot Z_i + \sum \gamma_j \cdot Year_j + \sum \eta_k \cdot Month_k + \varepsilon_i \qquad (1)$$

D_SUB_i is unit i's distance to its nearest subway station. X_i and Z_i are vectors of physical characteristics and locational attributes (other than subway accessibility) of the unit, respectively. Year and month-of-year dummies are included to control for market trend and seasonality (when sample observations come from a period instead of a single time point). A log-log functional form estimates capitalization effect as home value – station distance elasticity (λ). As long as λ is negative, as suggested by most existing studies, it implicitly assumes the diminishing effect of distance on property value – the same absolute distance differential affects property value more (in either absolute value or percentage) when it gets closer to the subway station.

The hedonic estimate, however, may be biased due to unobservable neighborhood characteristics that correlate with subway accessibility. For example, λ may be overestimated (in absolute value) if households are sorted spatially based on their unobserved preference of subway accessibility, or instead, new subway services are planned to serve neighborhoods expressing stronger desire for subway, which is not controlled in the model. A before-after comparison or repeat-transactions model can mitigate such endogenous bias by inferring the value of subway access from the variations in the market values of the same properties around one or more time points when subway accessibility changes. Using the multiple transaction records of property *i*, differencing Equation (1) with its previous transaction and eliminating the unchanged physical characteristics and location attributes produce the repeat-transactions model as follows:

$$\Delta \ln VALUE_i = \Delta \text{Constant} + \alpha_1 \cdot \Delta \ln D\_SUB_i + \alpha_2 \cdot \Delta H_i + \sum \beta_j \cdot \Delta Year_j + \sum \chi_k \cdot \Delta Month_k + \eta_i \tag{2}$$

The Δ prefixes represent the temporal change in the variables between the current period and the period in which the house was last sold or rented out. ΔH_i represents any non-zero temporal difference of unit *i*'s physical characteristics or locational attributes between the adjacent transactions. The differenced time dummies take on the value −1 if the first transaction occurs during that period, +1 if the second transaction occurs during that period and 0 if no transaction occurs during that period. Thus, the differenced year or month dummy variable is no longer dichotomous. Equation (2) can be estimated using OLS regression with an error term of the usual sort.

As previously discussed, the same change in accessibility to subway service can be valued differently due to different supply conditions in local housing market. That is, where local housing supply is less responsive to price changes (i.e., less elastic), an upward shift in demand caused by improved access to subway service would result in a larger increase in the market value of housing as there will be less induced new supply. To examine how the capitalization of subway accessibility in housing value varies with housing supply elasticity, one can estimate the following equation:

$$\begin{aligned} \Delta \ln VALUE_i = {} & \Delta \text{Constant} + \alpha_1 \cdot \Delta \ln D\_SUB_i + \alpha_1' \cdot \varepsilon_i^S \cdot \Delta \ln D\_SUB_i + \alpha_2 \cdot \Delta H_i + \sum \beta_j \cdot \Delta Year_j \\ & + \sum \chi_k \cdot \Delta Month_k + \eta_i \end{aligned} \tag{3}$$

where ε_i^S represents the supply elasticity of unit *i*'s local housing market, which is mainly affected by the abundance of available developable land, local housing regulation, and local geographical conditions related to construction cost. In an intra-jurisdictional analysis and assuming homogeneous geographical conditions, the availability of developable land can be used to proxy supply elasticity.

4 DATA

To address the data limitations that have plagued existing estimates of the capitalization of local public goods in residential properties, we use a large longitudinal dataset of transactions in the rental housing market of Beijing. These repeat rental records come from the rental units brokered by *WoAiWoJia* (www.5i5j.com), the second largest broker in Beijing with a market share of more than 10 percent.[1] The initial dataset comprises 11,966 units located in 1,862 residential complexes in the city tracked by the company. A total of 43,598 transactions happened during the sample period from April 2005 to the end of 2011, with an average of 3.64 transactions for each unit. Figure 1 shows the spatial distribution of rental transactions in metropolitan Beijing.[2]

*** Figure 1 about here ***

For each rental transaction we have the information of transaction date, location, and the unit's physical attributes including size (*HSIZE*), number of rooms (*ROOMS*), level of decoration (*DECO*), and the total number of floors of the building (*FLOORS*), which can be used as a proxy of building quality as taller buildings are typically newer and structurally more sound in Beijing. The location attributes of units are collected at the housing complex level. Using GIS software, we calculate the straight-line distances of each residential complex from the city center[3] (*D_CENTER*) and the closest key primary school (*D_SCHOOL*) and city-designated park (*D_PARK*).[4] For each transaction record we calculate the residential complex's straight-line distance to the closest subway station (*D_SUBWAY*) open for operation before or on the date of transaction.

Prior to this century, Beijing had only two subway lines with a total length of about 54 km. In the summer of 2001, the city won the bid to host the 2008 Summer Olympics and accelerated plans to expand the subway. There were six new subway lines built from 2000 to 2008 (Lines No. 4, 5, 8, 10, 13 and *BaTong*), among which Subway Lines No.13 and *BaTong* were put into use before 2004, and Lines No. 5, 8 and 10 openned on the eve of the 2008 Summer Olympics. Until then subways were largely concentrated in the northern half of the city, where most of government branches, universities and schools are located. The following cycle of subway construction shifted to South Beijing. On December 30, 2010, five suburban lines including Lines No. 15 (Phase I), *ChangPing, FangShan, YiZhuang,* and *DaXing* commenced operation. The additional

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[1] "Study on the market share of Beijing real estate broker firms (June-October, 2012)" by China Index Academy.

[2] The Beijing Administrative Area consists of 18 districts: 4 inner city districts (Since July 2010, the four inner city districts, *Xuanwu*, *Xicheng*, *Chongwen,* and *Dongcheng* had been combined into two districts *Xicheng* and *Dongcheng*), 4 suburb districts, and 10 outer suburban districts. While the municipal government and the public both regard the inner eight districts (*Dongcheng*, *Xicheng*, *Chongwen*, *Xuanwu*, *Chaoyang*, *Haidian*, *Fengtai*, *Shijingshan*) as the urbanized area or "Beijing Metropolitan Area" (BMA), which has a total area of about 960 square kilometers, excluding mountain areas unsuitable for development. In the BMA, urban road network on the ground is almost complete, subway construction has been regarded as an important way to mitigate the current road congestion and meet the anticipated ridership growth (Zheng and Kahn, 2013).

[3] Unlike many cities with developed market economies, where employment and urban population have significantly suburbanized (Glaeser and Kahn, 2001), a dominant urban core exists in Beijing (as well as most other Chinese cities) (Wang, 2009, 2010, and 2011; Zheng and Kahn, 2008). Tian'anmen Square, with the surrounding traditional hubs of commercial, cultural, and administrative activities, is considered the city center. In 2004, 43 percent of Beijing's jobs were concentrated within three miles of Tian'anmen Square. The five ring roads circling Tian'anmen Square were built successively from the inside to the outside, demonstrating a monocentric urban structure.

[4] There are altogether 40 former Key Primary Schools and 64 city-designated parks in Beijing.

108 km track, a nearly 50 percent increase of the system, made Beijing's subway system the fourth longest in the world.[5] Figure 2 shows the spatial distribution of subway lines during the period of study.

*** Figure 2 about here ***

To ensure the accuracy of estimation, we drop any transaction record (and the rental unit if it is the only transaction) during its lease term the distances to the nearest subway station changed. This remains us a total of 11,578 units in 1,840 residential complexes with 37,161 transactions. The average rental unit is 61.4 square meters, and the mean rental price (*RENT*) is 2,152 RMB per month in January 2005 constant price.[6] The average length of lease is 323 days. By year, sample average monthly rent increased from 1,613 RMB in 2005 steadily to 3,015 RMB in 2011, with a small setback in 2009. The measured quality of housing (DECO) didn't change for individual properties over time in our data, suggesting that the rent increase was mainly due to things other than housing quality improvement. The sample shows significant changes in subway accessibility over time. Average distance to nearest subway station dropped steadily from 2.34 km in 2005 to 1.02 km in 2011.

To measure the housing supply condition of different submarkets in metropolitan Beijing, we obtain all auctioned residential land parcels by year from the China Real Estate Index System. We combine three to six adjacent street offices[7] with a continuous concentration of economic activities and relatively homogeneous communities into one zone, totaling 25 zones, as the basic geographic unit of housing submarkets in Beijing. We first calculate the aggregated amount of residential land leased during 2005-2011 as a share of zone size (*SUPPLY*) to describe the spatial variation of residential land supply in each of the 25 zones. Needless to say, the amount of land actually leased (instead of potentially leasable) reflects both supply and market demand for housing in different submarkets, which means that there exists an endogeneity problem if we use *SUPPLY* directly in Equation (3). As a solution, we follow Zheng et al.'s (2013) idea to use the density of state-owned manufacturing employment during the early years of state-owned enterprise (SOE) reform[8] as an instrument variable. Table 1 summarizes all the variables.

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[5] From 2011 to 2013, another nine new or extended subway lines were constructed. Now the Beijing subway system has grown to 17 lines, 227 stations and 456 km track in operation, making it the second longest subway system in the world after the Seoul Metropolitan Subway.

[6] The common practice in Beijing is that the landlord pays for condo fee (property management fee) and winter heating fee, while the tenant pays utilities and other fees (there is no property tax in Chinese cities). The sum of condo fee and winter heating fee is about 10% to 15% of the gross rent. Therefore we can roughly estimate the annual cap rate of about 2.8% to 3%, which is much lower than that in the U.S. market even in top cities like NY and Boston.

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

[8] Due to the industrialization-focused urbanization during the pre-reform socialist era, state-owned manufacturing

*** Table 1 about here ***

5 RESULTS

5.1 The cross-sectional rent – accessibility relationship

Using monthly rent as the dependent variable, regression estimates of the standard hedonic model (Equation (1)) are presented in column (1) of Table 2. The capitalization of subway accessibility in rent is statistically significant ($p<0.001$). Rent increases by about 0.7 percent when a unit's distance to closest station decreases by 10 percent, suggesting a rent-distance elasticity of -0.07. This is very close to the estimated -0.066 using a new home sales dataset from 2005 to 2008 in Beijing (Zheng et al. 2013). By-year OLS estimates (omitted here) of the rent-distance elasticity range between -0.06 and -0.08, without a clear time trend.

*** Table 2 about here ***

The other estimated coefficients are mostly as expected. For physical characteristics, unit size and number of rooms are positively correlated with rent. Units in higher buildings and those better decorated are also more expensive. Longer length of lease has an insignificant positive effect on rent. For the location attributes, proximities to the city center, nearest key primary school, and nearest subway station all result in price premiums. Proximity to nearest park, however, has an insignificant negative effect on rent, probably due to the fact that many city-designated parks are major historical heritages and tourist attractions that can bring congestion, noise, and other disturbances to neighborhoods. Overall, the OLS hedonic model explains two thirds of the rent variations.

To better understand how subway accessibility affects rent in different market segments (e.g., affordable vs. high-end), we conduct quantile regressions, which, in addition to being more robust against outliers in rent, allow us to see how the variation in regressors may have heterogeneous effects on rental values at different quantiles in market. The estimates, shown in columns (2) through (6) of Table 2, are fairly consistent with the OLS results, with some interesting patterns across market segments. It is clear that the estimated rent-distance elasticities are slightly larger (in absolute value) at the 10^{th}, 25^{th}, and 50^{th} quantiles (ranging from -0.073 to -0.075) than in the high-end rental market (-0.069 at the 75^{th} quantile and -0.063 at the 90^{th} quantile). This is intuitive as those renting cheaper homes likely value transit accessibility more. Other patterns in estimated coefficients are also interesting and perhaps explain some of the

enterprises often occupied central and valuable locations in cities (Zheng et al., 2006). After the reinstatement of the urban land markets in the late 1980s and especially since the state-owned enterprise (SOE) reform started in the late 1990s, SOEs, in particular the state-owned manufactures (large land users), have been gradually moved away from their premier locations. The relocation or disassembly of old state-owned manufacturing firms thus became an important source of land for new development.

insignificant results in the OLS estimates. Longer length of lease is associated with higher rent at the 10^{th} and 25^{th} quantiles but lower rent at the 90^{th} quantile. This may be indicate that renters at the lower-end market may be more risk averse and/or less mobile (in terms of location and/or rent-buy flexibility) than renters at the high end. Proximity to the city center also associates with larger rent premium at the lower-end market, consistent with the expectation that higher-end renters either have more freedom in transportation choices or have jobs that are less concentrated (e.g., the information technology industry is located in the northern part of the city). Proximity to nearest park reliably decreases the rental value of homes at the higher-end market, suggesting that higher-end renters may be more sensitive to neighborhood congestion and disturbances brought by park visitors.

5.2 The effect of subway accessibility on rent

Table 3 presents the estimates of the repeat-sales model in Equation (2). Column (1) shows the estimates with time dummies only. The time trend and seasonal fluctuation explain 47 percent of the rent variations in sample. Rent rose rapidly from 2005 to 2011, with a six-year difference of 87.4 percent ($e^{0.628}$-1). The only slow year was 2009, which basically had the same level of rent as in 2008. A rental contract starting in January turns out to have the lowest rent compared to other months, likely due to the annual out-migration of rural migrant labor around the Chinese Lunar New Year (usually between mid-January to mid-February). September, the beginning of fall semester of all public schools and universities, is the month we see the highest rent level.

*** Table 3 about here ***

Column (2) introduces the time-varying attributes of subway accessibility and length of lease on top of temporal variation. The rent-distance elasticity is negative and significant, but the estimated elasticity of -0.02 is much smaller compared to the -0.07 from the OLS hedonic regression. That is, the real rent premium of improved subway access is more than two-thirds less when we remove the effect of unobserved neighborhood characteristics. Also worth noting is the unambiguous positive and significant coefficient of $\Delta\log(LEASE)$, suggesting that longer leases are valued more. This is different from the OLS results but not a surprise given the monotonic rise of market rent in Beijing during recent years – lower frequency of rent renegotiation (upward adjustment) has to be compensated by a higher fixed rent in longer leases.

5.3 The effect of submarket supply condition on capitalization

Column (1) in Table 4 estimates Equation (3) using the percentage of land leased for residential development during 2005-2001 in the 25 submarkets to interact with temporal changes in subway accessibility of individual properties. The estimated rent-distance elasticity remains negative. The interaction term, $SUPPLY*\Delta\log(D\_SUB)$, has a positive coefficient, suggesting submarkets with more residential land supply tend to have a smaller net effect of capitalization, as expected. However, the estimated interaction term is statistically insignificant.

*** Table 4 about here ***

To address the endogeneity of *SUPPLY*, we instrument *SUPPLY*$*\Delta$log(*D_SUB*) with *SOE*$*\Delta$log(*D_SUB*) using *SOE* as an exogenous historical variable that affects amount of residential land leased through the availability of developable land, which eliminates the effects of demand-side factors. Test statistic confirms the endogeneity of the instrumented variable and the IV also passes the weak instrument test. Column (2) presents the two-stage least squares (2SLS) regression results. The coefficients of subway access and the interaction term continue the same signs as in column (1), while both become statistically significant. The estimated rent-distance elasticity is now -0.121, which of course happens only when the submarket supply of additional rental housing is completely inelastic. As the submarket supply becomes more elastic, the net rent-distance elasticity drops in magnitude, confirming that an improvement in subway proximity boosts rent less where additional housing supply is abundant.

6 CONCLUSION

This study is one of the earliest to use repeat-transactions model in the analysis of transportation project's impact on property value. A key finding is the significant gap in estimated home value premiums of subway accessibility between the repeat-transactions model and the popular cross-sectional hedonic model. Unobserved neighborhood differences that spatially correlate with subway seem responsible for over 70 percent of the home value premium. As a result, project fiscal impact analyses using cross-sectional evidence can seriously overestimate additional property tax or land leasehold revenue brought by investments in urban rail transit, which can lead to a false sense of project financial feasibility. On the other hand, using cross-sectional evidence may lead to exaggerated worries in public investment-induced loss of neighborhood affordability and gentrification.

This paper also links the transportation literature to the economic theory that elastic supply in property market reduces the extent of capitalization of local amenities in housing value. Our results empirically confirm this prediction. This does not imply, however, government will fiscally benefit more by building subways where there is limited room for additional housing supply. The demand for subway accessibility reflects in both value appreciations of existing housing stock and additional supply to the market. The quantity effect can outweigh the price effect, meaning government may collect more property tax or land leasehold revenue by building subways where there is plenty of room for new supply. This is particularly true when there is a strong demand in the metropolitan housing market, because otherwise subway-induced new developments may well be shifted from other locations.

Using rental instead of sales data is a double edged sword. On the one hand, there are much more rental transactions during a fixed time period and renters, unlike owners, do not value subway access before the subway is usable. On the other hand, it is questionable whether results based on rents are consistent to those based on either new or resale housing market. Compared to new units, rental units are older and typically smaller, thus may not be sufficiently representative of the whole housing stock. More importantly, one may suspect that renters' preference over local public goods may differ from that of owner-occupiers. However, given the wide acceptance of subway as a desirable and also affordable travel option in Beijing (Beijing heavily subsidizes its subway and bus fares[9]), the valuation of subway access, the focus of this study, might not be much different between the renters and the owner-occupiers. In fact, the cross-sectional rent-distance elasticity estimated in this study is quite similar to those previously found using sale price data in Beijing, as suggested in Section 5.1.

[9] A flat fare—2.00 RMB (about $ 0.32) per ride with free transfers has been adopted on all lines except for the Airport Express Line.

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FIGURES

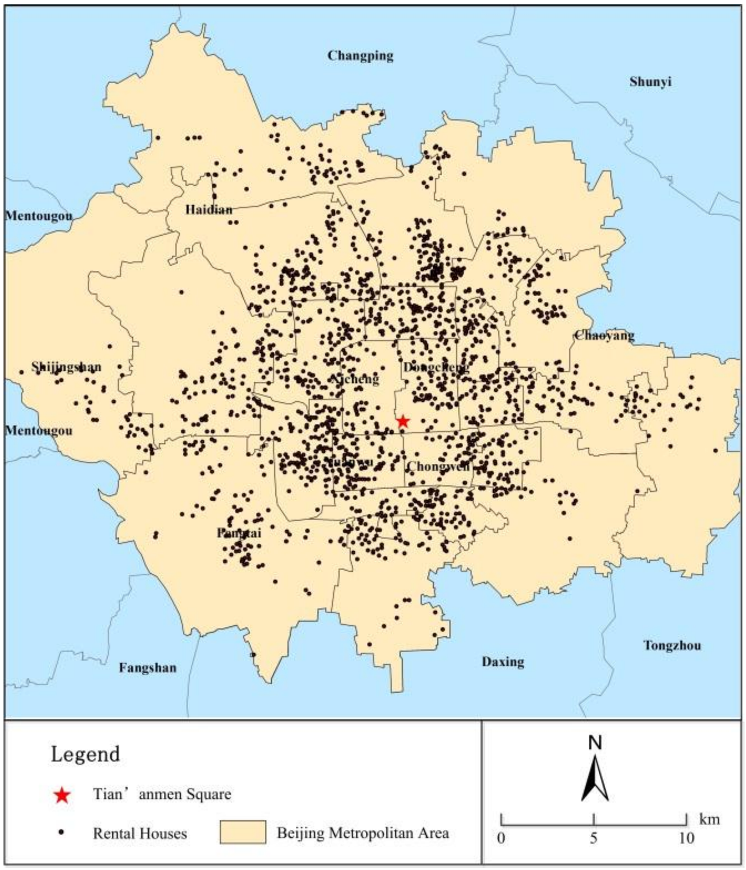
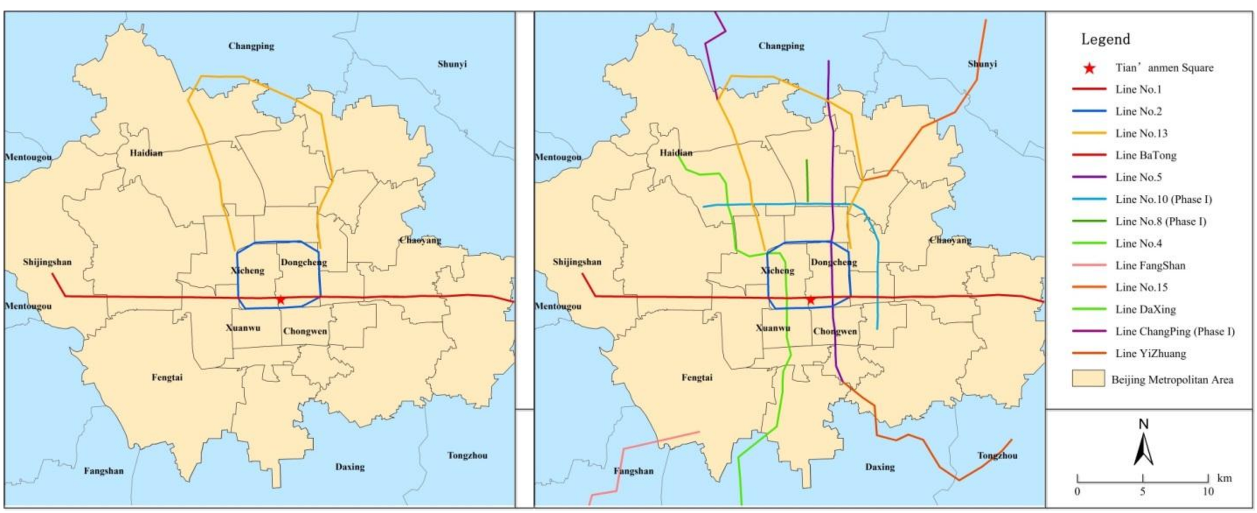


Figure 1. Sample rental home units



January 2005 January 2011

Figure 2. Subway system development in Beijing

TABLES

Table 1: Variable Definitions and Summary Statistics

Variable	Definition	Obs.	Mean	Std. Dev.	Min	Max
RENT	Monthly rent (RMB yuan)	37161	2152.002	690.808	392	9082
HSIZE	Housing unit size (m^2)	37161	61.408	17.095	10	190
HEIGHT	Total number of floors of the building	37161	11.798	7.222	1	39
ROOM	Number of rooms in unit	37161	1.709	0.595	1	3
DECO	Decoration status: 1=no decoration, 2=simple decoration, 3=medium decoration, 4=full decoration	37161	2.689	0.990	1	4
LEASE	Length of lease (day)	37161	323.270	84.856	30	730
D_CENTER	Distance to Tian'anmen Square (km)	37161	7.957	3.307	0.694	21.827
D_SCHOOL	Distance to closest key primary school (km)	37161	1.544	1.140	0.019	9.782
D_PARK	Distance to closest park (km)	37161	1.437	0.792	0.023	5.507
D_SUB	Distance to closest subway station (km)	37161	1.720	1.408	0.024	13.563
SUPPLY	Total new residential land leased from 2005 to 2011 as a share of zone size	25	0.0215	0.0113	0	0.0374
SOE	State-owned enterprise employment density in 2000 (employees/km^2)	25	566.31	569.51	48.18	2023.86

Table 2. Hedonic regressions

Dependent variable: log(RENT)

	(1)	Quantile Regressions				
		(2)	(3)	(4)	(5)	(6)
	OLS	*p10*	*p25*	*p50*	*p75*	*p90*
log(*HSIZE*)	0.426***	0.396***	0.393***	0.402***	0.427***	0.464***
	(0.0180)	(0.00921)	(0.00724)	(0.00650)	(0.00678)	(0.00928)
FLOORS	0.00339***	0.00392***	0.00287***	0.00226***	0.00236***	0.00358***
	(0.000532)	(0.000235)	(0.000185)	(0.000166)	(0.000173)	(0.000237)
ROOMS	0.0689***	0.0718***	0.0796***	0.0794***	0.0740***	0.0582***
	(0.00613)	(0.00393)	(0.00309)	(0.00277)	(0.00289)	(0.00395)
DECO=2	0.170***	0.156***	0.157***	0.171***	0.173***	0.177***
	(0.00954)	(0.00872)	(0.00686)	(0.00615)	(0.00642)	(0.00878)
DECO=3	0.197***	0.189***	0.194***	0.202***	0.192***	0.199***
	(0.0152)	(0.0128)	(0.0101)	(0.00905)	(0.00944)	(0.0129)
DECO=4	0.277***	0.274***	0.266***	0.271***	0.267***	0.288***
	(0.0104)	(0.00897)	(0.00705)	(0.00633)	(0.00660)	(0.00904)
log(*LEASE*)	0.00151	0.0158***	0.00997**	0.00467	-0.00264	-0.0151***
	(0.00348)	(0.00387)	(0.00304)	(0.00273)	(0.00285)	(0.00390)
D_CENTER	-0.00826***	-0.0126***	-0.00924***	-0.00587***	-0.00478***	-0.00386***
	(0.00210)	(0.000536)	(0.000421)	(0.000378)	(0.000394)	(0.000539)
log(*D_SCHOOL*)	-0.0507***	-0.0492***	-0.0491***	-0.0497***	-0.0462***	-0.0456***
	(0.00768)	(0.00213)	(0.00167)	(0.00150)	(0.00157)	(0.00214)
log(*D_PARK*)	0.00265	-0.00288	-0.000884	0.00383*	0.00922***	0.00733**
	(0.00912)	(0.00249)	(0.00196)	(0.00176)	(0.00184)	(0.00251)
log(*D_SUB*)	-0.0701***	-0.0733***	-0.0746***	-0.0754***	-0.0690***	-0.0632***
	(0.00585)	(0.00208)	(0.00164)	(0.00147)	(0.00153)	(0.00210)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	5.142***	4.990***	5.113***	5.203***	5.257***	5.262***
	(0.0651)	(0.0407)	(0.0320)	(0.0287)	(0.0299)	(0.0410)
Obs.	37161	37161	37161	37161	37161	37161
Adj./Pseudo R^2	0.664	0.409	0.429	0.445	0.434	0.428

Notes: (1) standard errors are reported in parentheses. (2) ***, **, *: significant at the 0.1%, 1%, and 5% levels, respectively. (3) standard errors are clustered by residential complex in OLS regression.

Table 3. Repeat rentals model

Dependent Variable: $\Delta\log(RENT)$

	(1)		(2)	
	Coefficients	Standard errors	Coefficients	Standard errors
$\Delta Year_{2006}$	0.0760***	0.00357	0.0881***	0.00355
$\Delta Year_{2007}$	0.164***	0.00511	0.191***	0.00498
$\Delta Year_{2008}$	0.303***	0.00679	0.339***	0.00657
$\Delta Year_{2009}$	0.307***	0.00837	0.353***	0.00794
$\Delta Year_{2010}$	0.450***	0.0101	0.504***	0.00954
$\Delta Year_{2011}$	0.628***	0.0117	0.692***	0.0110
$\Delta Month_{2}$	0.157***	0.00297	0.158***	0.00294
$\Delta Month_{3}$	0.193***	0.00312	0.194***	0.00303
$\Delta Month_{4}$	0.202***	0.00319	0.203***	0.00309
$\Delta Month_{5}$	0.198***	0.00326	0.200***	0.00317
$\Delta Month_{6}$	0.254***	0.00320	0.257***	0.00305
$\Delta Month_{7}$	0.191***	0.00311	0.196***	0.00293
$\Delta Month_{8}$	0.246***	0.00322	0.250***	0.00312
$\Delta Month_{9}$	0.276***	0.00337	0.280***	0.00327
$\Delta Month_{10}$	0.252***	0.00340	0.257***	0.00333
$\Delta Month_{11}$	0.259***	0.00343	0.267***	0.00332
$\Delta Month_{12}$	0.268***	0.00343	0.278***	0.00325
$\Delta\log(LEASE)$			0.0294***	0.00159
$\Delta\log(D\_SUB)$			-0.0201**	0.00633
Constant	-0.0118***	0.00145	-0.0195***	0.00133
Obs.	22591		22591	
Adj. R^2	0.470		0.490	

Notes: (1) ***, **, *: significant at the 0.1%, 1%, and 5% levels, respectively. (2) standard errors are clustered by residential complex.

Table 4. Repeat rentals model with supply constraints

Dependent Variable: ⊿log(*RENT*)

	(1) OLS	(2) 2SLS
⊿log(*LEASE*)	0.0261***	0.0262***
	(0.00131)	(0.00108)
⊿log(*D_SUB*)	-0.0528*	-0.121**
	(0.0240)	(0.0435)
*SUPPLY**⊿log(*D_SUB*)	1.978	4.475*
	(1.400)	(2.182)
⊿Year dummies	Yes	Yes
⊿Month dummies	Yes	Yes
Constant	-0.0189***	-0.00840***
	(0.00125)	(0.00159)
Obs.	22412	22412
Adj. R^2	0.498	0.356

Notes: (1) standard errors are reported in parentheses. (2) ***, **, *: significant at the 0.1%, 1%, and 5% levels, respectively. (3) standard errors are clustered by residential complex.