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Abstract

China is experiencing rapid urbanization. Its capital city, Beijing, experienced a 53 percent increase in population from 2001 to 2013. To address traffic congestion and air pollution, two of the most pressing urban challenges, Beijing has been investing heavily in transportation infrastructure. In particular, the subway system added 15 new subway lines with a total length of 410 km over a 12-year period. We quantify the capitalization of large-scale subway construction into property values in a first-differenced hedonic price framework while controlling for confounding factors and reverse causality. Our analysis finds a positive and significant impact of subway proximity on property values: a reduction in the distance to a subway station by 1 km increases the value of properties within 3 km of the station by 15 percent, and by 3.4 percent for properties within 3 to 5 km. Our analysis shows that the increase in property values can more than cover the capital cost of subway construction.

Key Words: subway, property values, hedonic method, infrastructure funding

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1. Introduction

During the last decade, Beijing has experienced unprecedented growth along several dimensions: its population grew from 13.8 million to 21.1 million from 2001 to 2013 (Figure 1); household disposable income nearly quadrupled from 11,600 Yuan (about $1,900) to 40,300 Yuan; and total new housing construction amounted to 368 million square meters, accounting for 44 percent of the total housing stock in 2013.

This rapid expansion and income growth were accompanied by dramatic increases in vehicle ownership: the number of automobiles increased from 1.1 to 5.4 million from 2001 to 2013. Once a city of bicycle riders at the turn of the 21st century, Beijing is now routinely ranked as one of the most traffic congested cities in the world, with an average travel speed of less than 15 miles per hour during peak travel times. To address rapid urbanization and worsening traffic congestion, Beijing has invested heavily in public transportation infrastructure. Beijing now has the second longest subway network in the world (after Shanghai) at 465 km. The total investment in these subway lines amounted to 217.9 billion Yuan.

This study examines the capitalization in property values of proximity to subway stations and conducts a cost-benefit analysis of subway construction by taking advantage of the rapid expansion in Beijing since 2001. These questions are motivated by the following two observations.

First, an often cited benefit of subway construction is its ability to reduce traffic congestion. However, due to the lack of data, there is little empirical evidence that the subway lines have relieved traffic congestion in Beijing. Theoretically, the impact of subway construction on property values should capture the benefits of easier subway access as well as

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improved air quality for nearby residents.[1] Studies by Davis (2004), Chay and Greenstone (2005), Gamper-Rabindran and Timmins (2011), Linn (2013), and Muehlenbachs et al. (2013) are a few of the many which have used changes in property values to infer the benefit of non-market amenities. These analyses can inform the cost-benefit debate about policy interventions.

Second, subway construction and public transit infrastructure investment constitute a significant portion of government spending. Large-scale capital projects like subway construction can pose significant funding challenges. However, such infrastructure projects can often lead to a large increase in nearby property values. Therefore, such projects almost always involve a substantial transfer of wealth from the broad base of taxpayers to a small group of property owners. Some researchers argue that public transit infrastructure should be self-funding through the increased property values generated by the investment (Tideman et al. 2002; Harrison 2006). In the United States, where property tax is levied, the capitalization of infrastructure projects into property values is partially captured, depending on the rate of property tax. In China, there is no systematic taxation of property. However, property taxation in China is under debate and is being tested in selected cities as a way to increase government revenue in the wake of the housing boom. There is no consensus on whether and how property tax will be structured and how the tax revenue should be used. Our analysis can inform this debate from the perspective of infrastructure investment and funding mechanisms.

Recognizing the potential benefit of infrastructure investment for property values, local governments in Japan often explicitly tie the development of infrastructure together with the surrounding property development by using the same developer (for example, through an open bidding process). This can lead to a lower cost because the developers recognize the benefit transfer, and thus bid low on the infrastructure projects. This mechanism essentially taps into the future increase in property values to fund current infrastructure construction.

Hong Kong's principal rail operator, the MTR Corporation (MTRC), has advanced the practice of transit value capture more than any public transport organization in the world (Cervero and Murakami 2008). It has done so through its "Rail + Property" development approach, or R+P. The specific mechanism for capturing rail's added value is as follows. MTRC purchases development rights from the Hong Kong government at a "before rail" price and sells

[1]The expansion of subway networks should also reduce air pollution as commuters switch from driving to using the subway. This benefit can be capitalized into property values to the extent that air quality improves disproportionately more in areas near subway lines compared to those farther away.

these rights to a selected developer (from a list of qualified bidders) at an "after rail" price. The differences are often substantial and are able to cover the cost of railway investments.

The subway and transport infrastructure construction in Beijing lags behind the rapid urbanization process, causing a disconnect between land-use planning and transportation planning. As these two processes are better integrated, these approaches to funding infrastructure construction could potentially be used to reduce the cost of large-scale investments.

Our study is based on a unique survey data set of 3,819 properties consisting of apartments in condominium buildings, the dominant form of housing in Beijing. For each property, the data set includes information on housing values at two points in time – the time of move-in and the time of the survey– as well as rich information on property attributes and household demographics. The large wave of subway construction since 2001 provides rich variation across properties in the distance to the nearest subway station. We estimate a first-difference hedonic price function to quantify the impact of subway construction on property values. The identification is essentially a differences-in-difference (DID) approach based on the variation across properties in the changes in distance to the subway within a defined area.

Even though our distance-based DID approach with locational fixed effects controls for time-invariant unobservables at both the property and neighborhood levels, such as school quality or local amenities determined before subway construction, there are two potential identification issues: first, the presence of confounding factors, including omitted local amenities and (time-varying) housing attributes; and, second, reverse causality (subway planning in response to land value changes). Regarding the first, Zheng and Kahn (2008) argue that many local amenities such as schools and parks in Beijing are exogenously determined, as they are the legacy of the former planned economy; this mitigates the concern about omitted variables. Regarding the second, transportation planning and land-use planning are considered to be disjoint even among policy makers in Beijing, partly due to the lack of experience in dealing with rapid urbanization; we will discuss this further. These circumstances mitigate our concerns about reverse causality. If the location choice of subway lines is based on time-invariant factors, our first-differenced hedonic price function can fully address this type of reverse causality by controlling for locational fixed effects.

Nevertheless, our analysis treats omitted variables and reverse causality with care. For example, local air quality could be affected by changes in the subway network and could also affect housing prices. The variation in move-in time across properties allows us to include area-specific time trends in the regression to control for continuous changes in area amenities that

might be correlated with subway construction. To deal with reverse causality, we include time trend interactions with housing attributes at both the property and neighborhood levels (in addition to area-specific time trends) in the spirit of Bajari et al. (2014). To the extent that transportation planning takes into account these future changes in property values and neighborhood amenities, this method can control for reverse causality.

Three findings emerge from our empirical analysis. First, there is a positive and economically significant impact of subway access, measured as distance to subway, on property values; a reduction of the distance to the subway by 1 km increases the property value by 0.94 percent on average from our benchmark specification. Second, there is significant heterogeneity in the impact; a reduction in distance to the nearest subway station by 1 km increases the property value by over 15 percent for properties within 3 km of a subway station, whereas the effect reduces to 3.4 percent for properties within 3-5 km and 1.2 percent for properties over 5 km from a subway station. Third, our analysis shows investment in subway expansion has the potential to more than pay for itself through capitalization in nearby property values. Using a particular subway line, our analysis suggests a total increase of 38.5 billion Yuan in property value, compared with the total construction cost of 15.76 billion. A modest property tax of 0.3 percent would be able to fully recoup the construction cost in 10 years.

Our paper adds to the rich literature on identifying the impacts of transportation infrastructure construction on housing prices and the capitalization of urban amenities – such as public transportation accessibility, air quality, open space and parks, and school quality – into property values. The unprecedented scale of recent subway construction in Beijing offers a unique context, in that the rapid expansion facilitates the realization of a network effect. Regarding the network effect, Baum-Snow and Kahn (2000) focus on five major American cities that upgraded their rail transit systems in the 1980s, while Baum-Snow and Kahn (2005) further study sixteen cities that significantly expanded their rail infrastructure between 1970 and 2000. These studies find that the benefits from new transit lines are not uniformly distributed, in that nearby residents have larger tangible benefits. They further find that new transit lines are more likely to be successful in more densely populated and centralized cities. Bowes and Ihlanfeldt (2001) disentangle the effects and find evidence for both positive (e.g., reduced commuting time) and negative (e.g., increased crime rates) impacts of rail station proximity on property values in Atlanta, Georgia. McMillen and McDonald (2004) examine the effect of the new rapid transit line from downtown Chicago to Midway Airport on housing prices and find that capitalization occurred at the time that plans for the new line were announced. Gibbons and Machin (2005)

estimate the benefit of rail access to consumers based on the construction of new stations in London and find large positive impacts on housing prices.

Our study is closest in context to Zheng and Kahn (2008) and Zheng and Kahn (2013), both of which focus on Beijing's housing market. The former documents the capitalization of a variety of local public goods, including access to public transit infrastructure, using housing data at the housing project level in 2004 and 2005. The latter examines the consequences of gentrification from the construction of the Olympic Village and two recent subway lines using detailed data at the property level (i.e., housing units) from 2006 to 2008. Zheng and Kahn (2013) find that proximity to the Olympic Village and the new subway lines increase housing prices.

Our paper differs from these studies in two important ways. First, unlike the cross-sectional nature of the data used in those analyses, our data set has a panel structure, where we observe property values and distances to the nearest subway station at two points in time. Our empirical strategy relies on a distance-based DID approach to control for both time-invariant and time-varying unobserved amenities and housing attributes. Second, we focus on the capitalization of the subway construction and document the rich heterogeneity in the impacts across both spatial and temporal dimensions. Our results allow us to estimate the total increase in property values, which can offset project costs.

This paper is organized as follows. Section 2 provides background information on the housing market and the transportation system in Beijing and describes our data. Section 3 presents the empirical framework and challenges. Section 4 discusses the empirical results. Section 5 conducts policy simulations and Section 6 concludes.

2. Background and Data

2.1 Housing Market in China and Beijing

Prior to 1978, a private market for housing was nonexistent and the state was the only source of housing investment in Chinese cities. Under this system, housing was treated as a component of employment benefits, generally provided free by government institutions and state-owned enterprises. The privatization of the public housing stock started in 1988 and employers throughout the country started to sell or rent houses to existing tenants at heavily discounted prices (Wang and Murie 1999; Deng et al. 2011).Then, in 1998, significant housing reform started when the central government issued a policy that specifically prohibited

employers from buying or building new housing for employees (Deng et al. 2011). In addition, to address the housing affordability problem faced by low- and middle-income urban residents, the Chinese government initiated various social housing programs in 1994, such as the Affordable Housing program and the Subsidized Rental Housing (SRH) program.

Thirty years of housing reform have brought about a highly complex system of housing tenure in urban China. In general, we distinguish four major types of housing in our analysis according to the source through which housing is provided. The first type is employer-subsidized ownership, whereby properties were sold by employers to their employees at below-market prices. These properties are the relics of a central planning regime and represent privatization without commercialization. The second type includes commercialized properties which are traded freely in the market without any state subsidies. The third type is social housing properties, which include those acquired through the Affordable Housing program and SRH program. The fourth type is resettlement properties. The developers are required to provide resettlement housing to residents affected by development projects.

Over the last fifteen years, the housing market in Beijing has experienced an unprecedented housing construction boom along with income and population growth. This explosive growth in construction is changing the face of urban centers in China. The municipality of Beijing now consists of 16 districts spanning two rural counties, with a total land area of 16,400 square kilometers. Along with this urban expansion, demand for intra-city travel has increased enormously. Mass transit can and should play a strategic role in improving mobility and in facilitating sustainable urban growth (Zhang and Wang 2013).

2.2 Subway and Transportation Systems in Beijing

The housing market and the transportation system are intimately linked through the rapid growth in population and per capita income. Since the new millennium, vehicle ownership and demand for intra-city travel in Beijing have both increased enormously. Vehicle stock increased from 1.6 million in 2000 to over 5 million in 2013. The growth in vehicle stock outpaced the growth of road infrastructure, resulting in serious traffic congestion. Traffic speed on arterial roads within the city core (e.g., the 5th Ring Road[2]) during rush hour (7:00-9:00 a.m. and 5:00-

[2]Beijing has a system of ring roads;the ring road nearest to the city center is the 2nd ring road, and the 6th ring road is the farthest away.

7:00 p.m.) averaged less than 15 miles/hour (mph) in 2013, reduced from 21 mph in 2005. This quagmire led the municipal government to prioritize mass transit development in its agenda.

Before 2000, Beijing had only two subway lines (Line 1 and Line 2), as shown in Figure 2. Line 1, completed in 1969, was the first subway line. It originally connected the city center, Chaoyang district, with the western suburbs. In 2004, it was extended (Batong Line) to connect with Tongzhou district in the eastern suburb of Beijing. Line 2, which opened in 1987, runs in a rectangular loop over the old city center of Dongcheng and Xicheng districts and skirts the western edge of Chaoyang district. New subway lines were not added in the next 15 years.

In 2002, Line 13 (known as the City Rail Line) opened to serve the northern suburbs, running 41 km with 16 stations. To prepare for hosting the 2008 Olympics, Beijing invested heavily in building new subway lines. New lines were opened every year starting in 2007. Line 5, which opened in October 2007, is the first subway line with a north-south route, totaling 28 km of rail. The second loop line, Line 10, which opened in July 2008, is the longest subway loop line in the world, with a total length of 57 km. Similar to Line 2, Line 10 circles the old city, but the route is situated 6 km outside of Line 2. Line 4, totaling 28 km of rail, began operation on September 28, 2009. It also goes from north to south, parallel and to the west of Line 5.

In all, 12 new subway lines and one airport expressway were built, with a total length of 351 km, from 2007 to May 2013. Another 12 subway lines are under construction and scheduled to open before the end of 2015, with a total length of nearly 660 km.

2.3 Data Description

Our data comes from a household travel survey conducted from June to October in 2009 by the Beijing Transportation Research Center (BTRC). In order to capture the spatial differences in Beijing, the survey areas are chosen to represent differences in public transport accessibility, as well as household characteristics. As depicted in Figure 3, the survey focused on 11 areas in various parts of Beijing. Within these areas, 9,800 households were surveyed, with roughly equal sample size across the areas.[3] The survey was conducted in person. Well-trained enumerators followed pre-defined procedures to randomly select the participants in the neighborhoods of subway stations within each area.

[3]For three survey areas, 1,000 households were randomly selected for each of them. For the other eight survey areas, 850 households were randomly selected for each of them.

The survey provided price information at two points in time for each property: the time of move-in and the survey date. The price as of the move-in date represents the transaction price, while the price at the time of the survey is the market price perceived by the respondent. Although real estate transaction prices in the U.S. are readily available and data with repeat transactions are commonly used in analyses, similar data are hard to obtain in China, and studies on China's housing market often rely on cross-sectional or market-level data (Zheng and Kahn 2008 and Zheng and Kahn 2013). One might worry about the measurement error introduced by the perceived price given by the respondent at the time of the survey. The measurement error would introduce bias if it were correlated with the change in the distance to the subway, the key explanatory variable. Although we do not have empirical evidence to directly refute this, we offer some discussion to ease this concern.

Since 2005, housing prices in Beijing have increased dramatically. Between 2006 and 2010, prices increased at a rate of 20 percent per year. The housing market boom is a very salient issue, not the least because it directly ties to homeowners' wealth. Housing market trends are covered extensively in news media and are perhaps the most talked-about issue in regular conversations among residents.[4] We argue that residents should have a good idea of the market price of their property given the active and salient nature of the market. We offer two pieces of evidence to further support this. First, in Figure 4, we plot the average housing price in our sample based on the price at the time of move-in, from 1996 to 2009. The average price nearly quadrupled from approximately 2,500 Yuan per square meter in 1996 to approximately 9,300 Yuan in 2009. This is consistent with the overall price trend in the aggregate Beijing housing market. Second, according to a market report by the largest real estate broker in the second-hand market, Lian Jia Real Estate Broker Corporation, which has a 55% market share in Beijing, the average asking price was only slightly higher than the final price, with a spread of about 2%, during our survey period, June to October 2009.[5]

In addition to price information, the survey provided a rich set of housing attribute data, as well as neighborhood characteristics and household demographic data. Based on the location information, we use ArcGIS software to calculate the distance to the nearest subway station at the time of move-in and at the time of the survey. Our analysis is based on 3,820 observations

[4] Asking about prices that others pay for a commodity is fairly normal. Residents routinely ask for price information from neighbors, friends, or even strangers.

[5] http://news.dichan.sina.com.cn/bj/2010/01/25/115402.html

from the total sample. These observations are chosen based on the following criteria: (1) the respondents live in one of the survey areas (e.g., rather than just visiting the survey area), to allow for better control for neighborhood unobservables;[6] (2) the respondents live in owner-occupied properties, to avoid the long-term contract issue in rental properties (rental prices usually do not adjust within the contract period); and (3) the move-in date is after 1995, to minimize the effect of recall bias and, more importantly, the effect of housing reform.

Table 1 presents summary statistics of housing attributes and household demographics in our data set. The average property appreciated from 4,192 Yuan per square meter to nearly 12,000 Yuan over an average tenure of six years. The average distance to the nearest subway station was reduced by 2.43 km, from 4.83 to 2.27 km. The sample household demographics are largely representative of Beijing residents. For example, the average monthly family income in our sample falls between the middle two income categories defined in the survey (5,000-7,500 Yuan and 7,500-10,000 Yuan); similarly, the average family income in Beijing is approximately 7,200 Yuan per month.[7]

Table 2 illustrates the relationship between distance to the subway and property values and attributes. Considering five groups of distance measures, the average housing price is at its highest (12,578 Yuan per square meter) for properties closest to a subway station (within 1 km). Housing price decreases with distance to a subway station, except for those in the fifth category of properties farthest from subway stations (over 4 km). The increase in average price at the extreme distances is likely due to variation in other housing attributes, both observed and unobserved. Exploiting the panel structure of our data, we control for time-invariant housing attributes in a first-difference hedonic price equation.

Table 3 mimics Table 2, but it highlights the relationship between the reduction in distance to the nearest subway station, as measured from the move-in date to the survey date, and property values and attributes. The category with the smallest reduction in distance (no more than 1 km) saw the smallest price increase (253.7 percent) during an average 55 months of tenure. The second group (1-2 km reduction in distance) had a 387.5 percent price increase during an average 71 months of tenure. Our analysis will focus on the change in prices and the

[6]Some observations are from surveys conducted in the subway stations; hence, the respondents do not necessarily live in the sample area adjacent to the subway station. For this reason, we drop these observations.

[7] China Statistical Yearbook 2010.

change in distances to isolate the effect of subway access on property values while controlling for a variety of confounding factors, both observed and unobserved.

3. Empirical Framework

3.1 Hedonic Price Equation

We rely upon the hedonic price model as the basis for our analysis by characterizing housing value as a function of housing attributes. Rosen (1974) shows that the hedonic price function arises as an equilibrium outcome of the demand and supply sides of the housing market and that the gradient of the hedonic price function can be interpreted as the marginal willingness to pay for an incremental change in housing attributes. Researchers have used this method extensively to estimate consumer valuation of non-market goods in a variety of settings, including environmental quality and health risks (Davis 2004; Chay and Greenstone 2005; Gamper-Rabindran and Timmins 2011; Linn 2013; Muehlenbachs et al. 2013; Kahn and Kok 2014).

In our context, the distance to the nearest subway station is the key attribute of interest. Its impact on housing price embodies the net benefit of subway proximity to consumers. The benefit stems from easier access to subway lines and savings in travel time. However, close proximity to a subway may bring about disruptions to nearby residents, including increased foot traffic and noise levels. These two countervailing forces determine the sign and magnitude of the net benefit.

Denote *j* as the property index and τ_j as the year of move-in for household *j*. The move-in year varies across properties. The hedonic price function at the year of move-in is specified as follows:

$$\ln\left(P_{j\tau_j}\right) = D_{j\tau_j}\beta + Z_j\gamma + \delta_{j\tau_j} + \eta_{\tau_j} + \mu_{m_j}\tau_j, \qquad (1)$$

- $P_{j\tau_j}$ is the price of property *j* at the time of move-in;
- $D_{j\tau_j}$ is the distance to subway for property *j* at the time of move-in;
- Z_j is time-invariant price determinants such as housing size and vintage;
- $\delta_{j\tau_j}$ is unobserved time-varying determinants of housing price at the time of move-in;

- η_{τ_j} is year fixed effects that capture common shocks to the housing market such as common housing price increases due to the real estate market boom;
- $\mu_{m_j}\tau_j$ captures time-specific trends, where *m* denotes a district;
- $\varepsilon_{j\tau_j}$ is idiosyncratic demand shocks.

Similarly, at the time of the survey, (T), which does not vary across properties (i.e., 2009), the hedonic price equation is specified as follows:

$$\ln(P_{jT}) = D_{jT}\beta + \delta_{jT} + Z_j\gamma + \eta_T + \mu_{m_j}. \quad (2)$$

Differencing these two equations, we obtain:

$$\Delta\ln(P_{jT}) = \Delta D_j\beta + \Delta\delta_j + \left(\eta_T - \eta_{\tau_j}\right) + \mu_{m_j}(T - \tau_j). \quad (3)$$

ΔD_j is the change in the distance to the nearest subway station for property *j* at these two points in time and β is the main coefficient of interest. β reflects the capitalization of the net benefit from proximity to subway stations. Because η_T is the same across properties, it serves the same purpose as a constant. η_{τ_j} is a set of year dummies based on the time of move-in. $T - \tau_j$ is the duration of tenure (the number of years since move-in).

We expect that the net benefit of being close to a subway station will be positive overall, though we expect the benefit will exhibit heterogeneity across both space and time. The spatial heterogeneity may arise due to nonlinearity of the benefit with respect to a unit change in the distance to subway. For example, a drop of 1 km in distance from the nearest station for properties that are within 3 km may have larger impacts than the same change in distance for properties that are within 10 km of a subway station. The net benefit could even be negative for some areas. For example, construction of a new subway line in an area with preexisting access to a subway (such as a new transfer station) may bring little incremental benefit but could lead to a large increase in traffic and noise, with a resulting decline in housing values. In the empirical analysis, we investigate this spatial heterogeneity based on the number of stations within 3 km of a property as well as the distance to a subway station at the time of the move-in.

The second type of heterogeneity has to do with the timing of capitalization (price increase). The capitalization could happen fully and immediately at the time of the

announcement of planned construction, or it could be realized gradually over time following the announcement. Agostini and Palmucci (2008) provide evidence of a strong announcement effect in the capitalization of a new metro line in Santiago, Chile. The price change in our analysis is between the time of move-in and the time of the survey. For some observations, a subway line opened between these two periods; however, the announcement or construction could have commenced prior to the move-in date. The analysis based on these observations would underestimate the full impact of subway construction on housing prices due to the immediate announcement effect. In some specifications, we focus on observations where the move-in date is one year before the start of construction and find a slightly larger price impact. This result is consistent with the fact that the capitalization occurs in multiple stages as information on the new subway line gets fully dispersed.

3.2 Identification Challenges

There are two main threats to the identification of β: confounding factors captured by $\Delta\delta_j$ and reverse causality. We discuss these two challenges in turn. First, the price change $\Delta\ln(P_{jT})$ could be due to unobserved time-varying factors $\Delta\delta_j$. If these time-varying factors correlate with the change in subway distance and are not controlled for in the regression, the coefficient estimate β will suffer from omitted variable bias. These confounding factors $\Delta\delta_j$ include three categories: (1) changes in neighborhood amenities such as parks and schools; (2) changes in housing attributes due to housing renovation; and (3) unobserved policy changes that affect property values differentially depending on their distance to the subway.

The regression includes a district-specific time trend $\mu_{m_j}(T-\tau_j)$ to control for city district-specific unobservables such as continuous improvement in amenities. However, we need to be concerned about discrete changes in neighborhood characteristics that may have occurred simultaneously with subway construction. As we discussed above, the new round of subway construction started in early 2000 in preparation for the 2008 Olympics games in Beijing and to prepare for dramatic increases in traffic. The changes in subway distance are driven by this construction. In contrast, neighborhood amenities such as hospitals, parks and schools have largely remained static since 2000.

Beijing's history dates back three millennia and it has been the political center of China for nearly eight centuries. Beijing is renowned for its parks, palaces, temples, historical walls and gates, many of which have been in place for decades or centuries. City development within the 5th Ring Road was largely complete before 2000. Thus, the majority of public service facilities such as hospitals and schools had been established prior to the study period (Zheng and Kahn,

2013). For example, among all 46 Third Tier A hospitals in Beijing, which afford the highest quality medical service, all but one were built before 2000 and the newest one was established in 2001.[8] Similarly, 89 percent (263) of all primary schools and 92 percent (189) of all high schools were built before 2000.[9] Therefore, we argue that discrete changes in neighborhood attributes during the subway construction boom have been rare, especially within the 5th Ring Road. In one of the robustness checks, we focus on the survey areas within the 4th Ring Road, which were developed even earlier, and obtain similar results. Further, we believe that changes in housing attributes due to renovation, beyond those controlled for by the neighborhood-specific time trend, are unlikely to be correlated with subway construction.

For unobserved policy changes that could affect property values, we are particularly concerned with policies that affect traffic congestion and the preference for subway use. We can think of two important policies adopted in recent years to deal with worsening traffic congestion and air pollution: driving restrictions and vehicle purchase restrictions. Starting in July 2008, Beijing instituted a driving restriction policy, which permits vehicles to drive only on certain days, depending on the last digit of the license plate (Viard and Fu 2014). In January 2011, a vehicle license quota system was implemented to restrict vehicle purchases (Li 2014). These policies could increase consumer valuation of proximity to the subway and affect property values differentially depending on distances to the subway. Our time fixed effects and time trend variables can control for this to some extent. In one of the robustness checks, we drop the 258 properties with a move-in date after 2008 and obtain results very similar to the model with the full sample. In addition, we estimate a specification where we allow the preference parameter for subway proximity to be different for 2008 and 2009 than for previous years, to examine the impact of these policy changes on consumer preference.

The second potential issue for identification is simultaneity. For example, the government may selectively choose to build subways in areas where they expect housing values to grow more quickly or more slowly. This concern is partially offset by the fact that urban transportation planning and land-use planning are disjoint, partly due to lack of experience in rapid urbanization, as argued by Quan et al. (2006).[10] Instead of guiding and working in tandem with

[8] Source: Sougou map:http://map.sogou.com/

[9] Source: Beijing Municipal Commission on Education: http://www.beijingmap.gov.cn/bjjw/

[10] Quan is the former head of the Beijing Transportation Research Center, and the deputy minister of the Academic Committee of Chinese Urban Transportation Planning.

urban development, transportation planning has lagged behind rapid urbanization. This problem contributes to significant urban challenges in China, including traffic congestion and air pollution. Responding to ever-changing traffic congestion issues, the Beijing municipal government had to make adjustments to the subway planning scheme several times, issuing six versions of the urban subway construction plan between 2004 and 2012. Yet, during the same period, they issued only one land-use plan. This reflects the fact that transportation planning and land-use planning are not well integrated in Beijing's development process. The construction and siting of subway lines are largely determined by contemporary traffic conditions and are unlikely to be correlated with time-varying unobserved factors that affect housing prices.

Our approach to controlling for time-varying unobservables at both the property and neighborhood levels is to specify the following equation for $\Delta\delta_j$:

$$\Delta\delta_j = H_j\alpha + H_j(T - \tau_j, \tag{4}$$

where H_j includes housing attributes (e.g., housing size and number of bedrooms) and average housing attributes in the neighborhood. We also interact these variables with tenure duration $T - \tau_j$. The rationale for this control function approach is two-fold. First, the frequency and magnitude of housing renovation could be correlated with observed housing characteristics. For example, households with a larger property may update their houses more frequently or more extensively. Second, changes in neighborhood amenities (e.g., distance to schools or hospitals) could be correlated with neighborhood characteristics (for example, a neighborhood with more economical and comfortable housing could see fewer changes in neighborhood amenities). Therefore, variations in observed housing attributes at the property and neighborhood levels may capture changes in unobserved neighborhood amenities.

In a rational expectation framework, Bajari et al. (2014) proposes the use of pre-sample neighborhood characteristics (such as average property price) interacted with time trends to address time-varying unobservables. To the extent that property values capture expected future changes in amenities and that transportation planning takes these future changes into consideration, the method of adding pre-determined property attributes interacted with time trends can also control for reverse causality. Although we do not have pre-sample prices, many of the housing attributes in our data, such as housing size and housing type, are pre-determined.

4. Empirical Results

Table 4 presents estimation results from seven regressions with different sets of control variables based on Equation (3). The dependent variable is the change in the log of housing price between the time of move-in and the survey date. The key explanatory variable is the change in distance to the nearest subway station during these two points in time. The benchmark specification with the most control variables is in Column (6); the results there suggest that a 1-km reduction in proximity to the subway can increase property value by 0.94 percent.

Column (2) adds year fixed effects and district dummies interacted with duration. This specification is equivalent to having year fixed effects, property fixed effects, and district-specific time trends, as given in Equations (1) and (2). Thus, it controls for (time-invariant) property unobservables and common time trends at the city district level. Adding these controls diminishes the coefficient estimate from -2.04 percent to -1.16 percent.

Columns (3) to (6) deal with time-varying unobservables at both the property and neighborhood levels by successively adding more control variables. Column (3) adds a set of housing characteristics, while Column (4) further adds their interactions with the duration variable. This follows the approach described in Equation (4), where these variables can be used to control for time-varying unobservables. While many of the coefficient estimates on housing characteristics and their interaction with duration are statistically significant, the coefficient estimates on the distance variable maintain the same sign and magnitude. Column (5) further adds average housing attributes in the neighborhood, while Column (6) includes the interactions of housing attributes with duration. The coefficient estimates on the distance variable in Columns (5) and (6) are similar. The estimate from Column (6), our benchmark specification, suggests that the impact of closer proximity to a subway by 1 km is an increase of 0.94 percent in property value. The last specification in Column (7) includes a quadratic term of the distance variable and suggests that the effect is stronger for initial changes in distance, a point we will investigate further below.

A key challenge in property value hedonic analysis is accounting for the unobservables that contribute to property value. The issue is particularly severe in cross-sectional settings. Our analysis controls for time-invariant unobservables at both the property and neighborhood levels by taking advantage of the price information at two points in time. This is similar to the repeat-sales approach, where multiple data points are available for the same property (Bailey et al. 1963; Shiller 1993). The approach has been widely used to construct housing price indices, including a recent application in China (Guo et al. 2014). The identification challenge in this

context comes from omitted variables and simultaneity. There could be unobservables such as changes in neighborhood amenities and household attributes that vary with the key explanatory variable, the change in proximity to subway. Alternatively, the location choices of subway lines could be a response to expected future growth in property values of different neighborhoods.

We argue that these concerns are mitigated in our study for historical and institutional reasons. Following Bajari et al. (2014), we find coefficient estimates on the distance variable that are similar in magnitude across different specifications, which supports our argument. Bajari et al. (2014) propose the use of pre-determined housing attributes interacted with time trends to control for time-varying unobservables. We do not have data on housing attributes before the move-in. However, the housing attributes that we use, such as housing size and number of bedrooms, are unlikely to change. As a robustness check to address possible confounding policy changes, such as the driving and vehicle purchase restrictions discussed in the previous section, we drop 258 properties with a move-in date after 2008. The coefficient estimate on the distance change variable is -0.092 with a standard error of 0.004 when we use this restricted sample based on Specification (6), compared to -0.094 using the full sample as shown in Table 4.

To allow for different consumer preferences for subway proximity in 2008 and 2009 – for example, different responses to the driving restriction policy that started in July 2008 – we rewrite the coefficient on the distance variable as $\beta' = \beta + \tilde{\beta}$, where $\tilde{\beta}$ is the change in preference for access to a subway station. A negative estimate for $\tilde{\beta}$ would imply an increase in willingness to pay (WTP) for subway proximity. We re-write Equation (3) to allow for this possibility:

$$\begin{aligned}\Delta\ln(P_{jT}) &= (D_{jT}\beta' - D_{j\tau_j}\beta) + \Delta\delta_j + \left(\eta_T - \eta_{\tau_j}\right) + \mu_{m_j}(T - \tau_j) + \Delta\varepsilon_j \\ &= \Delta D_j\beta + D_{jT}\tilde{\beta} + \Delta\delta_j + \left(\eta_T - \eta_{\tau_j}\right) + \mu_{m_j}(T - \tau_j) + \Delta\varepsilon_j.\end{aligned}$$

With the same controls as in the specification in Column (6) of Table 4, the estimate of β is -0.0098, with a standard error of 0.0041, and the estimate of $\tilde{\beta}$ is -0.0089, with a standard error of 0.0105. The coefficient estimate of $\tilde{\beta}$ itself indeed suggests a significant increase in consumer WTP for subway proximity but it is not statistically significant.[11]

[11] There could be a number of explanations for the imprecision of the estimates. For instance, it is possible that changes in consumer preference had not yet fully materialized between the date when the policy started and the date when the survey was conducted (about a year later), due to uncertainty about the policy's duration.

To allow the price impact to occur before a subway line opens, we focus on observations for which the move-in date is one year before the construction start date of the nearest subway line. If the capitalization starts to materialize prior to the operation of the subway line, we would expect to see a larger impact with this smaller set of observations (1,152). The coefficient estimate on the distance change variable is -0.012 in Specification (6), compared to -0.094 in Table 4 using the full sample.[12] The parameter estimates from Specifications (4) and (5) using the smaller sample are -0.015 (0.008) and -0.014 (0.009), respectively. The implied impact is quite a bit stronger than that from the regression with all observations. This suggests that our results from Table 3 provide a lower bound on the full capitalization.

We postulated in the introduction that there could exist heterogeneity in the impacts of subway proximity with respect to the number of subway stations in the adjacent area. In areas that already had easy access to the subway, the construction of a new subway line may bring little incremental benefit and may even lead to a decline in housing values due to increases in road traffic and noise. To test this, we conduct a regression as in Equation (3), adding an interaction term between the distance change variable and the number of stations within 3 km (at the time of the survey).[13] The coefficient estimate on the distance change variable is -0.026 (0.011) and the estimate on the interaction term is 0.0044 (0.0020). These estimates confirm that the benefit of subway construction in areas with good subway access is smaller and may even be negative.

We now investigate the findings that the effect of subway proximity is nonlinear, shown in the last column in Table 4. The first column in Table 5 specifies the hedonic price function in log-log form. The coefficient estimate on log of distance suggests that a one percent reduction in the distance to a subway station increases the property value by 0.04 percent. The second column allows the distance variable coefficient estimates to vary across properties with different distances to subway stations at the time of move-in. We categorize the properties into eight groups, with the first seven groups having a 1-km increment, while the eighth group includes all properties with a distance to the subway greater than 7 km at the time of move-in.

[12] The standard error is 0.009 for the coefficient estimate of -0.012, so the coefficient estimate is not statistically significant. This is likely due to the small sample size.

[13] For the properties in the sample,the average number of stations within 3 km at the time of survey was 3.7, with a range from 0 to 12.

The coefficient estimates suggest that the effect of subway proximity is much larger for properties close to subway lines. A reduction of 0.1 km in distance to the subway station increases the property value by 1.8 percent for properties within 1 km of a subway station, while the same change in subway proximity increases the property value by 1.4 to 1.7 percent for properties within 1 to 3 km of a subway station. These effects are economically significant but not overwhelmingly so, relative to the nearly three-fold increase in property values during our data period. Between 1996 and 2010, the average reduction in distance to a subway for properties within 1 km of a subway station at the time of move-in was 0.035 km, implying an increase of 0.73 percent in value for these properties. Properties within 1 to 2 km of a subway line at the time of move-in experienced an average reduction in distance to a subway station of 0.26 km, implying an increase of 3.38 percent in property value. The parameter estimates and their 95 percent confidence intervals are plotted in Figure 5. The effect of subway proximity on property values clearly diminishes when properties are farther away from a subway line.

To further examine the heterogeneous effects, we estimate a semi-parametric specification of Equation (4), following Kepner and Robinson (1988), where the effect of the distance variable is specified non-parametrically. The non-parametric estimates of the marginal effect of the distance variable and their 95 percent confidence intervals are shown in Figure 6. To facilitate exposition, the smoothed lines are local polynomial estimates of the marginal effect and their 95 percent confidence intervals. The pattern is largely consistent with those presented in Column (2) of Table 5: the effect is strongest for properties within 3 km of a subway line. The effect levels off after 5 km and dissipates after 9 km, where we have very few observations.

Based on the estimation results from the second column in Table 5 (depicted in Figure 5) and the semi-parametric estimates in Figure 6, we re-categorize the properties into three groups based on the distance to the subway at the time of move-in: within 3 km, between 3 and 5 km, and over 5 km. The estimates from both Figures 5 and 6 suggest that we can use three distance categories to parsimoniously characterize the impact of subway access on property values. These distance categories can also be understood as follows: residents who live within 3 km of the stations can travel to the stations by walking, bicycling or riding buses; those who live within 3-5 km of the stations can travel to the stations by bicycling or riding buses; and those who live farther than 5 km are much less likely to use subways (Givoni and Rietveld 2007; Leopairojna

2013; Li and Kim 2014).[14] This re-categorization increases the precision of individual parameter estimates on the distance variables. We use the results from this specification for our policy analysis in the next section. The results suggest that a 1-km reduction in distance to a subway station increases the property value by 15 percent, 3.4 percent and 1.2 percent for these three groups, respectively.

To better compare our results to those in the literature, we convert our estimates to elasticities of housing price with respect to changes in distance to subway. Our parameter estimates imply that a 10 percent reduction in the distance to the nearest subway station increases the value of properties by 1.9, 1.7 and 1.1 percent for properties located within 3 km, 3 to 5 km, and over 5 km from the nearest stations, respectively. These findings are similar in magnitude to previous literature on the effects of distance to subway on housing prices in Beijing. Zheng and Kahn (2008) estimate that a 10 percent reduction in distance to subway lines increases property prices by 1.6 percent. Zheng and Kahn (2013) show that housing prices increase by 0.6 percent when the distance to the nearest subway station decreases by 10 percent. The estimate from this study is smaller, partly because it captures only the impact due to subway construction rather than subway completion, and hence may not capture the full effect. Our estimates are lower than those of Gibbons and Machin (2005), who found that a reduction of 1 km in distance to a station increased housing prices by about 1.5 percent, based on the construction of new train stations in London in the late 1990s. However, the unique nature of Beijing's housing market, in particular the 300 percent appreciation in housing prices, makes it difficult to compare our estimates with other countries.

5. Policy Analysis

As a percentage of the overall market trend in Beijing, the increase in housing prices due to the construction of subway lines is quite modest. However, even if proximity to subway stations accounts for only a small increment in the appreciation in property values, the resulting capitalization is still substantial relative to the cost of building and operating public transportation.

[14] The perception of the optimal walking distance in China is usually farther than that in western societies (Yang et al. 2013).

Rapid subway expansion has imposed huge financial burdens on central and especially local governments; the latter are responsible for both capital investment and operating expenses. The capital cost of building subways is increasing. For example, the average construction cost for 1 km of subway rail in Beijing was 0.57 billion Yuan between 2007 and 2009; this increased to 0.85 billion Yuan in 2012 and then to 1.07 billion Yuan in 2013.[15] At the same time, subway fares are subsidized and subway operations rely heavily on subsidies from the municipal government. The subsidy for public transit operations alone amounted to 53.2 billion Yuan from 2011 to 2013, accounting for 5.3 percent of the government's revenue during this period.

This financial burden takes away resources from other critical government programs such as medical services and education. Therefore, it is important to develop an alternative long-term strategy for funding public transit. We now examine a mechanism whereby capital spending on public transit is funded through the capitalization of public transit proximity into property values (Tideman et al. 2002; Harrison 2006).

Our empirical results indicate that proximity to subway stations increases property values and that the impact is particularly strong for properties within 3 km of a subway station. To quantify the capitalization of subway construction in the housing market, we focus on subway Line 5, which opened in 2007 with a price tag of 15.76 billion Yuan. Line 5 passes through the densely populated city center, traveling from south to north, with a total length of 27.6 km.

Ideally, we want information on housing stock within different distance bands to this line. However, this type of data is not available. We instead approximate the housing stock within different distance bands to Line 5 using information on the population within different distance bands and their average living space per capita.[16] We focus on housing stock in two distance bands: within 3 km and between 3 and 5 km. We ignore properties that are over 5 km away from Line 5 because, for the vast majority of these properties, Line 5 will not be the closest subway line. To estimate total property value in these two distance bands, we multiply the housing stock by the 2005 average residential housing price of 6,162 Yuan per square meter in Beijing.

The housing stock within 3 km of Line 5 is estimated to be 58.64 million square meters, while the housing stock between 3 and 5 km amounts to 42.64 million square meters. Our

[15] http://rail.ally.net.cn/html/2014/xinjialanmu_0709/31118.html

[16] Population data along subway lines comes from the 2010 Census. Average living space per capita is about 19.49 square meters (Beijing Statistical Yearbook 2011).

analysis shows that a 1-km reduction in the distance to a subway station increases property values by 15.4 percent for properties within 3 km of a subway station and 3.4 percent for those between 3 and 5 km. Assuming the average reduction in distance to be 0.26 km and 2.69 km for these two types of properties based on our sample, the total increase in property values amounts to 38.5 billion Yuan, well above the total subway construction cost of 15.76 billion.

This increase in property values can reflect multiple benefits, such as reductions in both commuting time and pollution. The estimates imply a benefit-cost ratio of 2.4, suggesting that subways are a high-return investment. This is consistent with a recent study by Anderson (2013), who estimated the congestion relief benefit realized by the Los Angeles rail system to be nearly twice the capital cost.

The self-funding mechanism involves recovering the capital cost of public transit through capitalization. One method is through a property tax. Assuming an annual discount rate of 5 percent and a constant total property value within 5 km of Line 5 of 624.1 billion Yuan, it would take approximately 10 years, 3 years and 15 months to fully recoup the cost at an annual tax rate of 0.3 percent, 0.9 percent and 2 percent, respectively.

Another self-funding mechanism is the "Rail + Property" (R+P) development approach mentioned in the introduction. The government can create a system where Beijing's rail operator could purchase development rights from the government at a "before subway" price and sell the rights to a developer at an "after subway" price. The difference, partly reflected in the estimated price effect, could be used to cover the cost of subway investments.

6. Conclusion

China's 12th national five-year plan (2011-2015) proposed the construction of 69 new subway lines during this period, with a total length of 2,100 km, and 800 billion Yuan (or $131 billion) in costs. While these large-scale investments can potentially bring substantial benefits to consumers, they also represent a serious financial burden on central and local governments.

We estimate the capitalization of subway proximity in property values in Beijing by exploiting the rapid expansion of the subway networks in recent years. Our survey data set provides price information on individual properties at two points in time: the time of move-in and the survey date. We employ a hedonic price method with first-differencing to control for time-invariant unobservables. We also control for potential time-varying unobservables following the rational expectation method of Bajari et al. (2014) by including a rich set of household demographics and housing attributes and their interactions with housing tenure.

Our estimation results suggest capitalization of subway expansion into property values is significant: a 1-km reduction in proximity to a subway station increases property values by 14 percent and 3.9 percent for properties within 3 km and between 3 and 5 km of a subway station, respectively. A back-of-the-envelope calculation focusing on one particular new subway line implies a total increase of property values of 38.5 billion Yuan for properties within 5 km of that line, compared with its construction cost of 15.76 billion Yuan. If a property tax is levied to self-fund the capital investment, a very modest annual rate of 0.3 percent would fully recover the cost in 10 years.

Our study leads to at least two questions worthy of future research. First, our hedonic analysis offers evidence of large public benefits from subway expansion. Examining the underlying mechanism for such benefits, such as the impact on congestion relief and air quality, merits further research. Second, the improved access to subways is expected to alter the choice set of travel modes for commuters. Examining travel mode choices and consumers' willingness to pay for different modes would further aid in understanding the broader public welfare impacts of subway expansion. A good understanding of the underlying mechanisms would help address the external validity issue, that is, whether subway expansion in other areas in China such as the second-tier cities would also be capitalized in property values.

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Tables and Figures

Table 1: Housing Prices and Household Characteristics

Variable	Mean	SD	Min	Max
Housing Price at Move-in (Yuan/m²)	4192.83	2488.03	110	25000
Housing Price at Survey (Yuan/m²)	11720.88	3998.75	5000	80000
Housing Price Change (Yuan/m²)	7528.05	3839.80	0	77700
Distance to Subway at Move-in (km)	4.83	4.12	0.01	15
Distance to Subway at Survey (km)	2.27	2.58	0.01	13.83
Distance Change (km)	-2.43	3.14	-13.91	0
Move-in Year	2003	2.92	1996	2009
Tenure Duration (month)	67.43	35.12	0	163
Family Income	2.50	1.16	1	4
Age	42.59	13.50	20	88
College and Above	0.31	0.46	0	1
High School	0.51	0.50	0	1
Household Size	3.09	0.90	1	9
Number of Children	0.87	0.46	0	2
House Size (100 m²)	0.93	0.333	0.09	3.5
Number of Bedrooms	2.67	0.95	1	6
School within 2 km	0.91	0.28	0	1
Employer Subsidized Housing	0.08	0.27	0	1
Open Market Purchased	0.56	0.50	0	1
Social Welfare Housing	0.25	0.43	0	1
Resettlement Housing	0.11	0.32	0	1

Note: The number of observations is 3,819. Data are from household surveys by the Beijing Transportation Research Center (BTRC). Household demographics and housing characteristics are at the time of the survey. Family monthly income (in Yuan) is categorized as follows: 1 - less than 5,000, 2 – 5,000-7,500, 3 – 7,500-10,000, 4 - more than 10,000.

Table 2: Housing Price and Characteristics by Distance to Subway

	Distance to Subway for Survey Date				
	<=1km	(1,2]km	(2,3]km	(3,4]km	>4km
Average Housing Price for Survey Date (Yuan/m²)	12578	11203	9323	9106	11357
Average Duration of Tenure (Months)	64.6	67.5	66.0	62.7	74.3
Average House Size (100 m^2)	0.94	0.91	0.91	0.87	0.97
Average Number of Bedrooms	2.8	2.7	2.9	2.3	2.3
School within 2 km	0.89	0.93	0.94	0.64	0.94
Employer Subsidized Housing	0.07	0.11	0.07	0.13	0.04
Open Market Purchased	0.40	0.62	0.73	0.79	0.77
Social Welfare Housing	0.41	0.17	0.19	0.09	0.04
Resettlement Housing	0.12	0.10	0.01	0.00	0.15
Number of observations	1620	1306	138	47	709

Notes: The total number of observations is 3,819. The table presents the property attributes at the time of the survey in 2009.

Table 3: Housing Price and Characteristics by Reduction in Distance to Subway Station

	Reduction in Distance to Subway				
	<=1km	(1,2]km	(2,3]km	(3,4]km	>4km
Average Housing Price for Move-in Date (Yuan/m²)	4723	3013	3112	4306	3560
Average Housing Price for Survey Date (Yuan/m²)	11985	11675	11969	14888	10968
Change in Average Housing Price (Yuan/m²)	7262	8662	8857	10581	7408
Percent Change in Average Housing Price	253.7%	387.5%	384.6%	345.7%	308.1%
Change in Distance to Subway (km)	-0.2	-1.4	-2.6	-3.6	-6.5
Average Duration of Tenure (Months)	55.0	71.2	68.8	101.7	86.1
Average House Size (100 m^2)	0.92	0.89	1.19	1.04	0.92
Average Number of Bedrooms	2.7	2.5	2.6	2.4	2.7
School within 2 km	0.95	0.97	0.99	0.89	0.84
Employer Subsidized Housing	0.04	0.11	0.10	0.11	0.13
Open Market Purchased	0.60	0.28	0.15	0.78	0.58
Social Welfare Housing	0.25	0.38	0.75	0.04	0.19
Resettlement Housing	0.11	0.22	0.00	0.07	0.11
Number of observations	2166	201	146	98	1209

Notes: The total number of observations is 3,819. The table focuses on changes in property values from move-in to the time of the survey with respect to changes in distance to the nearest subway line.

Table 4: Estimation Results for Various Specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Distance Change (km)	-0.0204*	-0.0116*	-0.0063	-0.0077*	-0.0083*	-0.0094**	-0.0201*
	(0.0104)	(0.0062)	(0.0042)	(0.0039)	(0.0042)	(0.0043)	(0.0121)
Distance^2 Change							0.0008
							(0.0008)
House Size (100 m²)			-0.2580**	-0.0047	0.0609	-0.0093	-0.0040
			(0.1033)	(0.2049)	(0.1964)	(0.1753)	(0.1772)
Number of Bedrooms			0.0727	0.0490	0.0392	0.0798	0.0793
			(0.0516)	(0.1033)	(0.1153)	(0.1268)	(0.1269)
School within 2 km			0.1050***	0.0988	0.0788	0.0867	0.0872
			(0.0345)	(0.1045)	(0.0875)	(0.0636)	(0.0646)
Open Market Purchased			-0.7465***	-1.2221***	-1.1555***	-1.1709***	-1.1704***
			(0.0532)	(0.1387)	(0.1405)	(0.1572)	(0.1573)
Social Welfare Housing			-0.3640***	-0.7198***	-0.6894***	-0.7607***	-0.7629***
			(0.0827)	(0.2042)	(0.2125)	(0.2008)	(0.2009)
Resettlement Housing			-0.5811***	-0.8510***	-0.7843***	-0.8803***	-0.8785***
			(0.0679)	(0.1952)	(0.1873)	(0.2120)	(0.2127)
Year fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
District × Duration	No	Yes	Yes	Yes	Yes	Yes	Yes
House attributes × Duration	No	No	No	Yes	Yes	Yes	Yes
House attributes in the neighborhood	No	No	No	No	Yes	Yes	Yes
Neighborhood attributes × Duration	No	No	No	No	No	Yes	Yes
Adjusted R-squared	0.011	0.347	0.477	0.486	0.492	0.496	0.497

Notes: The number of observations is 3,819. The dependent variable is change in log of housing price. All regressions are from OLS. House attributes in the neighborhood are the average house attributes in the neighborhood (or neighborhood attributes). The average distance reduction to subway in the sample is 1.146 km. Clustered standard errors at the neighborhood level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Heterogeneous Impacts with Different Distance to Subway

	(1)	(2)	(3)
Log(distance) Change	-0.0410*		
	(0.0240)		
Distance Change × if Move-in Distance <=1		-0.1842	
		(0.2378)	
Distance Change × if Move-in Distance (1,2]km		-0.1711	
		(0.1442)	
Distance Change × if Move-in Distance (2,3]km		-0.1521***	
		(0.0493)	
Distance Change × if Move-in Distance (3,4]km		-0.0353	
		(0.0230)	
Distance Change × if Move-in Distance (4,5]km		-0.0345***	
		(0.0126)	
Distance Change × if Move-in Distance (5,6]km		-0.0121	
		(0.0159)	
Distance Change × if Move-in Distance (6,7]km		-0.0175	
		(0.0108)	
Distance Change × if Move-in Distance >7 km		-0.0121***	
		(0.0044)	
Distance Change × if Move-in Distance (0,3]km			-0.1540***
			(0.0530)
Distance Change × if Move-in Distance (3,5]km			-0.0337**
			(0.0142)
Distance Change × if Move-in Distance >5km			-0.0120***
			(0.0041)
Constant	2.8450***	2.8158***	2.8448***
	(0.6516)	(0.6387)	(0.6433)
Adjusted R-squared	0.4968	0.4984	0.4990

Notes: The number of observations is 3,819. The dependent variable is change in log of housing price. All regressions are from OLS and include the full set of control variables as shown in Table 4. Clustered standard errors at the neighborhood level are in parentheses. * p< 0.10, ** p< 0.05, *** p< 0.01.

Figure 1: Beijing's Growth from 2001 to 2013

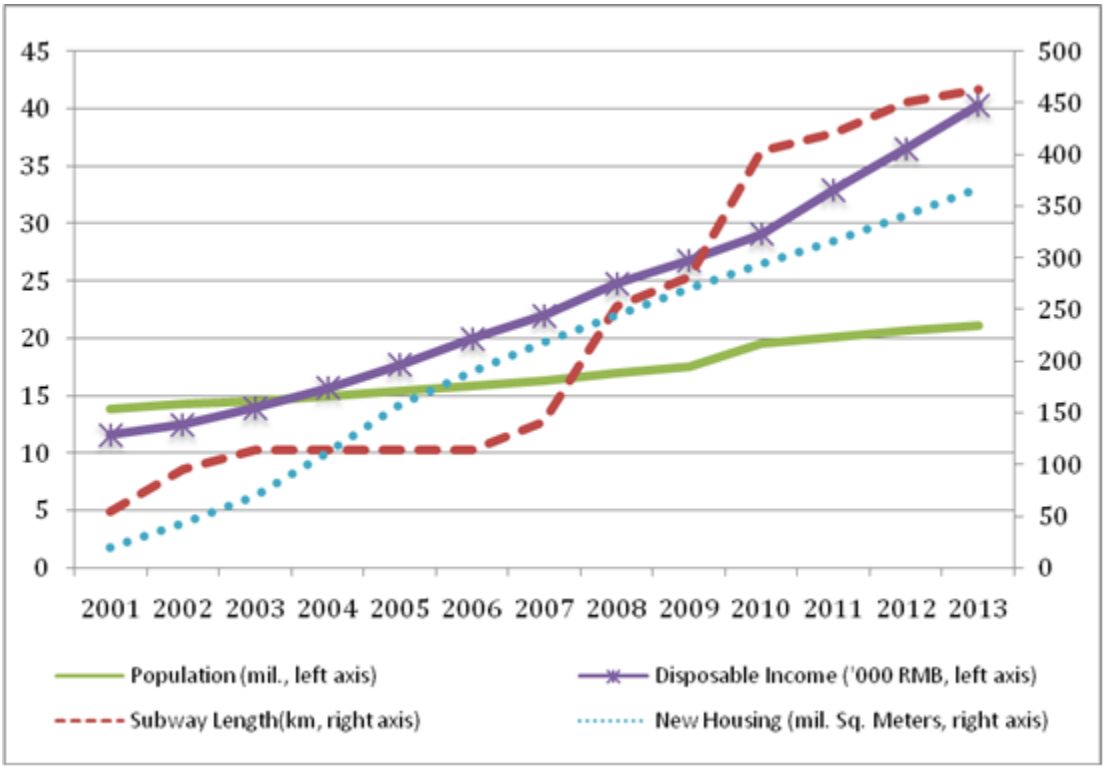


Figure 2: Beijing's Subway System in 2009

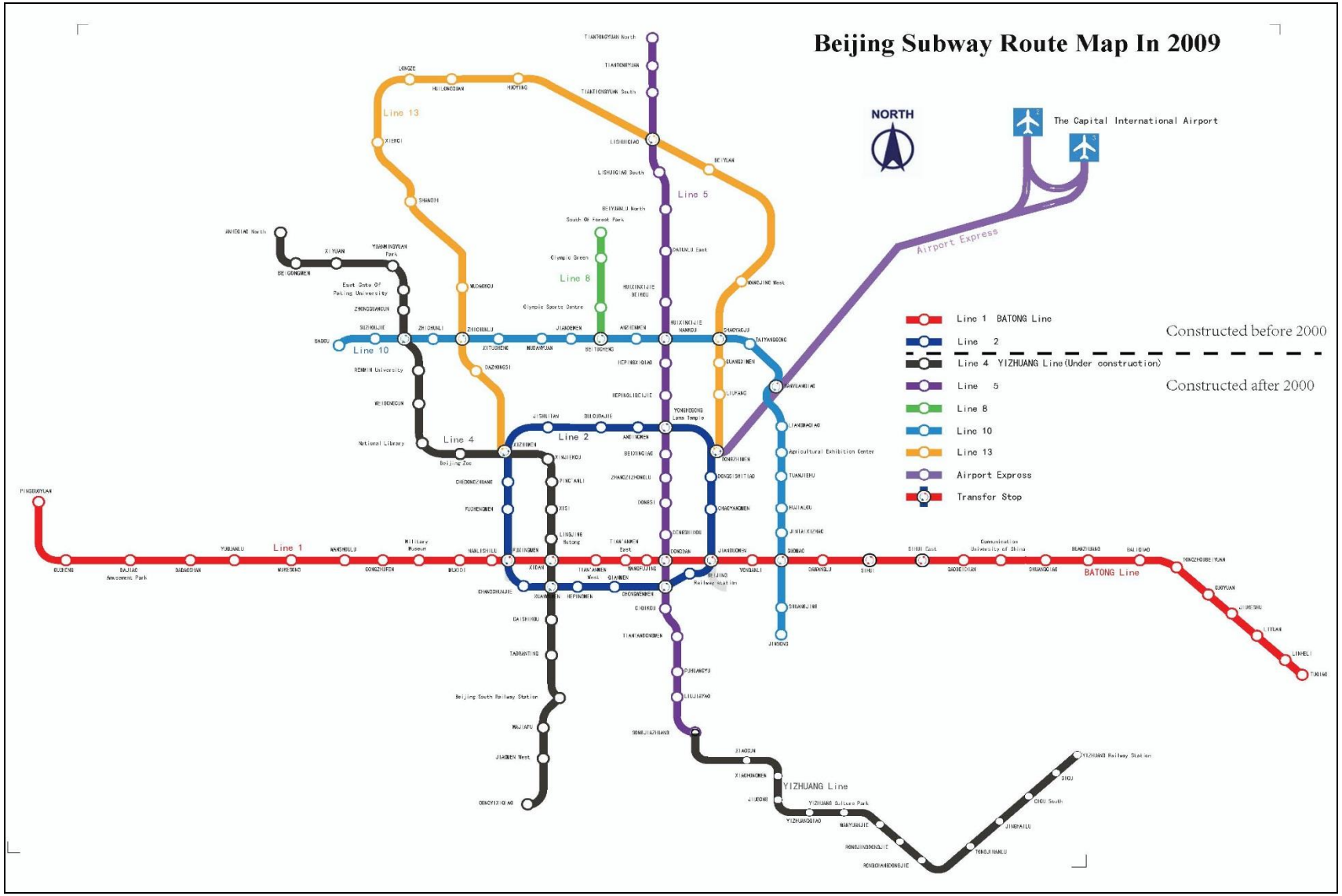


Figure 3: Survey Areas along Subway Lines

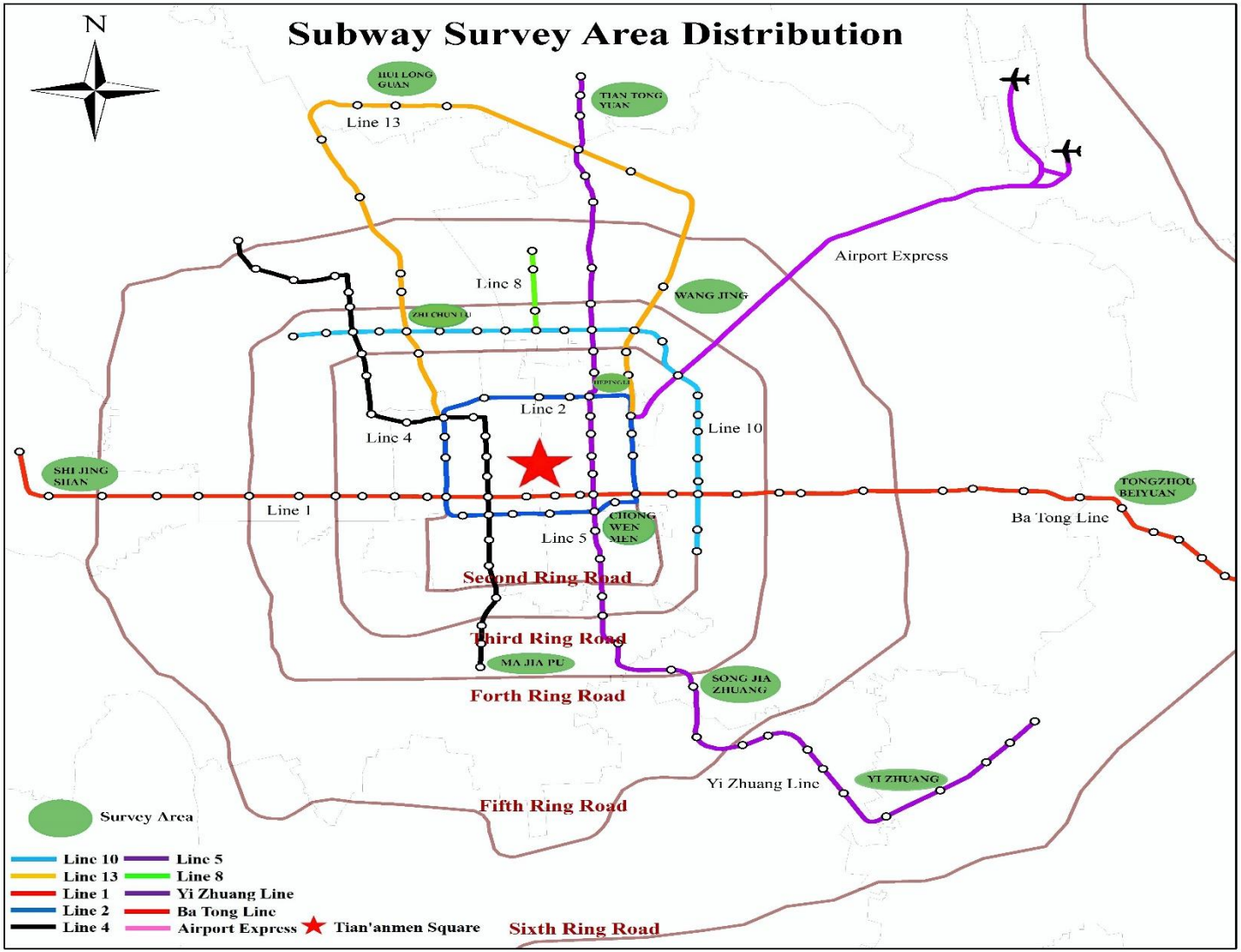
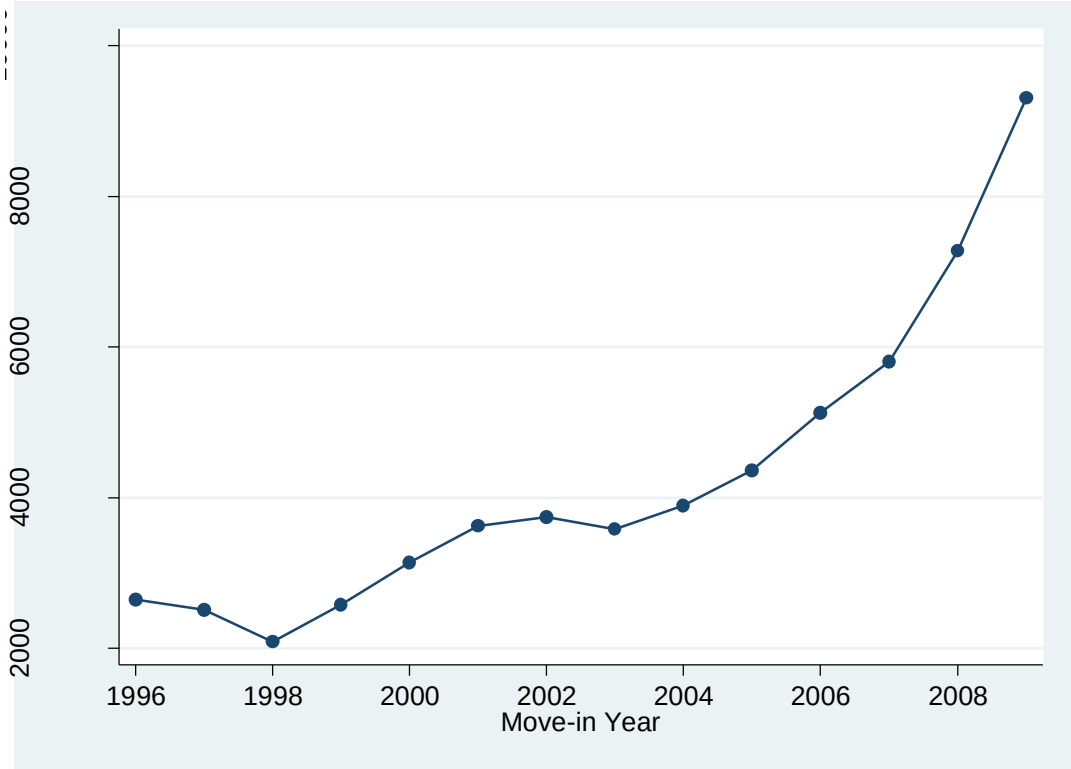
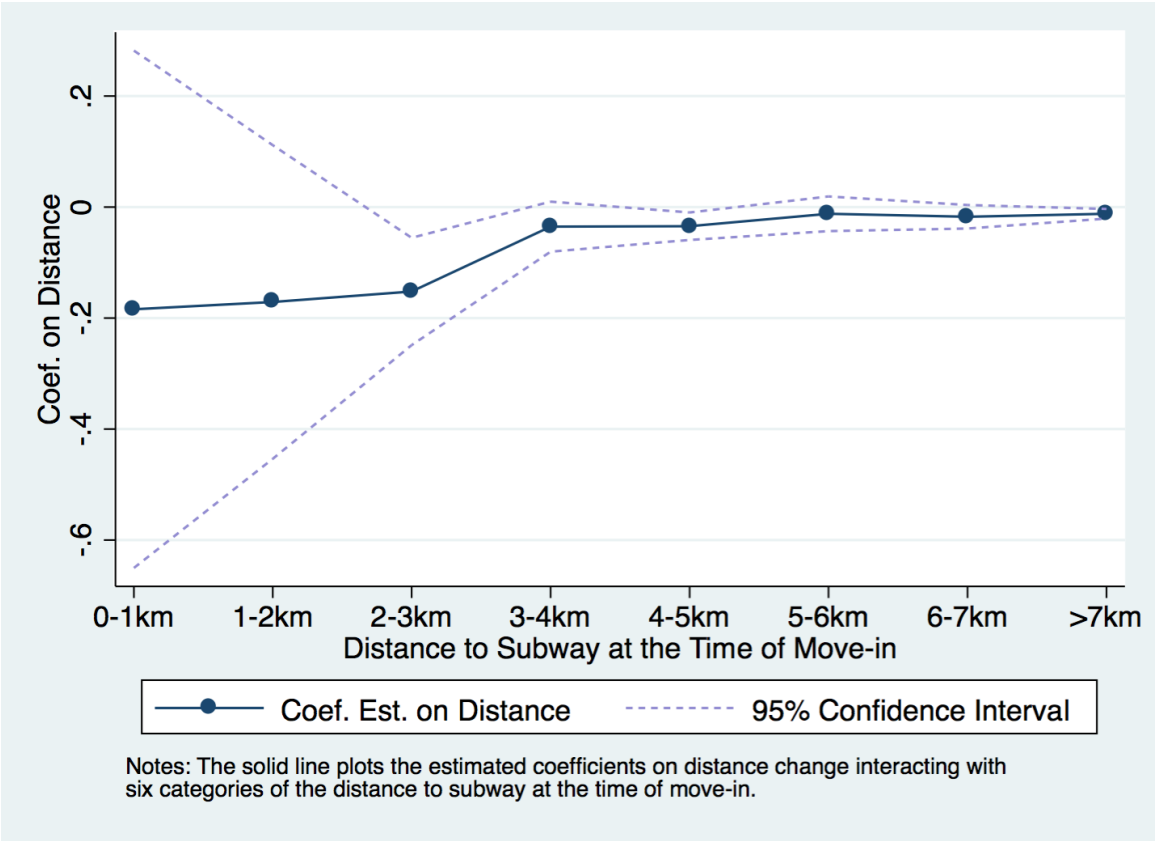


Figure 4: Average Housing Price in Beijing, 1996-2009



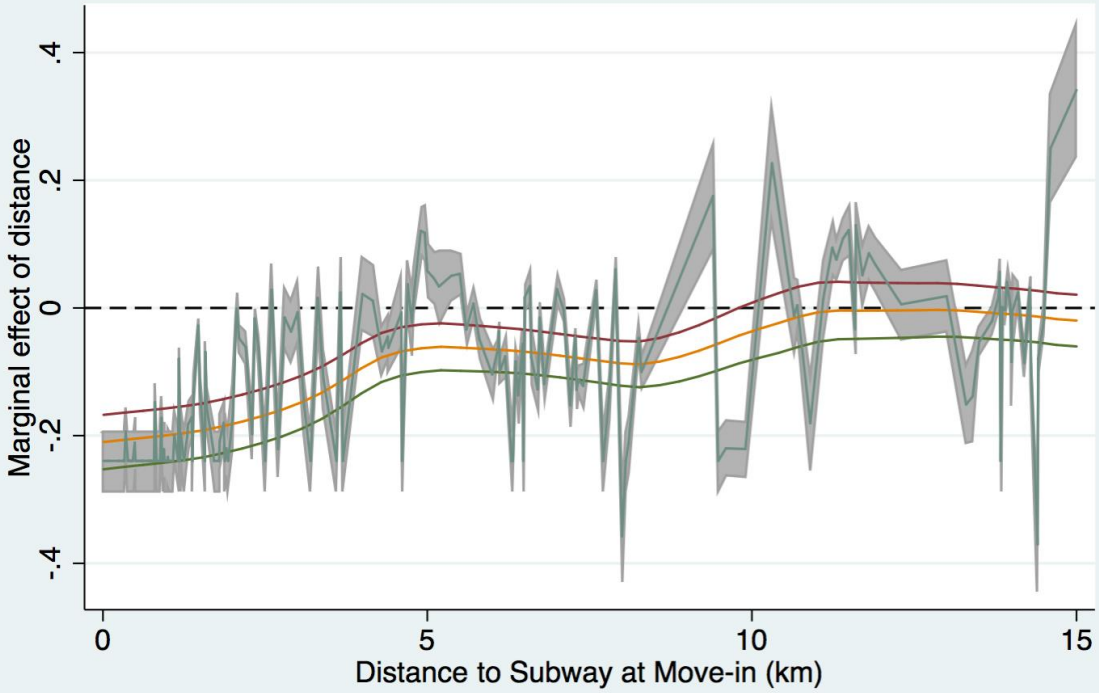
Notes: The plot shows the average price (Yuan per square meter) for 3,819 properties in our data. The prices are the reported price at the time of move-in.

Figure 5: Heterogeneous Effects across Properties with Different Distance to Subway at the Time of Move-in



Notes: The solid line plots the estimated coefficients on distance change interacting with six categories of the distance to subway at the time of move-in.

Figure 6: Marginal Effects of Distance Change across Properties with Different Distance to Subway at the Time of Move-in



Notes: The plots show non-parametric estimates of marginal effects of distance to subway on property values and their 95% C.I. based on Robinson's (1988) semiparametric estimator. The smoothed lines are local polynomial estimates with 95% C.I.