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RESEARCH ARTICLE

Evaluating the Impact of the Completion of Beijing Subway Line 6 on House Prices and Its Implications for Urban Planning

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ABSTRACT: The paper examines the impact of the completion of a new urban rail transit (URT), Line 6, on nearby community housing prices between 2011-2014 in Beijing, well ahead of the Chinese government's repression of speculative housing investments and the fall of China's newborn in 2016, the government restriction on developers' leverage ratio in 2020, and the structural decline of China's total population in 2022. It estimates empirically the pulling effect of the completion of a new urban rail transit on the average housing prices of the communities along the route. The conclusion, with the integration of the hedonic pricing method (HPM) and the difference in difference (DiD) method, is that the completion of subway Line 6 has a significant impact on nearby communities' housing prices. In addition, the difference between walkable and non-walkable distances is evaluated, and the clustering effect is refuted. Finally, the difference in impact among urban, semi-urban, and suburban areas is quantified with the finding that the completion of a new subway has the most significant impact on the communities in semi-urban areas. Based on the findings, advice in urban planning for other big cities with large populations in fast-growing economies is provided.

KEYWORDS: Behavioral and Social Sciences, Sociology and Social Psychology, Urban Rail Transit (URT), Housing Price, Urban Planning.

Introduction

Although it seems apparent that the addition of a public transport line will increase the land value along its route, given residents' reduced cost of commute and improved accessibility to the central business district (CBD), it is critical to differentiate between correlation and causality. Whether the completion of a new subway fosters more economic activities and then causes higher housing prices or economic development is the key driver behind the subway construction and housing price appreciation remains unclear. In our examination, we try to identify and quantify the cause and the result, and we intentionally exclude the first and last stations of the subway line that we examine to remove the excess distortion due to speculations on government policy announcements.

Our particular interest in this topic resides in its quantitative evaluation of the impact of public transportation investment on the urban economy. As of the end of 2024, there are 50 cities in the world that have a population of above 7 million, about 2/3 (34 cities) of these cities are in Asia, among which 56% (19 cities) are outside of China. With the fast population growth in Southeast Asia and the further urbanization of rural migrants in these economies, lessons learned from China's fast urbanization period are relevant. Where and how a limited fiscal budget should be invested to maximize the outcome and benefit most people are puzzling questions facing all policy makers and urban planners. Our research provides a reference for decision makers on these issues.

Another reason for our study is the limited number of comparable studies for Mainland China, particularly during the specific period examined, right after the completion of a new subway line. There are, however, plenty of empirical analyses done across many developed countries. Just to name a few, Baldassare[1] examined the impact of transit rail on the nearby land value based on social elements and environmental attributes, while Prior[2] and Riley[3] investigated property value along the new Joban line in Tokyo and the London Metro Jubilee extension, respectively.

Among the China-focused research, Xiao, Webster, and Orford[4] explored the linkages between urban configuration (including the subway network) and micro-level house price movement, taking the case of the city of Nanjing. The paper employed a spatial-network analysis method to track changes in transport accessibility and implied a generally positive relationship between accessibility and property prices and a negative relationship where spillover effects led to new congestion hot spots. Tan, Zhao & Li[5] found that the opening of new subway stations has led to significant increases in subway usage, trip duration, and trip distance within a 2000-m radius, and that commuting trips have been more affected than home-based non-commuting trips.

Lai[6] investigated the factors influencing housing prices in Beijing using a multiple linear regression model (MLR) and found that subway accessibility positively correlates with housing prices, while increased square footage is negatively associated with price. The paper suggests that smaller homes with better subway access are more valuable. Wang[7] discussed how urban rail transit has influenced China's urban spatial structure and real estate supply, and produced externalities on real estate value. The impact of rail transit on housing prices shows a trend of first increasing and then decreasing, depending on the distance from the subway stations.

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In our study, we combined the Hedonic Price Model (HPM) and Difference in Difference (DiD) method to capture the price changes in the housing market along the new subway line, with particular comparisons between the prior and post-completion period, which will be discussed in more detail in the later sections.

The Beijing Subway started operations in 1969 and is a rapid transit rail network that serves the urban and suburban districts of Beijing. As of 2024, the network has 29 lines, 522 stations, and 879km of track in operation. Beijing's population increased 2.2 million from 19.6 million in 2010 to 21.8 million in 2015, and has been range-bound between 21.5-22.2 million thereafter. As the capital of China with ~3000 years of history and the best education and healthcare resources in the country, the stagnation of its population growth was a result of government intentional control since 2015 and the roll out of the construction plan of the Xiongan city, a completely new city 120 km from Beijing, to help promote regional development, disperse Beijing's non-capital function, and ease the pressure of Beijing.

The average housing price in Beijing was close to RMB 20,000/sqm in 2011, RMB 30,000/sqm in 2015, RMB 40,000/sqm in 2020, and RMB 45,000/sqm in 2024. The period we examined, between 2011 and 2014, was less affected by speculative investments, government-engineered lending crackdowns, or population control. By the end of 2014, the Beijing subway network had 23 lines, 340 stations, and 527 km of track in operation, and was one of the most loaded in the world at 3.4 billion trips per year, averaging 9.3 million per day. The existing network still could not sufficiently meet the city's mass transportation needs, and the government funded expansion planned for a 1/3 of extension in subway track length by 2015 and another 1/3 by 2020.

Beijing Subway Line 6 is a rapid transit rail line connecting the west and the east of the city, running north of and in parallel to Line 1, the oldest subway line in Beijing, to ease the congestion of the latter. Stage I of Line 6 extends between Wuluju Station in Haidian District in the west to the Caofang Station in Tongzhou District in the east, spanning 20 stations and 31km. It officially started operation on December 30, 2012. Stage II extends to the east, further from Caofang station to Lucheng station in Tongzhou District, adding 8 stations and 12km. It officially started operation on December 28, 2014. Stage III extends to the west from Wuluju station to Jinanqiao station in Shijingshan District, adding 6 stations and 10.6km, and started operation on December 30, 2018, while Stage IV extends further to the east to Pinggu District and started operation on December 31, 2021. As of the end of 2024, Line 6 has 35 stations in total and spans 53km. It is one of the key subway lines in Beijing. Six additional lines were built in Beijing after 2014.

The period we examined covers the completion of Stage I and the ramp-up of Stage II. The focus of our research is the causal effect of the completion of a new subway line on economic development. Instead of macro variables such as GDP per capita or GDP, we chose micro factors contributing to house prices as proxies for the impact of government infrastructure investments. There are three main reasons for doing so. First, GDP is an assessment of overall economic output; it cannot reflect in detail the segmented economic development driven by a particular subway line completion. Second, the Tiebout[8] model on local public finance claims that the quality of local public service, including public transportation, is capitalized into the housing prices through households' residential location decisions. Third, the housing prices we use are supported by market data and are more reliable.

Theoretical analysis

Travel costs, as measured by availability and convenience of transport, transportation expenses, and travel time, are the key elements that urban transit affects house prices. R. F. Muth[9] developed a theoretical framework to understand how households maximize their utility given their income and transportation costs. His framework explains the spatial distribution of population and housing within urban areas and shows that the location of a dwelling unit depends on the trade-off between transportation expenses and housing expenses.

W. Bruce Allen's study[10] examines the impact of the New Jersey Transit System on housing prices in the Philadelphia metropolitan area. Using the hedonic pricing model, his study finds that housing prices increase significantly with proximity to transit stations. Specifically, it reveals that for each dollar reduction in transportation expenses, housing values increase by approximately $149 (in 1971 dollars). The increase is attributed to the time savings and convenience provided by the transit system.

So, Tse & Ganesan[11] discovered in their study of the Hong Kong housing market that increased transportation facility enhances access to employment, and help stimulate economic activities through the large stream of people brought by the subway, forming new shopping complexes and offering extra job opportunities. The model includes structural, physical, and environmental attributes, and reveals that the accessibility of public transportation is highly valued by residents and is reflected in higher housing prices.

Another important factor is the location of the dwelling unit in the city, whether it is in the Central Business District (CBD) or a suburban area. Li H, Wei Y, Wu Y, & Tian G[12] examined the spatial variations of housing prices in Shanghai, focusing on the relationship between housing prices and distance to the CBD. The results show that housing prices generally decay with an increase in distance from the CBD. The study also highlights the impact of accessibility and service amenities on housing prices.

Stegman,[13] who researched the construction of a railway in San Francisco on the housing price, found that properties closer to Bay Area Rapid Transit (BART) stations experienced significant increases in value, reflecting the capitalization of reduced travel costs and improved accessibility. Separately, Rena Sitivanidou[14] pointed out that the degree to which the Rail Transit in Los Angeles affects the commercial property value varies from major CBD to minor CBD.

Other mechanisms of the subway's impact on house prices involve commercial speculation and irrational expectations. This is most obvious in the case where housing price experiences an abrupt increase upon the announcement of a new subway line passing through the neighborhood. DeFusco A, Nathanson C, & Zwick E.[15] finds, from 50 million home sales during the last U.S. housing cycle, that cities with larger speculative booms have sharper increases in unsold listings as the market turns, and more severe busts.

Model and Data

Baseline Model:

In our baseline model, we combine the HPM and the DiD method.

Hedonic price analysis is a technique that studies the demand side of housing, assuming that a property is sold as a package of inherent attributes (Rosen[16]). Hedonic prices are, in fact, the implicit valuations of the characteristics of the housing unit, such as quality, location, etc., which influence the market price of the house, and the implicit prices can be estimated by regression analysis. The model is particularly useful in understanding how consumers value different attributes and how these values are reflected in market prices.

The Difference in Difference method is a statistical technique used to evaluate the causal effect of a treatment or intervention by comparing the changes in outcomes over time between a treatment group and a control group. The method involves calculating the difference in outcomes between the treatment and control groups before and after the intervention. The basic idea is to isolate the effect of the treatment by comparing the changes in outcomes for the treatment group relative to the control group.

Based on the hedonic hypothesis, we first pinpoint the characteristics that significantly affect the average house price in a specific community, and then compare the difference in the house prices between the control group and the treatment group, before and after the subway's operation. In the baseline model, the treatment group includes all the communities near the subway station (within 1.5 km), and the control group consists of randomly picked communities, which are far from the subway Line 6 and do not have any newly established subway stations nearby during the time period.

Our baseline model is described as follows:

$$\log(P_{it}) = \beta_0 + \beta_1 Treated_i * Post_t + \beta_2 Post_t + \delta Z_i + \varepsilon_{it}$$

P_{it} is the dependent variable, and the average house price (per square meter) of community i in year t. The key independent variables include: 1) $Treated_i$, the dummy variable for the treatment group: 1 for the communities near the subway station and 0 for those far away and unlikely to be influenced by the subway line. 2) $Post_t$, the dummy for the subway's operation: 1 if later than December 30, 2012, and 0 if earlier. 3) Z_i, a vector of community characteristics attributing to the house price, among which a) Age_{it}, is measured by the years from the establishment of community i to year t; b) Bus_i, is the total number of bus lines within 1 kilometer; c) $CBDDist_i$, is the Euclidean distance from the community to the CBD; d) $Floor_i$ is the average floor numbers; e) D_{1i}, D_{2i}, D_{3i}, D_{4i}, are the dummy for 4 house types, tower-type, slab-type, bungalow and courtyard; f) $School_i$ is the dummy for school district; g) $Trans_i$, is the dummy for transfer station: 1 if the nearest subway station is a transfer station and 0 if not. Lastly, ε_{it} is the error term.

The data employed in this research were obtained from established real estate agent companies and websites. The housing attributes were collected through on-site observations and surveys. The sample size is 422 communities, over 4 years from 2011 to 2014.

The model measures the effect of the completion of the new subway Line 6 on the treated communities. β_1 measures the difference between the controlled group and the treatment group. β_2 measures the common trend of house prices among all the communities during the period; vector δ measures the house characteristics' impact on house prices.

Main caveats:

We highlight two main caveats of our baseline model.

First, the factors we examine are not complete: other hedonic pricing models could also incorporate additional characteristics that are positively correlated with house prices, such as the garage size, parking area, hospitals nearby, etc. As a result, the OLS (Ordinary Least Squares) estimators can be up-biased. However, during the first two decades of the 21st century, particularly in Beijing, location factors were extraordinarily significant in housing prices, and the other living conditions' impacts were subdued. In fact, since the commercial housing reform in 1998 in China, the apartments built during a certain period mostly have similar features and living conditions, thus most of the omitted attributes related to the community's quality can be reflected by the house age. Given that it is impossible to include all the characteristics in our model, we interpret our estimates as the upper-bound effect of the subway on house prices.

Second, the most likely limitation on the Hedonic pricing model is multicollinearity. Multicollinearity refers to a situation where two or more independent variables in a regression model are highly correlated with each other. This can lead to unstable and unreliable estimates of the regression coefficients, distort the estimated implicit prices of housing attributes, and make it difficult to accurately assess the impact. As Butler[17] comments, one is unlikely to find a fourteen-bedroom property with only one bathroom and vice versa! However, whether multicollinearity is an issue in concluding any given data set can only be tested statistically.

Results and Discussion

A. Descriptive Statistics:

Tables 1 and 2 display the descriptive statistics of all the variables used in our empirical analysis, listing the descriptive results of the communities along the subway line (treatment group in the baseline model) and off the subway line (control group), respectively.

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Table 1: Descriptive statistics of key variables (along subway communities). This table presents the summary statistics of the key characteristics of the communities along Beijing subway line 6. House Price 2011-2014 are the average house prices (RMB per square meter) of each community in each year. The distance to Subway is walking distance from the community center to the nearest subway station, measured by Google Maps in meters. Distance to CBD is the Euclidean distance from the community to Beijing's Central Business District (CBD) area measured in kilometers. House Type is a four-indicator variable, equal to one if the main building type of the community is tower, slab, bungalow, or courtyard, respectively, and zero if otherwise. Year of Build is the year when the community was built. Floor Number is the average number of floors across all the buildings in the community. The sample includes all communities along subway line 6 provided by the real estate agent companies. The data span from 2011 to 2014.

Variable	Obs	Mean	Std. Dev.	Min	Max
House Price 2011 (RMB/sqm)	170	28447	8548	10406	51786
House Price 2012 (RMB/sqm)	338	32021	10306	12145	64652
House Price 2013 (RMB/sqm)	354	42635	13230	15808	89277
House Price 2014 (RMB/sqm)	340	43719	12103	19687	98039
Distance to Subway (m)	420	755	316	4	1626
Distance to CBD (km)	422	10.5	4.6	3.5	23.8
House Type					
Dummy1 for Tower-type	421	0.22	0.41	0	1
Dummy2 for Slab-type	419	0.47	0.50	0	1
Dummy3 for Bungalow	421	0.02	0.14	0	1
Dummy4 for Courtyard	421	0.01	0.10	0	1
Year of Build	421	1995	10	1960	2014
Floor Number	421	13	8	0	57
Dummy for School District	421	0.32	0.47	0	1
Number of Bus Lines	422	18	7	5	29
Dummy for Transfer Station	422	0.54	0.50	0	1

As shown in the exhibits, the average housing prices kept rising for both groups, but the treatment group's price rose faster. The average house price of the control group in Table 2 rose by 5.2%, 10.3%, and 9.6% in 2012, 2013, and 2014, respectively. It is in line with the common trend of house prices in Beijing. However, the treatment group's price in Table 1 rose sharply from 2012 to 2013, specifically 33.1%, as the subway began to operate on December 30, 2012. This timing aligns closely with the theoretical expectation outlined in our analysis. The housing price growth rate in the treatment group slowed down dramatically from 2013 to 2014, to approximately 2.5%, even slower than the common trend. It is probably due to buyers' overreaction in the previous year, so there likely exists a mean reversion process.

Table 2: Descriptive statistics of key variables (off subway communities). This table presents the summary statistics of the key characteristics of the communities in the control group, which are located off the subway line 6. Variable definitions are the same as Table 1.

Variable	Obs	Mean	Std. Dev.	Min	Max
House Price 2011 (RMB/sqm)	20	23682	5425	15040	38745
House Price 2012 (RMB/sqm)	20	24917	4540	18498	36485
House Price 2013 (RMB/sqm)	20	27491	5201	17640	38485
House Price 2014 (RMB/sqm)	20	30134	5534	20192	46582
Distance to CBD (km)	20	12.7	3.8	7.7	21.8
House Type					
Dummyl for Tower-type	20	0.20	0.41	0	1
Dummy2 for Slab-type	20	0.25	0.44	0	1
Dummy3 for Bungalow	20	0.00	0.00	0	0
Dummy4 for Courtyard	20	0.00	0.00	0	0
Year of Build	20	1998	6	1980	2007
Floor Number	20	18	5	6	25
Dummy for School District	20	0.45	0.51	0	1
Number of Bus Lines	20	27	15	6	68
Dummy for Transfer Station	20	0	0	0	0

B. Pulling Effect on House Prices:

The "pulling effect" of subways on urban housing prices refers to the phenomenon where the construction and operation of subway lines significantly increase the market value of nearby residential properties. This effect is driven by several key factors, including improved accessibility, reduced commuting costs, and enhanced neighborhood desirability. We first examine the completion of Line 6's impact on average house prices. Table 3 shows the time series regression result of our baseline model.

As shown in Table 3, columns 1-3, we apply the model using the data of 2012 and 2013, 2011 and 2014, and 2011-2014, respectively, to balance between the pre-treatment and post-treatment periods. Not surprisingly, we find positive and significant (1% level) coefficients of the Post*Treated term, which indicates that the completion of the new subway line causes the house price to go up by 40.1% from 2012 to 2013, and 34.2% from 2011 to 2014. The immediate price jump was mainly due to buyers' irrational expectations and herding behavior, while the milder long-run appreciation mainly resulted from the improved convenience.

From the hedonic pricing model statistics, we conclude that, when determining the house prices, all the following characteristics play a significantly important role: distance to CBD, house age, whether in a school district, whether near a transfer station, floor number, and the number of bus lines around. With regard to the house type, whether it is tower-type, slab-type, or bungalow, does not matter, but given all other factors are the same, courtyard houses have significantly higher prices (around 70% higher).

Table 3: OLS estimation of the completion of the new subway on housing prices based on time series. We find positive and significant (1% level) coefficients of the Post*Treated term, which indicates that the completion of the new subway line causes the house price to go up by 40.1% from 2012 to 2013, and 34.2% from 2011 to 2014.

Dependent Variable	Log (Average House Price)		
Sample:	All Communities; Year: 2011-2014		
Years Selected	2012, 2013	2011, 2014	2011-2014
	(1)	(2)	(3)
Post*Treated	0.401***	0.342***	0.367***
	(0.0608)	(0.0524)	(0.0410)
Post	-0.100	0.105**	-0.010
	(0.0605)	(0.0527)	(0.0409)
Distance to CBD	-0.0333***	-0.0289***	-0.0317***
	(0.0027)	(0.0027)	(0.0020)
Age	-0.00390***	-0.00475***	-0.00397***
	(0.0013)	(0.0013)	(0.0009)
House Type			
Dummyl for Tower-type	-0.04	-0.01	-0.03
	(0.0281)	(0.0282)	(0.0203)
Dummy2 for Slab-type	0.03	0.02	0.02
	(0.0253)	(0.0246)	(0.0180)
Dummy3 for Bungalow	0.21	0.15	0.2
	(0.1820)	(0.2170)	(0.1400)
Dummy4 for Courtyard	0.631**	0.711***	0.665***
	(0.2550)	(0.2160)	(0.1710)
Floor Number	-0.00324**	-0.00329**	-0.00311***
	(0.0015)	(0.0016)	(0.0011)
Dummy for School District	0.222***	0.206***	0.213***
	(0.0213)	(0.0206)	(0.0151)
Number of Buses	0.00798***	0.00639***	0.00699***
	(0.0014)	(0.0014)	(0.0010)
Dummy for Transfer Station	0.0511**	0.0481**	0.0516***
	(0.0223)	(0.0222)	(0.0160)
Constant	10.53***	10.43***	10.50***
	(0.0626)	(0.0623)	(0.0450)
Observations	731	548	1279
R-squared	0.545	0.663	0.584

Notes: Standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1

Number of Bus Lines	0.00979*** (0.0012)	0.00980*** (0.0012)	0.00975*** (0.0012)	0.00970*** (0.0012)	0.00972*** (0.0012)
Dummy for Transfer Station	0.0345*** (0.0124)	0.0349*** (0.0124)	0.0349*** (0.0124)	0.0353*** (0.0124)	0.0350*** (0.0124)
Constant	10.45*** (0.0466)	10.45*** (0.0466)	10.46*** (0.0467)	10.46*** (0.0466)	10.46*** (0.0466)
Observations	1199	1199	1199	1199	1199
R-squared	0.593	0.593	0.593	0.593	0.593

Notes: Standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1

C. Clustering Effect vs. Spillover Effect:

The clustering effect of urban rail transit refers to the tendency of economic activities, population, and development to concentrate around rail transit stations. The spillover effect of urban rail transit refers to the unintended consequences or impacts that the URT system has on surrounding areas, including land use, economic activity, and environmental conditions. These effects can be both positive and negative, influencing property values, urban development, and overall economic growth.

The common assumption is that the completion of a new subway line can mostly affect the house price of the communities within the walkable distance (0.8 km) of the subway stations, because most people in the nearby communities tend to walk to the stations instead of driving there, while people owning private cars are unlikely to take the subway. People could also take buses to the subway stations, but those taking buses would then not live within 1.5 km of the stations.

As the supporter of this perspective, Heenan[18] investigated the clustering effect of urban rail transit, stating that as the distance increases, the houses beyond the walkable range may even experience a price decline, because buyers prefer houses within walkable distance, and the demand for outer houses will drop. The study discusses how rapid transit systems can lead to more efficient urban growth patterns and encourages development in areas with easy access to transit. Empirically, Cockerill and Stanley[19] confirmed Heenan's theory that the urban rail transits only have a significant influence on the price of the houses within 0.8 km of the stations.

Table 4: OLS estimation of clustering/spillover effect based on distance to subway station. The Post terms indicating the common trend are all significant at the 1% level, which implies that the completion of the new subway line has a very positive spillover effect on many nearby communities, even beyond the walkable distance.

Dependent Variable	**Log (Average House Price)**				
Sample:	Communities along the subway line; Year: 2011-2014				
Distance to Subway Station	0-200	0-400	0-600	0-800	0-1000
	(1)	(2)	(3)	(4)	(5)
Post*Treated200	0.0237 (0.0443)				
Post*Treated400		0.022 (0.0227)			
Post*Treated600			0.0095 (0.0194)		
Post*Treated800				-0.0095 (0.0183)	
Post*Treated1000					-0.0074 (0.0214)
Post	0.340*** (0.0141)	0.337*** (0.0146)	0.338*** (0.0153)	0.347*** (0.0171)	0.347*** (0.0215)
Distance to CBD	-0.0312*** (0.0019)	-0.0312*** (0.0019)	-0.0312*** (0.0019)	-0.0311*** (0.0019)	-0.0312*** (0.0019)
Age	-0.00401*** (0.0009)	-0.00398*** (0.0009)	-0.00397*** (0.0009)	-0.00401*** (0.0009)	-0.00401*** (0.0009)
House Type					
Dummyl for Tower-type	-0.034 (0.0211)	-0.0336 (0.0211)	-0.0334 (0.0211)	-0.0348 (0.0212)	-0.0343 (0.0211)
Dummy2 for Slab-type	0.0269 (0.0189)	0.0269 (0.0189)	0.0268 (0.0189)	0.0262 (0.0189)	0.0266 (0.0189)
Dummy3 for Bungalow	0.239* (0.1390)	0.234* (0.1390)	0.237* (0.1390)	0.240* (0.1390)	0.239* (0.1390)
Dummy4 for Courtyard	0.705*** (0.1690)	0.708*** (0.1690)	0.707*** (0.1690)	0.698*** (0.1700)	0.698*** (0.1700)
Floor Number	-0.00263** (0.0011)	-0.00261** (0.0011)	-0.00261** (0.0011)	-0.00262** (0.0011)	-0.00260** (0.0012)
Dummy for School District	0.217*** (0.0155)	0.217*** (0.0155)	0.217*** (0.0155)	0.216*** (0.0155)	0.216*** (0.0155)

For this particular analysis, we apply a discrete treatment method to the communities along the new subway line and use the baseline model again. The treatment groups are <200m, <400m, <600m, <800m, and <1000m, respectively, in Table 4, columns 1-5. We try to examine the difference in price change between the treatment group and the control group. However, our empirical results contrast with the common-sense clustering effect.

The Post*Treated term in these five regression results is not statistically significant, which means there is not much difference in the price change between the walkable and non-walkable distances. The Post terms indicating the common trend, however, are all significant at the 1% level, which implies that the completion of the new subway line has a very positive spillover effect on many nearby communities, even beyond the walkable distance. The spillover effect may come from the increased productivity and the prosperity of commerce in the communities.

D. Distance to CBD and Decentralization Effect:

We also examine the completion of the new subway line in urban areas, semi-urban areas, and suburban areas, defined by their distance to the Central Business District. In particular, in columns 1-5 of Table 5, we run the regression for the communities whose distances to the CBD are: <5km, 5-10km, 10-15km, 15-20km, and >20km, respectively.

Table 5: OLS estimation of the completion of the subway line's effect on house prices based on distance to the CBD. In urban areas (< 5km to CBD), the completion of a new subway line's pulling effect on house prices is the lowest (19.3%). In a semi-urban area (5-15km to CBD), the effect is most significant (42.1% for 5-10 km and 34.8% for 10-15 km). In a suburban area (>15 km), the effect falls again (20.4% for 15-20 km and 17.1% for >20 km).

Dependent Variable	**Log (Average House Price)**				
Sample:	Communities along the subway line; Year: 2011-2014				
Distance to CBD	<5km	5km-10km	10km-15km	15km-20km	>20km
	(1)	(2)	(3)	(4)	(5)
Post*Treated	0.193*** (0.0555)	0.421*** (0.0423)	0.348*** (0.0451)	0.204*** (0.0452)	0.171*** (0.0580)
Post	0.340*** (0.0141)	-0.0319 (0.0404)	0.0088 (0.0435)	0.175*** (0.0410)	0.192*** (0.0420)
Distance to CBD	-0.0138** (0.0060)	-0.0218*** (0.0042)	0.0116* (0.0067)	0.0045 (0.0061)	-0.0246*** (0.0060)
Age	0.0147*** (0.0031)	-0.00432*** (0.0011)	-0.0003 (0.0017)	-0.0115*** (0.0024)	-0.0029 (0.0036)
House Type					
Dummyl for Tower-type	-0.0051 (0.0495)	0.0528** (0.0264)	-0.0452 (0.0309)	-0.0760* (0.0420)	-0.0122 (0.0556)
Dummy2 for Slab-type	0.146*** (0.0355)	0.121*** (0.0225)	0.0028 (0.0313)	-0.0624** (0.0306)	0.053 (0.0489)
Dummy3 for Bungalow	0.415*** (0.1030)				
Dummy4 for Courtyard	0.730*** (0.1190)				
Floor Number	0.0169*** (0.0039)	0.0011 (0.0014)	-0.00395** (0.0019)	-0.0149*** (0.0026)	0.0158*** (0.0038)
Dummy for School District	0.0317 (0.0333)	0.160*** (0.0186)	0.223*** (0.0272)	0.0748*** (0.0280)	0.128*** (0.0394)

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Number of Bus Lines	-0.00460** (0.0021)	-0.0001 (0.0013)	0.0005 (0.0017)	0.0158*** (0.0013)	0.0003 (0.0023)
Dummy for Transfer Station	0.307*** (0.0827)	0.0298 (0.0197)	0.0384 (0.0264)	0.416*** (0.0391)	
Constant	9.817*** (0.1140)	10.50*** (0.0620)	10.07*** (0.1070)	10.05*** (0.1240)	10.05*** (0.1380)
Observations	135	565	446	276	148
R-squared	0.862	0.573	0.445	0.658	0.601

Notes: Standard errors in parentheses ***p<0.01,**p<0.05,*p<0.1

As shown in Table 5, in urban areas (< 5km to CBD), the completion of a new subway line's pulling effect on house prices is the lowest (19.3%). In a semi-urban area (5-15km to CBD), the effect is most significant (42.1% for 5-10 km and 34.8% for 10-15 km). In a suburban area (>15 km), the effect falls again (20.4% for 15-20 km and 17.1% for >20 km).

For urban areas, the transportation system, as well as other value-added amenities, is already well developed; thus, adding a new subway line does not have much impact. For suburb, residents' purchasing power is lower, and buyers' expectations for price appreciation are modest. In a semi-urban area, wage earners' residential density is extremely high. As such, people's demand for a cheap and convenient transportation system is correspondingly high. Thus, the completion of a new subway line has the most significant spillover effect on semi-urban areas.

Robustness Test

First, we pointed out earlier that multicollinearity is an unavoidable common problem in the hedonic pricing model. We test for collinearity of our model using the variance inflation factor (VIF) method, which measures how much the variance of an estimated regression coefficient is increased due to multicollinearity. A VIF value greater than 10 is generally considered indicative of a multicollinearity problem. Table 6 shows the test result of VIF, a range from 1.02 to 1.9 (less than 10), which suggests that multicollinearity is not a significant issue in our case.

Table 6: Multicollinearity test - VIF method. This table examines whether the variables used in the regression analysis exhibit multicollinearity using the Variance Inflation Factor (VIF) test. The VIF of each variable is equal to the inverse of (1 - R-squared), where R-squared is the coefficient of determination when regressing the variable on all other variables. A VIF value of 1 demonstrates no multicollinearity, above 5 or 10 suggests a multicollinearity problem that leads to unreliable regression output. A range from 1.02 to 1.90 suggests that multicollinearity is not a significant issue in our case.

Variable	VIF	1/VIF
Post	1.02	0.9843
Distance to Nearest Subway Station	1.03	0.9678
Distance to CBD	1.84	0.5421
Age	1.66	0.6015
Dummyl for Tower-type	1.68	0.5949
Dummy2 for Slab-type	1.90	0.5256
Dummy3 for Bungalow	1.04	0.9596
Dummy4 for Courtyard	1.03	0.9732
Floor Number	1.69	0.5906
Dummy for School District	1.19	0.8394
Number of Buses	1.34	0.7457
Dummy for Transfer Station	1.42	0.7029

Mean VIF: 1.4

Next, we conduct a homoscedasticity check of our model using the Cook-Weisberg test. Homoscedasticity is an assumption in linear regression models that the variance of the error terms is constant across all levels of the independent variables. This assumption is crucial for the validity and reliability of regression analysis. Violations of homoscedasticity, known as heteroscedasticity, can lead to biased standard errors and unreliable statistical inferences. The Cook-Weisberg test is a statistical test used to detect heteroscedasticity in a linear regression model. The results show that our regressions are all heteroscedastic.

We repeated our regressions using the White[20] heteroscedasticity correction, with the results shown in Table 7. The White heteroscedasticity correction is a method used to adjust the standard errors of the regression coefficients in the presence of heteroscedasticity. This correction ensures that the standard errors are robust to the presence of non-constant variance in the error terms, thereby providing more reliable statistical inferences. By comparing Table 3 and Table 7, we can draw similar conclusions. Therefore, despite the heteroscedasticity, the analysis results still hold.

Table 7: Heteroscedasticity correction. This table presents the same regression output as in Table 3 but relaxes the homoskedasticity assumption. To address the fact that residual terms in the regression are potentially heterogeneous across communities, we use the heteroskedasticity-robust standard errors developed by White to test the statistical significance of regression coefficients. The standard errors are reported in parentheses. ***p<0.01, **p<0.05, *p<0.1. By comparing Table 3 and Table 7, we can draw similar conclusions. Therefore, despite the heteroscedasticity, the analysis results still hold.

Dependent Variable	**Log (Average House Price)**		
Sample:	All Communities; Year: 2011-2014		
Years Selected	2012, 2013	2011, 2014	2011-2014
	(1)	(2)	(3)
Post*Treated	0.401*** (0.0500)	0.342*** (0.0445)	0.367*** (0.0345)
Post	-0.0980* (0.0506)	0.105** (0.0462)	-0.010 (0.0353)
Distance to CBD	-0.0333*** (0.0026)	-0.0289*** (0.0026)	-0.0317*** (0.0019)
Age	-0.00390*** (0.0013)	-0.00475*** (0.0013)	-0.00397*** (0.0009)
House Type			
Dummyl for Tower-type	-0.036 (0.0293)	-0.009 (0.0288)	-0.027 (0.0211)
Dummy2 for Slab-type	0.028 (0.0261)	0.020 (0.0248)	0.024 (0.0185)
Dummy3 for Bungalow	0.214 (0.2550)	0.153*** (0.0410)	0.204 (0.1580)
Dummy4 for Courtyard	0.631*** (0.0381)	0.711*** (0.0367)	0.665*** (0.0439)
Floor Number	-0.00324* (0.0019)	-0.003 (0.0020)	-0.00311** (0.0014)
Dummy for School District	0.222*** (0.0215)	0.206*** (0.0206)	0.213*** (0.0152)
Number of Buses	0.00798*** (0.0017)	0.00639*** (0.0016)	0.00699*** (0.0012)
Dummy for Transfer Station	0.0511** (0.0229)	0.0481** (0.0228)	0.0516*** (0.0165)
Constant	10.53*** (0.0592)	10.43*** (0.0589)	10.50*** (0.0427)
Observations	731	548	1279
R-squared	0.545	0.663	0.584

Notes: Standard errors in parentheses ***p<0.01,**p<0.05,*p<0.1

Conclusion and Policy Implications

Our regression analysis results show that the completion of the new subway Line 6 has a very significant pulling effect on the communities along its route. In addition, the pulling effect is approximately the same within 1.5 km, no matter whether the community is located within walking distance (0.8 km) or not, which is contrary to the clustering effect and implies the subway station's high spillover effect. Lastly, the completion of a subway line has the most significant impact on the housing prices in the semi-urban areas.

With regard to policy implications, we summarize some previous studies below for reference.

On planning and financing urban transit investment, Ma, Ye & Titheridge[21] find that properties near rail transit stations command a price premium of around 5%, with this effect being more pronounced in suburban and low-to-middle-income areas, where premiums can reach up to 10%. The study concludes that rail transit investment can effectively reshape urban spatial structures and suggests that a "rail + property development" model could be a viable financing solution for rail transit projects in China.

In addition, Yang's findings[22] reveal the significantly positive effect of improved transport accessibility on property prices, with notable variations across different cities and transport modes. The research highlights the importance of integrating environment-friendly transport into urban planning to enhance property values and promote sustainable urban development. It also suggests that value capture schemes can be effective in financing urban infrastructure investments.

On the relationship between urban planning and transportation infrastructure development, Pan & Li's study[23] underscores the role of urban spatial structure in determining property values, suggesting that areas with better connectivity and infrastructure tend to have higher property prices. The results highlight the importance of integrating urban planning and transportation infrastructure development to enhance property values and promote sustainable urban growth.

Yang, Chen, Xu, Zhao, Chau & Hong's study[24] indicates that the impact of rail transit on property prices is not uniform across the city, with some areas experiencing more significant price increases than others. This spatial heterogeneity suggests that urban planning and value capture strategies should consider local context and characteristics to maximize the benefits of rail transit investments. The study underscores the need for tailored approaches to urban development and transit planning.

Similarly, Costa, Sonnenschein & Zheng's study[25] examines the effects of subway expansions on the geographic concentration of consumer amenities in four global cities. It highlights that subway expansions can exacerbate spatial disparities within cities, as some areas may experience significant benefits while others see little to no improvement. It underscores the importance of considering spatial heterogeneity in urban planning and transit development to ensure equitable distribution of opportunities.

Lastly, in terms of technical suggestions, Li & Huang's findings[26] confirm that rail transit accessibility positively impacts housing prices, with a higher premium observed in areas with more mixed land uses. They suggest that transit-oriented development (TOD) strategies can effectively enhance property values by improving transit accessibility and promoting mixed-use development. The study also provides policy recommendations for TOD planning and land value capture near transit stations.

Hu's research,[27] on the other hand, finds that proximity to rail transit stations generally increases housing prices and reduces dwelling sizes, particularly in suburban areas. This suggests that rail transit investments can influence urban spatial structures by encouraging denser development near stations. The findings highlight the importance of government policies in promoting small-sized and affordable housing around suburban stations to maximize the benefits of rail transit investments.

According to the Tiebout model, the level of public goods provision is capitalized into the house prices. With budget constraints, urban planners aim to maximize social welfare, and house price is an effective indicator of the impact of public transit spending. Our empirical findings suggest that the subway network in Beijing could be more decentralized. Instead of too many subway lines crossing the downtown, building more subway lines leading to the semi-urban centers will have the most effective outcome. Our findings have significant implications for urban planning decisions in other fast-expanding metropolitan areas.

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