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The Impact of Subway Network Expansion on Housing Rents: An Empirical Study in Beijing, China

MA Xin* and HUANG Tao†
Guanghua School of Management, Peking University
Beijing 100871, China
**m.x@pku.edu.cn*
†*huangt@gsm.pku.edu.cn*

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Most previous studies have focused on the impact of subways on housing prices instead of rents, while the latter could better measure residential values. Based on a dataset collected from a real estate agency in Beijing, which contains more than 900,000 housing rental transaction records from 2011 to 2020, this paper empirically evaluates the causal effect of subway network expansion on housing rents. It employs a series of progressive difference-in-difference (DID) approaches, to estimate the impact and determine the impact scope. The findings demonstrate that a reduction of the distance to subway stations by 1 km increases the rents by 2.32%; the impact scope is about 1.5 km and the average rent appreciation within the range is 5%. The addition of a line for non-transfer stations raises the rents by 10% for houses 1.5–2 km away from the stations, extending the impact scope. Houses with large areas in upscale and old neighborhoods near the city center are affected less by subways. It also confirms the siphon effect in the rental market, i.e.: rents of houses far away from the new stations fall after the opening of the stations.

Keywords: Subway; housing rents; difference-in-difference; influence range; siphon effect.

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1. Introduction

Urban rail transit is one of the most important public transportation facilities and the first choice of commuting for many residents. After entering the 21st century, China's rail transit construction has experienced a blowout growth. From 2000 to 2019, the number of cities that have built rail transit has increased from 4 to 41; the length of built rail transit lines has increased from 117 km to 6,058.9 km; and another 5,594.1 km is under construction.

*Corresponding author.

Many cities have built their first subway, ushering in the "subway era", while Beijing, Shanghai, and other cities have expanded their original subway network by adding lines and stations. Taking Beijing as an example, by the end of 2020, 428 stations and 24 lines with a total mileage of 727 km have been built, of which 10 lines were newly built and nine lines have been extended since 2011.[1]

As a public resource to significantly improve the traveling convenience of residents, the subway system can effectively improve residential values of houses near stations by improving the punctuality rate and reducing transportation time, thus creating network externality. There are many studies on the spillover effect of rail transit on housing prices from the perspective of capitalization of accessibility, such as Bajic (1983), Baum-Snow and Kahn (2000), Cervero and Duncan (2002), McMillen and McDonald (2004), Sun *et al.* (2015, 2016), Wang (2017), Im and Hong (2018), Wen *et al.* (2018), Lee *et al.* (2018), Tan *et al.* (2019), and Tian *et al.* (2020). However, housing price often deviates from residential value as it contains residents' expectation, speculation, and other factors (Clayton, 1997; Levin and Wright, 1997; Malpezzi and Wachter, 2005) due to the investment attribute. Whether there is a bubble in Beijing's housing price is still doubtful (Li and Chand, 2013; Feng and Wu, 2015). Therefore, the increase in housing prices is not a good measure of the improvement of residential values. By comparison, we argue that housing rent is a better indicator of residential value especially under the context of studying the impact of subways, mainly because of the following reasons. (1) Compared with the housing market, the turnover of the rental market is larger. Taking 2018 as an example, the number of transactions of stocking housing market in Beijing was 148,000, and that of the new housing market was 48,000, while the total number of transactions of the housing rental market was 2.54 million, about 13 times of the sales markets. (2) As a non-negligible part of the citizens, renters are more dependent on the subway system because a high proportion of them take subways as one of the most important commuting choices. According to the sixth population census of China, about 37.2% of the urban residents in Beijing solved the housing problem through renting in 2010. And a 2016 survey showed that the average age of renters in Beijing is less than 27 years old, and monthly income is mostly below 5,000 yuan (about $753 at the exchange rate of 2016). It is easy to infer that the proportion of renters who choose to travel by public transportation is far higher than that of residents living in their own houses, implying that the subway system has a greater impact on the renters. (3) The rental market is more rational because of the low entry threshold and transaction cost and high replaceability. Rental prices can better reflect real residential values as renters have richer choices and fewer factors to be considered when making decisions.

Most relevant studies focus on the influence of subways on housing prices and rarely consider the impact on residential values; moreover, there are some shortcomings in the contents and methods of previous studies. (1) Previous studies on the impact of subways on housing values mostly depend on the artificial setting of influence radius, on which the literature has yet not reached a consensus. For example, Gu and Zheng (2010) and

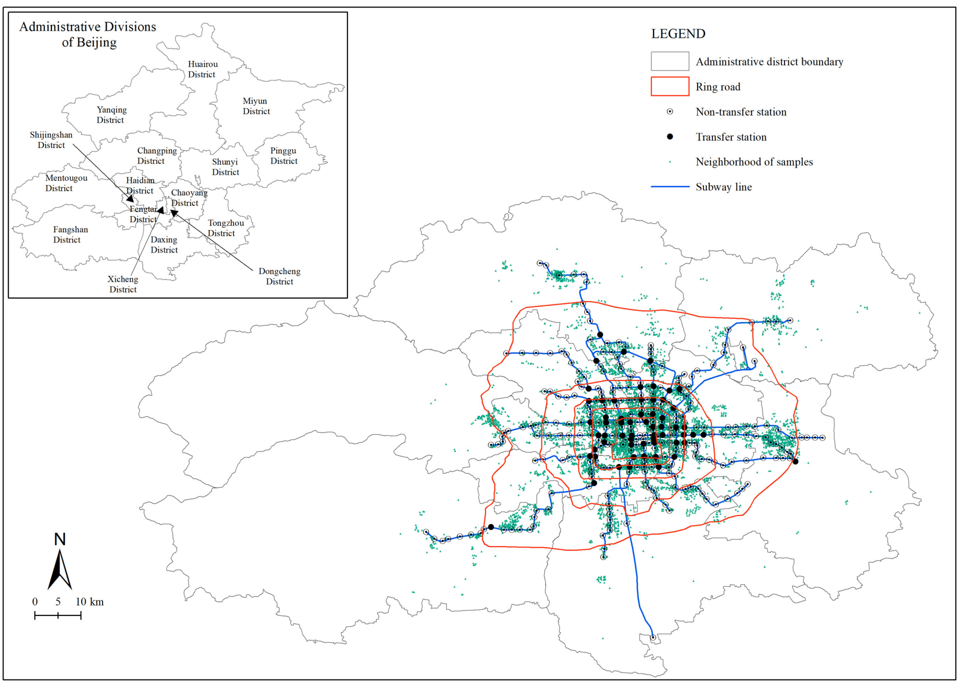
[1] The data were calculated by us according to the information on the official website of Beijing Subway.

Tian *et al.* (2020) had set the influence radius to 1 km; Wang Lin (2009) had set the radius to 1.5 km; Wen *et al.* (2018) had set the radius to 2 km; and Zhang *et al.* (2014) showed that the influence radii of Beijing Subway and light rail are 1,600 m and 800 m, respectively. In addition, the recent researches show that the impact of subway on housing value depends on urban structure (Zhang *et al.*, 2019) and infrastructure represented by bike sharing (Chu *et al.*, 2021). Thus, it is of great necessity to measure the impact on housing value and identify the impact scope. (2) Many works in the literature regard houses within the influence radius of subway stations as being affected by subway, and other houses as not being affected, and usually employ a difference-in-difference (DID) method taking some "not affected" houses as the control group to identify the impact (Gu and Zheng, 2010; Im and Hong, 2018; Tian *et al.*, 2020). But recent research shows that housing prices far away from the newly constructed subway stations are negatively affected by the announcement of the subway planning, i.e. the impact of subways on housing prices contains a siphon effect in addition to the spillover effect (Fan *et al.*, 2018). This means the studies based on the traditional DID method which takes houses beyond the influence radius of stations but within a certain range as the control group may overestimate the impact, since the control group is negatively affected. (3) Some of the previous literature take the announcement of subway planning as the time point of event study (McDonald and Osuji, 1995; Fan *et al.*, 2018), while others take the opening of subway stations as the time point (Lin and Hwang, 2004; Wen *et al.*, 2018; Tian *et al.*, 2020), and it is not clear which one is appropriate for analyzing the impact on housing rents. Most literature support the existence of the announcement effect, such as Agostini and Palmucci (2008) and Loomis *et al.* (2012), which point out that the capitalization of benefits of proximity to rail transit in the construction stage is different from that of the operation stage. The announcement effect on housing prices is mainly because the market has formed expectations after the announcement of subway planning, which are reflected in transaction prices and form the anticipated capitalization effect, even if the actual benefit has not reached that moment. But it is not clear whether this announcement effect also holds in housing rental market since we cannot answer it theoretically. Renters only enjoy residential value but not investment value of housing, which means they benefit from the proximity to the subway system but not from the housing price appreciation due to the capitalization. Only after the corresponding subway stations come into operation, renters benefit from it and are willing to pay more rents. However, some research suggests that there exists a transmission mechanism from house price to rent, i.e. high price causes high rent because landlords take the initiative to raise rents (Hirota *et al.*, 2020).

In this context, it is of great significance to study the impact of subway network expansion on housing rents with empirical evidence. This paper focuses on the following issues: What influences will the building of subway stations and the addition of a line to non-transfer stations have on adjacent housing rents? Does the announcement of subway planning affect housing rents? Does the siphon effect found in the housing market (Fan *et al.*, 2018) also exist in the rental market? The paper answers these questions using data of 934,000 housing rental records in Beijing over the past decade. Compared with existing literature, the marginal contribution of this paper is mainly reflected in four aspects. First, based on the detailed historical transaction data, the paper systematically measures the influence of expanding subway network on housing rents and enriches literature on the impact of public transportation on housing values. Second, the paper identifies the influence range of subway stations on housing rent and confirms this conclusion through several tests. Third, the results show that the opening of subway stations is more suitable for analyzing the rent appreciation than the announcement of subway planning. In addition, the results also partially verify the transmission mechanism of housing price to rent. Finally, the findings support the existence of the siphon effect in the housing rental market, which is an important factor to consider when choosing empirical identification strategies for future studies.

2. Data

The study uses a housing rental transaction dataset collected from a leading real estate agency in Beijing for analysis, which contains more than 934,000 transaction records from January 2011 to November 2020. Besides the transaction date and price, other attributes of the houses are also recorded in every observation, including house area, configuration of rooms, floor, total floors of the building, and neighborhood name. To avoid the influence of extreme outliers, a winsorization at the 2nd and 98th percentiles is employed and a total of 896,618 valid observations are retained. Taking the names as keywords, the neighborhood



Source: Made by the authors.

Fig. 1. The spatial distribution of the sample houses.

information recorded in observations is matched from another dataset, including the total number of buildings, the construction year, property costs, longitude, latitude, etc. According to the observations' coordinates and transaction date, and the opening dates of subway stations, the nearest subway station to the house at the time of transaction is matched, and the time-varying distance between each house and the nearest subway station can be obtained. Thus, the number of changes in the nearest subway station can be calculated accordingly. As shown in Fig. 1, sample houses are mainly distributed within the sixth ring road, most of them are along the subway lines.

Table 1 summarizes descriptive statistics of the key variables used in the subsequent regressions. The average rent per unit area of each year is displayed separately to show the time trend. From 2011 to 2016, Beijing's average rent rose rapidly, from 58.75 yuan/m^2/month to 110.59 yuan/m^2/month, nearly doubling. But it gradually fell since 2017 and reached a level of 86.28 yuan/m^2/month by 2020. Averagely, the sample area is 66.85 m^2, with a total of 14.28 floors, 1.97 bedrooms, and 1.02 living and dining rooms. Low-floor, medium-floor and high-floor houses account for 29.4%, 38.6%, and 32%, respectively. Of all the transaction records, 15.8% are from a branded rental apartment while the rest are from private landlords. The average distance to the nearest subway station is 1.045 km.

Table 1. Descriptive statistics of key variables.

Variable	Description	Count	Mean	SD	Min	Max
ln(rent)	Log of rent (yuan/m^2/month)	896,618	4.383	0.479	3.303	5.597
rent_2011	Rent in 2011 (yuan/m^2/month)	15,499	58.746	25.936	27.206	269.231
rent_2012	Rent in 2012 (yuan/m^2/month)	54,476	60.593	24.159	27.206	267.666
rent_2013	Rent in 2013 (yuan/m^2/month)	66,890	65.454	25.945	27.206	269.327
rent_2014	Rent in 2014 (yuan/m^2/month)	84,983	67.746	28.445	27.206	269.412
rent_2015	Rent in 2015 (yuan/m^2/month)	16,574	87.315	52.337	27.218	269.474
rent_2016	Rent in 2016 (yuan/m^2/month)	144,281	110.587	57.568	27.206	269.565
rent_2017	Rent in 2017 (yuan/m^2/month)	170,582	103.369	53.117	27.206	269.524
rent_2018	Rent in 2018 (yuan/m^2/month)	105,867	98.205	43.406	27.205	269.524
rent_2019	Rent in 2019 (yuan/m^2/month)	112,589	89.208	34.454	27.220	269.411
rent_2020	Rent in 2020 (yuan/m^2/month)	124,877	86.277	32.361	27.216	268.182
Size	Floor space (m^2)	896,618	66.847	35.505	8.240	186.920
Floors	Total number of floors of the building	896,618	14.284	7.958	1	63
Middle	Dummy, 1 if on the middle floor	896,618	0.386	0.487	0	1
High	Dummy, 1 if on the high floor	896,618	0.320	0.467	0	1
Bedrooms	Number of bedrooms	896,618	1.972	0.887	1	5
LvDnRooms	Number of living and dining rooms	896,618	1.017	0.435	0	3
Branded	Dummy, 1 if a branded rental apartment	896,618	0.158	0.364	0	1
PropMgtFee	Property management fee (yuan/m^2/month)	847,033	2.186	2.192	0.010	76.450
YrBuilt	Year built of the neighborhood	890,701	1996.577	14.332	1900	2020
Buildings	Number of buildings	891,298	18	19.320	1	600
DistCenter	Distance to the city center (km)	883,401	12.897	7.441	0.457	41.918
Distance	Distance to the nearest station (km)	883,401	1.0449	0.974	0.0374	10.998
StaCgNum	Number of changes in the nearest station	883,401	0.622	0.706	0	4

Source: Summarized by the authors; collected from a leading real estate agency in Beijing.

Table 2. Routes and stations opened in Beijing from 2011 to 2019.

Date	Lines (stations) opened on the date	Number of stations opened
2011/11/31	North section of the 2nd phase of Line 8; South section of Line 9; East section of the 1st phase of Line15	17
2012/10/12	Transfer station (Fengtai Dongdajie)	1
2012/12/30	1st phase of Line 6; North section of Line 9; 2nd phase of Line 10. Transfer stations (Anhua Qiao, Gulou Dajie)	32
2013/5/5	Line 10 stations (Niwa, Jiaomen Dong); West section of Line 14; Transfer station (Fengtai Railway Station)	8
2013/12/28	The part connecting Changping of Line 8	4
2014/12/28	2nd phase of Line 6; 1st phase of Line 7; East section of Line 14; West section of 1st phase of Line 15	41
2015/12/26	Line 8 stations (Andeli Beijie); Changping Line; Transfer station (Datunlu Dong)	6
2016/12/31	Line 14 station (Chaoyang Park); Line 15 station (Wangjing Dong); Line 16	10
2017/12/30	Line 16 station (Nongda Nanlu); Line S1; Yanfang Line; Xijiao Line	21
2018/12/30	West extending section of Line 6; Line 6 station (Beiyunhe Dong); Line 7 station (Fatou). South section of 3rd phase of Line 8; 4th phase of Line 8; Yizhuang Line station (Yizhuang Railway Station)	21
2019/9/26	Daxing International Airport Express	2
2019/12/28	2nd phase of Line 7; Transfer station (Shuangjing)	9
2019/12/30	Line 13 station (Qinghe)	1

Source: Collected by the authors.

The average number of changes in the nearest subway station is 0.62, and the maximum is 4, which shows that a considerable proportion of the sample houses are affected by the expansion of the subway network in the sample period.

The data of subway stations and routes are from the official website of Beijing Subway, including each station's longitude and latitude, opening time, routes, etc. A total of 340 stations and 23 lines were recorded after excluding the stations and lines that were not in operation until the end of the sample period, of which 173 stations were newly opened during the period, 22 non-transfer stations added lines and became transfer stations, nine lines were newly built during the sample period, and another nine lines underwent extension. Table 2 summarizes the lines and stations newly opened during the period.

3. Empirical Results

3.1. *The impact of shortening the distance to subway stations*

To analyze the impact of shortening the distance to subway stations on housing rents, we choose the observations with one change of the nearest station as regression samples to exclude the influence of multiple impacts and discard the observations whose nearest station is a transfer station to exclude the transfer impact. Because the distances to the nearest stations changed at different times and to different extents, a progressive DID model is employed to determine the impact of the decrease in the distance to subway stations on housing rents to avoid the influence of artificial radius on the estimated results. For any housing estate, the distance to the nearest station remains unchanged before opening a closer subway station, and this distance changes to a smaller value after the opening of a closer station, thus producing a contrast. At one point in time, the housing estates with unchanged nearby stations constitute the control group of those whose nearest stations have changed, creating another contrast. By controlling the neighborhood fixed effects and time effects, we get the following progressive DID model:

$$\ln(\text{rent}_{ijt}) = \alpha + \beta\Delta\text{Distance}_{jt} + \theta X_{ijt} + u_j + v_t + \delta_{dy} + \varepsilon_{ijt}, \tag{3.1}$$

where rent_{ijt} is the rent of transaction record i in neighborhood j at time t. $\Delta\text{Distance}_{jt}$ is the change in the distance to the nearest subway station. It remains 0 until a closer station comes into operation and then becomes a negative value. The coefficient β is the average effect, which means that the rent increases by $-\beta \times 100\%$ for every 1-km decrease in the distance to the nearest subway station. X_{ijt} denotes a series of control variables for house characteristics, including house area, floor, total floors of the building, number of bedrooms, number of living and dining rooms, and whether it is a branded rental apartment. u_j is neighborhood fixed effect, and v_t is time fixed effect in months. δ_{dy} is the product of year dummies and commercial district dummies to control for the heterogeneous time trend of different regions. The standard errors are clustered at neighborhood level.

Table 3 reports the estimated coefficients and clustered standard errors in Eq. (3.1). Columns (1)–(4) limit the sample as follows: The nearest station has only changed once in the sample period, and the nearest station is a non-transfer one. Column (5) cancels the restriction of non-transfer stations, and column (6) cancels all the restrictions. The dependent variable is the logarithm of rent per unit area in all columns except for column (4), while it is the logarithm of total rent in column (4). Column (1) only includes neighborhood fixed effect and time fixed effect, where the coefficient of ΔDistance is -0.0419, significant at the 1% level. Column (2) adds the heterogeneous district trend item, where the coefficient is -0.0158, significant at the 10% level, which means that the heterogeneous trend does exist and has a noticeable influence on the estimated results. Column (3) is the complete model with the addition of control variables; the estimated coefficient is -0.0232, significant at the 1% level, which indicates that rent per unit area increases averagely by 2.32% for every 1-km reduction in the distance to the nearest station with the expansion of the subway network. In column (4), the dependent variable is the logarithm of total rent, and the estimated coefficient is -0.0272, significant at the 1% level, which indicates the total rent increases by 2.72% on average for every 1-km decrease in the distance to the nearest station. We note that, on average, the distance to the nearest subway station decreased by 2.15 km in the regression sample, which means that the average appreciation of rent per unit area and total rent appreciation caused by the shortening distance to subway stations are 4.99% and 5.85%, separately. Column (5) relaxes the non-transfer sample restriction and the estimated coefficient is -0.018. Column (6) regresses for the whole sample and the coefficient is -0.0206. This shows that loosening the restrictions on the sample would understate the impact.

Table 3. Impact of shortening the distance to subway stations on housing rents.

	The nearest station is a non-transfer one, and only has changed once				Changed once	Whole sample
	ln(rent)	ln(rent)	ln(rent)	ln(totalRent)	ln(rent)	ln(rent)
	(1)	(2)	(3)	(4)	(5)	(6)
ΔDistance	−0.0419***	−0.0158*	−0.0232***	−0.0272***	−0.0180***	−0.0206***
	(0.00456)	(0.00817)	(0.00324)	(0.00336)	(0.00317)	(0.00256)
Size			−0.00738***	0.00986***	−0.00708***	−0.00693***
			(0.000167)	(0.000102)	(0.000113)	(0.0000766)
Floors			−0.000252	−0.00139**	−0.000450	−0.000773***
			(0.000662)	(0.000568)	(0.000421)	(0.000262)
Middle			−0.00224	−0.00215	−0.00181	−0.00119
			(0.00171)	(0.00164)	(0.00120)	(0.000740)
High			−0.00991***	−0.0116***	−0.00613***	−0.00601***
			(0.00189)	(0.00205)	(0.00131)	(0.000834)
Bedrooms			0.101***	−0.0407***	0.104***	0.102***
			(0.00290)	(0.00244)	(0.00194)	(0.00126)
LvDnRooms			0.0265***	0.00532	0.0264***	0.0244***
			(0.00572)	(0.00722)	(0.00413)	(0.00262)
Branded			0.287***	−0.0170*	0.264***	0.273***
			(0.0129)	(0.00922)	(0.00765)	(0.00456)
Constant	4.336***	4.298***	4.533***	7.742***	4.613***	4.615***
	(0.00663)	(0.0119)	(0.0156)	(0.0116)	(0.0110)	(0.00676)
Neighborhood fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
District-year effects	No	Yes	Yes	Yes	Yes	Yes
N	214,774	214,743	214,743	227,578	360,908	883,047
Adjusted R^2	0.595	0.616	0.894	0.896	0.885	0.881

Note: Neighborhood-level clustered standard errors in parentheses: ***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$.
Source: Made by the authors.

3.2. *Identifying the influence range of subway stations*

To identify the influence range of subway stations, we estimate the impact of opening a closer subway station on the rent of houses that are within a certain radius of some subway stations. We consider the samples meeting the following conditions: There is already a subway station within the radius of the observation at the beginning of the sample period, and a station with a closer distance has come into operation in that period. Again, we focus on those whose change of the nearest station has only occurred once, which is denoted as the dummy variable NewStation. The following method is employed to identify the influence range of subway stations:

$$\ln(\text{rent}_{ijt}) = \alpha + \beta \text{NewStation}_{jt} + \theta X_{ijt} + u_j + v_t + \delta_{dy} + \varepsilon_{ijt}, \tag{3.2}$$

where NewStation_{jt} equals 1 if a subway station closer to the neighborhood j has come into operation at time t, and 0 otherwise. Other variables and model settings are consistent with Eq. (3.1).

Table 4. Impact of opening a closer subway station on housing rents.

	≤2 km	≤1.5 km	≤1 km	1–1.5 km	1.5–2 km
	(1)	(2)	(3)	(4)	(5)
NewStation	0.0102**	0.00407	0.000231	0.00602	0.0244***
	(0.00428)	(0.00523)	(0.00743)	(0.00670)	(0.00662)
Size	−0.00708***	−0.00726***	−0.00718***	−0.00731***	−0.00670***
	(0.000170)	(0.000213)	(0.000281)	(0.000280)	(0.000248)
Floors	−0.00103*	−0.00123**	−0.000476	−0.00154*	−0.000547
	(0.000533)	(0.000613)	(0.000655)	(0.000819)	(0.00104)
Middle	0.00220	0.00331	0.00203	0.00365	0.0000513
	(0.00182)	(0.00234)	(0.00298)	(0.00303)	(0.00251)
High	−0.00109	−0.000767	−0.00241	−0.000147	−0.00172
	(0.00205)	(0.00269)	(0.00345)	(0.00349)	(0.00269)
Bedrooms	0.107***	0.107***	0.0991***	0.110***	0.107***
	(0.00279)	(0.00322)	(0.00436)	(0.00418)	(0.00463)
LvDnRooms	0.0312***	0.0290***	0.0256**	0.0298***	0.0357***
	(0.00708)	(0.00899)	(0.0115)	(0.0115)	(0.0102)
Branded	0.229***	0.220***	0.239***	0.211***	0.256***
	(0.00998)	(0.0123)	(0.0121)	(0.0166)	(0.0122)
Constant	4.695***	4.715***	4.725***	4.712***	4.651***
	(0.0151)	(0.0142)	(0.0182)	(0.0194)	(0.0343)
Neighborhood fixed effects	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes
District-year effects	Yes	Yes	Yes	Yes	Yes
N	160,052	112,622	34,526	78,096	47,430
Adjusted R^2	0.855	0.851	0.849	0.853	0.866

Note: Neighborhood-level clustered standard errors in parentheses: ***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$.
Source: Made by the authors.

Taking 2, 1.5, and 1 km as the radii successively, we estimate Eq. (3.2) using the samples mentioned above and report the results in columns (1)–(3) in Table 4. The estimated coefficient of NewStation can be explained as the impact of opening a closer subway station on the rent of houses that are within the radius of existing stations. Take column (1) as an example, the coefficient of NewStation is 0.0102, significant at the 5% level, which means a rent appreciation of 1.02% for the houses within 2 km of the existing subway stations because of the opening of a closer station to these houses. Comparing the first three columns, it can be seen that the impact of opening a closer subway station on housing rents decreases rapidly with the reduction of the radius, from 1.02% when the radius is 2 km to 0.023% for 1-km radius. What is more, the coefficients of columns (2) and (3) are both insignificant, which indicates that the influence range of subway stations may be 1.5 km. We further divide the area of 1–2 km into two ring areas with an interval of 500 m, and estimate and report in columns (4) and (5). The coefficient of NewStation in column (4) is 0.00602 and insignificant. The coefficient in column (5) is 0.0244 and significant at the 1% level, which means a rent appreciation of 2.44% for the houses between 1.5 km and 2 km of the existing subway stations because of the opening of a closer station. This confirms that the influence range of subway stations is within 1.5 km and indicates that opening a closer subway station has no significant impact on the rent of houses within the influence range of existing stations.

3.3. *Robustness check and the non-linear impact*

The baseline analysis shows that the reduction in the distance to the nearest station causes an average rent appreciation of about 5%, and the influence range of subway stations is within 1.5 km. To check the robustness of the results and analyze the spatial distribution of the rent appreciation, we employ the method used by Fan *et al.* (2018) for analysis. By setting a series of influence radii, a progressive DID model is constructed to identify the average impact of subway station opening on the surrounding housing rents. The observations within a certain radius of the new stations (those that came into operation during the sample period) are taken as regression samples. For a certain new station, the surrounding houses are regarded as the control group when the station has not opened and are regarded as the treated group after the station opens. The samples around the same station form a contrast before and after the opening of the station, and the samples around the opened stations and the unopened stations form another contrast at a given time. In this way, the difference-in-difference method can eliminate the common trend, and obtain the causal effect of the opening of subway stations on the samples' rent within a given influence range. To ensure it is not affected by the old stations and transfer stations, we remove the observations whose initial distance to the nearest station at the beginning of the sample period is no more than 2 km and the observations around transfer stations. Besides, we also apply the once-changed restriction to exclude the influence of multiple impacts. The model set is as follows:

$$\ln(\text{rent}_{ijst}) = \alpha + \beta \text{Subway}_{st} + \gamma \text{Dist}_{is} + \theta X_{ijt} + \lambda Z_j + \delta_s + v_t + t \times \delta_s + \varepsilon_{it}, \qquad (3.3)$$

where the subscript s denotes the nearest subway station of house i in neighborhood j. Subway_{st} is a dummy variable, which is equal to 1 if the station s has opened at time t, and 0 otherwise. Dist_{is} is the distance of house i to station s. X_{ijt} denotes a series of house-level control variables, consistent with the baseline model. Z_j denotes a series of neighborhood-level control variables, including property costs, built year, number of buildings, and distance to the city center. δ_s is station fixed effects, and v_t is the month fixed effects. The product of time trend t in months and the station fixed effect δ_s is added to control for the heterogeneity time trend of different stations. ε_{ijt} is the stochastic disturbance term. The standard errors are clustered at the neighborhood level.

Taking 500 m, 750 m, 1 km, 1.5 km, and 2 km as the influence radii of subway stations successively, observations within the radius of new stations are considered as the initial sample. Then we remove the observations whose initial distance to the nearest station at the beginning of the sample period is no more than 2 km and the observations around transfer stations from the samples to exclude the influence of old stations and transfer stations. Finally, we remove the observations affected by multiple new stations and get the final regression sample.

Table 5. Impact of opening subway stations on housing rents within the given radius.

	≤500 m	≤750 m	≤1 km	≤1.5 km	≤2 km	≤2 km
	(1)	(2)	(3)	(4)	(5)	(6)
Subway	0.0516***	0.0542***	0.0570***	0.0500***	0.0431***	0.0616***
	(0.0149)	(0.0114)	(0.01000)	(0.00910)	(0.00841)	(0.0190)
Dist	0.0575	0.0243	−0.00705	−0.0916***	−0.0743***	−0.0578***
	(0.0680)	(0.0562)	(0.0485)	(0.0209)	(0.0179)	(0.0216)
Subway × Dist						−0.0208
						(0.0183)
Size	−0.00663***	−0.00589***	−0.00566***	−0.00577***	−0.00553***	−0.00553***
	(0.000599)	(0.000397)	(0.000480)	(0.000422)	(0.000411)	(0.000411)
Floors	−0.000466	0.00102	0.00165*	0.00110	0.000363	0.000390
	(0.00137)	(0.00107)	(0.000960)	(0.000873)	(0.000761)	(0.000764)
Middle	−0.00414	−0.00242	−0.00237	−0.00345	−0.00314	−0.00314
	(0.00451)	(0.00347)	(0.00307)	(0.00279)	(0.00263)	(0.00263)
High	−0.0107**	−0.0102***	−0.0114***	−0.0153***	−0.0158***	−0.0158***
	(0.00472)	(0.00358)	(0.00313)	(0.00304)	(0.00286)	(0.00287)
Bedrooms	0.106***	0.105***	0.106***	0.0998***	0.0980***	0.0980***
	(0.0107)	(0.00851)	(0.00790)	(0.00629)	(0.00628)	(0.00629)
LvDnRooms	0.0272	0.0229	0.0115	0.00914	0.0103	0.0102
	(0.0219)	(0.0141)	(0.0116)	(0.0105)	(0.0103)	(0.0103)
Branded	0.293***	0.351***	0.358***	0.357***	0.374***	0.374***
	(0.0505)	(0.0391)	(0.0374)	(0.0311)	(0.0299)	(0.0299)
PropMgtFee	0.0147**	0.0225***	0.0240***	0.00882**	0.0107**	0.0107**
	(0.00595)	(0.00809)	(0.00690)	(0.00441)	(0.00524)	(0.00524)
YrBuilt	0.00437***	0.00322**	0.00419***	0.00623***	0.00621***	0.00620***
	(0.00127)	(0.00128)	(0.00112)	(0.00108)	(0.00103)	(0.00103)
Buildings	−0.00106	−0.000140	0.00130	0.00194**	0.00160**	0.00160**
	(0.000744)	(0.000607)	(0.00104)	(0.000923)	(0.000793)	(0.000796)
DistCenter	−0.190***	−0.100***	−0.0563***	−0.0360***	−0.0240*	−0.0242*
	(0.0403)	(0.0241)	(0.0180)	(0.0128)	(0.0124)	(0.0124)
Constant	−1.107	−0.383	−3.123	−7.458***	−7.642***	−7.630***
	(2.574)	(2.565)	(2.257)	(2.167)	(2.050)	(2.050)
Station fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Station-month trend	Yes	Yes	Yes	Yes	Yes	Yes
N	23,525	42,776	62,551	85,539	97,372	97,372
Adjusted R^2	0.873	0.859	0.842	0.839	0.836	0.836

Note: Neighborhood-level clustered standard errors in parentheses: $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.
Source: Made by the authors.

Columns (1)–(5) in Table 5 report the estimated coefficients and clustered standard errors in Eq. (3.3), taking the above influence radii, respectively. The regression results show that within all these influence ranges, the rent appreciation is significantly positive, but the values are different: With the expansion of influence radius, the rent appreciation first increases and then decreases. The average rent appreciation is 5.16% within 500 m,

Table 6. Spatial heterogeneous impact of opening subway station on housing rents.

	≤500 m	0.5–1 km	1–1.5 km	1.5–2 km
	(1)	(2)	(3)	(4)
Subway	0.0516***	0.0726***	0.0300***	−0.000754
	(0.00592)	(0.00526)	(0.00662)	(0.00992)
Dist	0.0575***	−0.127***	0.114***	−0.180***
	(0.0124)	(0.00983)	(0.0126)	(0.0204)
Control variables	Yes	Yes	Yes	Yes
Station fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Station-month trend	Yes	Yes	Yes	Yes
N	23,525	39,026	22,987	11,829
Adjusted R^2	0.864	0.821	0.842	0.867

Note: Neighborhood-level clustered standard errors in parentheses: $^{***}p < 0.01$.
Source: Made by the authors.

5.42% within 750 m, 5.70% within 1 km, 5% within 1.5 km, and 4.31% within 2 km, basically at a comparable level with the baseline results. Since the small-radius sample is a subset of the larger-radius ones, the increase of average rent appreciation of samples within the radius from 500 m to 1 km indicates that in a certain range, the rent appreciation increases with the increase of distance to the nearest station, and the coefficient of Dist is the confirmation of this phenomenon. To test the heterogeneous impact, the product of Subway and Dist is introduced based on Eq. (3.3), and the corresponding estimated results are reported in column (6). The interaction term coefficient is not significant, which means that the relationship between the rent appreciation and the distance to subway stations is not simply linear but more complex.

To explore the non-linear heterogeneity impact of subway opening on housing rents at different areas, we divide the 2-km-radius circular area into a series of concentric rings with an interval of 0.5 km, regress on these ring areas separately, and report the regression results in Table 6. The subsample regressions show that there is a non-linear relationship between the rent appreciation caused by the opening of subway stations and the distance to subway stations. With the increase of the distance to subway stations, the impact on rents first increases and then decreases, and it is no longer significant beyond 1.5 km. The non-linear relationship could be due to the noise and other negative effects when the house is too close to subway stations, which offset the positive effect of travel convenience. This is consistent with the research conclusion by Bowes and Ihlanfeldt (2001). The above results again confirm that the impact of subway stations on housing rents is within 1.5 km.

4. Further Discussion

4.1. *The impact of adding a line to non-transfer stations*

According to previous literature such as Dai *et al.* (2016), residential prices around transfer stations changed more dramatically than those around non-transfer stations. Even though there is no difference in subway proximity, the operation of a new line for current stations is predicted to increase the rent of neighboring properties due to expanded travel options. To analyze the impact of adding a line to non-transfer stations on housing rents around the stations, we limit regression samples as follows: At the start of the sample period, there was already a non-transfer station within a giving radius of the house, which has always been the nearest station, and a line was added during the period. Using an identification approach similar to that stated in Sec. 3.3, the following progressive DID model is employed, treating the operations of new lines to existing stations as research events.

$$\ln(\text{rent}_{ist}) = \alpha + \beta \text{Transfer}_{st} + \gamma \text{Dist}_{is} + \theta X_{ijt} + \delta_s + v_t + t \times \delta_d + \varepsilon_{it}, \tag{4.1}$$

where the dummy variable Transfer_{st} represents whether the station s has added a new line at time t. Other variables and model settings are consistent with Eq. (3.3).

Taking 2, 1.5, and 1 km as the influence radii of subway stations successively, the regression results of Eq. (4.1) are reported in columns (1)–(3) in Table 7. It can be seen that the transfer impact on housing rents decreases with the reduction of the influence radius. When setting the influence radius as 2 km, housing rents increase averagely by 1.73% due to adding new lines to the nearest subway station. The transfer impact is 1.69% when setting the radius as 1.5 km and is 1.55% when setting the radius as 1 km. But all the estimated results are not significant statistically. To explore the spatial heterogeneity of the

Table 7. Impact of opening new lines on housing rents.

	$\leq$2 km	$\leq$1.5 km	$\leq$1 km	$\leq$2 km	$\leq$2 km
	(1)	(2)	(3)	(4)	(5)
Transfer	0.0173	0.0169	0.0155	−0.00188	
	(0.0113)	(0.0115)	(0.0122)	(0.0211)	
Dist	−0.0613*	−0.0700**	−0.0735*	−0.0864*	−0.0683*
	(0.0316)	(0.0330)	(0.0438)	(0.0494)	(0.0379)
Transfer × Dist				0.0323	
				(0.0345)	
Transfer × $I(\leq 1$ km)					0.0162
					(0.0112)
Transfer × I(1–1.5 km)					0.0192
					(0.0285)
Transfer × I(1.5–2 km)					0.1000***
					(0.0366)
Control variables	Yes	Yes	Yes	Yes	Yes
Station fixed effects	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes
Station-month trend	Yes	Yes	Yes	Yes	Yes
N	35,916	35,570	33,230	35,916	35,916
Adjusted R^2	0.684	0.682	0.667	0.684	0.684

Note: Neighborhood-level clustered standard errors in parentheses: ***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$.
Source: Made by the authors.

impact, we introduce the interaction term Transfer $\times$ Dist and report the estimated results in column (4). The coefficient of Transfer $\times$ Dist is 0.0323 and is not significant.

We then replace the transfer impact with interaction terms between Transfer and a series of dummy variables representing the distances to subway stations and report the regression results in column (5), which show that the impact of adding new lines decreases rapidly with the shortening of the distance to subway stations. For the houses 1.5–2 km away from non-transfer stations, the adding of new lines improves the housing rents by 10%. These transfer impacts are 1.92% and 1.62% at the ring areas 1–1.5 km and within 1 km, respectively, which are both not statistically significant. This indicates that only the rent of houses far away from the non-transfer subway stations has a significant appreciation when adding a new line for the stations, while the houses near the stations have no rent appreciation. In other words, the influence range of transfer stations is larger than that of non-transfer stations, and the influence range of subway stations can be extended by adding lines, which is consistent with Dai *et al.* (2016) and Fan *et al.* (2018).

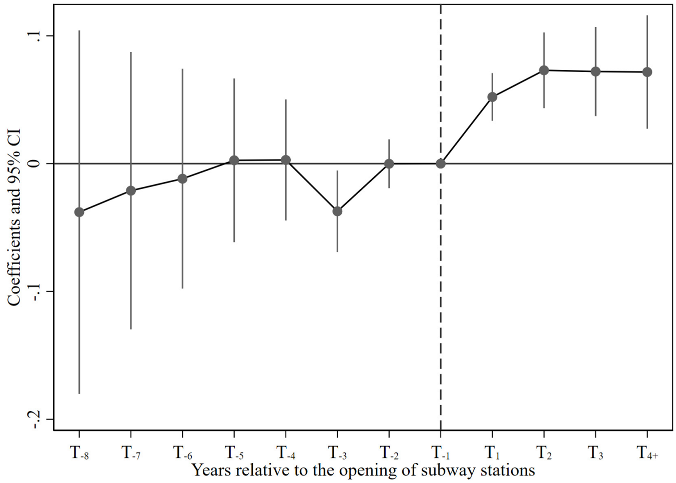
4.2. *Parallel trend test and dynamic impact analysis*

The DID model requires the data to meet the parallel trend assumption, which means that for the regression samples, the rent is not significantly different from 0 before the opening of the corresponding stations, controlling other factors and the fixed effects. Referring to the common practices of the progressive DID method, we introduce the following model to test the parallel trend and analyze the dynamic impact:

$$\ln(\text{Price}_{ijt}) = \sum_{\tau=-8}^{-2} \beta_\tau T_{\tau,\,st} + \sum_{\tau=1}^{3} \beta_\tau T_{\tau,\,st} + \beta_{4+} T_{4+,\,st} + X_{ijt}\lambda + \omega_t + c_j + t\varphi_d + \varepsilon_{ijt}, \quad (4.2)$$

where the dummy variables $T_{-8,\,st}, T_{-7,\,st}, \ldots, T_{3,\,st}, T_{4+,\,st}$ equal 1 if the transaction time t is τ years after the opening of the subway station s (a negative value of τ means $|t|$ years before the opening), and 0 otherwise. For example, the "Chaoyang Park" station opened for operation on December 31, 2016, so T_{-1} equals 1 if its corresponding observations' transaction time is between January and December 2016, T_1 equals 1 if its corresponding observations' transaction time is between January and December 2017, and so on. As we mainly focus on the parallel trend test in this subsection, we merge the variables $T_4, T_5, \ldots, T_9$ as T_{4+}. The coefficients β_τ are of interest, and they should not be significantly different from zero when $\tau < 0$ if the parallel trend assumption holds.

Taking the rent per unit area as the dependent variable, we choose the same samples as the baseline and plot the coefficients and 95% confidence intervals estimated from Eq. (4.2) in Fig. 2. It can be seen that the coefficients are not significantly different from 0 before the opening of subway stations, which means the parallel trend assumption holds. In addition, we can also analyze the dynamic impact of the opening of subway stations on housing rents. The rent appreciation is 4.99% in the first year after the opening, 6.73% in the second year, and remains at a level of about 6% after three or more years, which means a long-term rent appreciation of about 6%. Compared with the continuously improving dynamic impact of Hangzhou Subway on housing prices (Wen *et al.*, 2018), the results



Note: The points in the figure represent the estimated coefficients of T_τ from Eq. (4.2), taking T_{-1} as the baseline. The vertical bars represent 95% confidence intervals, respectively. From the figure, we can obtain the improvement of rent of the treated group compared with the control group at a given year. The same for Fig. 3.
Source: Made by the authors.

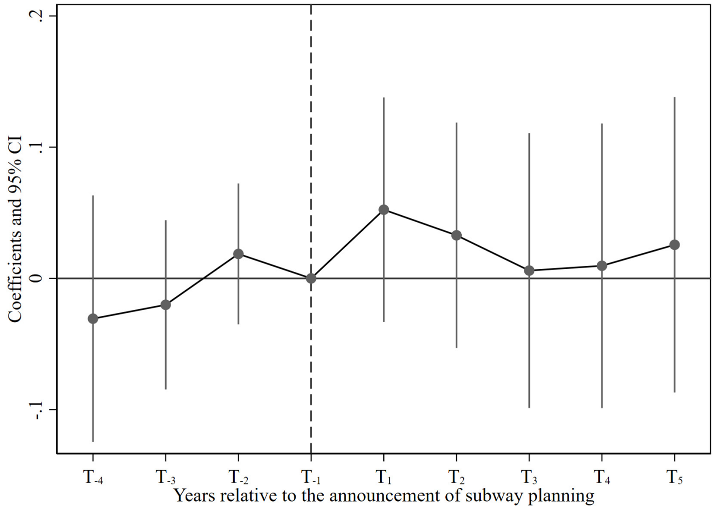
Fig. 2. The parallel trend and dynamic effect of the opening of subway stations.

show a stable long-term rent appreciation caused by opening of subway stations, suggesting that the housing rental market is more resilient to external shocks than the housing sale market. It also shows the rationality of the housing rental market and reaffirms the legitimacy of using rent as a measure of housing value.

4.3. *Is the opening of subway stations the right time point?*

Literature on the influence of subway stations on housing prices points out that housing prices will increase significantly after the announcement of subway planning, but it is not clear whether this announcement effect also holds for the rental market. If so, then the opening of subway stations may not be the appropriate time point for the above analysis and we may underestimate the impact. Theoretically, the announcement effect on housing prices is due to the investment attributes of real estate in addition to its residential attributes. Renters only enjoy the residential value of residences and not the investment value, this means that their utility will improve only after they benefit from proximity to the subway system, and the same for housing rents. However, some literature indicate a transmission mechanism of the housing price to rent (Hirota *et al.*, 2020), i.e. the landlords will raise the rent when the housing price rises. We argue that such an announcement effect is unlikely to exist in the completely competitive rental market because the affected houses are only a small fraction of the rental housing supply. Renters can vote with their feet when the landlords of affected houses raise the rents.

We take the planning announcement of Beijing Subway Line 12 to apply an event study of the announcement impact on housing rents. In September 2015, the National Development and Reform Commission (NDRC) approved the second-phase construction



Source: Made by the authors.

Fig. 3. The parallel trend and dynamic effect of the announcement of subway planning.

plan (2015–2021) of Beijing Urban Rail Transit, in which the Line 12 plan was announced to the public for the first time. According to the plan, there are 24 stations on Line 12, including seven new non-transfer stations, and the planned construction period is from 2017 to 2021. The construction of Line 12 began in 2016, and it has not been completed and opened for operation until the end of the sample period (the end of 2020). If there is a rent appreciation caused by the announcement, then we expect to get a significant positive value when we apply a DID method to the event study, which takes the houses within 1.5 km around the new planning stations as the treatment group and those between 1.5 km and 2.5 km around the stations as the control group. Controlling house characters, neighborhood fixed effects, time fixed effects, and heterogeneous commercial districts' time trends, the regression coefficient is 0.0336 and the t-value is 0.72, which is not significant at 10%. The parallel trend and dynamic effect are shown in Fig. 3, which shows that after the announcement of the subway plan, the rent per unit area has a slight rise, which is not significantly different from 0. By the third year after the announcement of the plan, this effect has been close to 0. This indicates that the planning announcement has a weak short-term impact on rents, i.e. there is a relatively weak transmission mechanism from housing price to rent only in the short term after the planning announcement. This also ensures the rationality of choosing the opening of subway stations as the research time point, consistent with Wen *et al.* (2018) and Tian *et al.* (2020).

4.4. *Is there a siphon effect in the rental market?*

Fan *et al.* (2018) point out that subway stations have a siphon effect in addition to the spillover effect on the housing market, i.e. the price of houses far away from new subway stations will depreciate because of the announcement of subway planning. Does such a siphon effect also exist in the rental market? To answer this question, we estimate the

Table 8. Test of the siphon effect of subway stations on the rental housing market.

	≥2 km	≥3 km	≥2 km	≥3 km
	(1) ln(rent)	(2) ln(rent)	(3) ln(totalRent)	(4) ln(totalRent)
Subway	−0.0329***	−0.0346***	−0.0369***	−0.0453***
	(0.00717)	(0.00904)	(0.00647)	(0.00842)
Control variables	Yes	Yes	Yes	Yes
Station fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Station-month trend	Yes	Yes	Yes	Yes
N	25,111	13,311	29,058	15,699
Adjusted R^2	0.805	0.808	0.847	0.856

Note: Neighborhood-level clustered standard errors in parentheses: $^{***}p < 0.01$.
Source: Made by the authors.

impact of the opening of subway stations on housing rents beyond 2 km and 3 km, respectively, and report the regression results in Table 8. From the results, it can be seen that both the rent per unit area and the total rent decrease with the opening of the subway stations, no matter whether they are 2 km or 3 km away. What is more, the further the distance, the greater the depreciation, which is consistent with the research conclusion of the new housing market in Fan *et al.* (2018). Therefore, the siphon effect also exists in the rental market. It also shows that identifying the impact of subway stations on housing prices or rents based on the traditional DID method which takes the opening of a single line as a research event may cause a certain degree of overestimation because the control group is negatively affected. Recall that the regression result in Sec. 4.3 is not significant even if it is possibly overestimated, which further shows the robustness of the conclusion.

4.5. *Heterogeneous impact*

Consistent with the previous literature (Gu and Zheng, 2010; Bowes and Ihlanfeldt, 2001), the paper focuses on the following five kinds of heterogeneity: (1) distance to the city center, (2) the ring road areas where it is located, (3) property costs of neighborhood, (4) buildings' age, and (5) house area. Taking 1.5 km as the influence radius, the interaction terms between the subway and the above features are introduced based on Eq. (3.3). To avoid collinearity problems, the interaction terms of all continuous variables (dist_center, lnpropertyCosts, age, and house area) are obtained after decentralization. The interaction terms corresponding to different ring road areas are obtained by the product of Subway and a series of dummy variables I(2nd–3rd ring), I(3rd–4th ring), . . . , I(outside 6th ring). The dummy variable I(2nd–3rd ring) equals 1 if the observations are located in the area between 2nd ring road and 3rd ring road, and 0 otherwise, and other dummy variables are defined similarly. The heterogeneous analysis results are reported in Table 9.

In Table 9, column (1) indicates that the distance to the city center positively moderates the impact of subway stations on housing rents, i.e. the impact is greater at the area away from the city center, which is consistent with the conclusions of Gu and Zheng (2010).

Table 9. Heterogeneity analysis of space, community, and housing characters.

	(1)	(2)	(3)	(4)	(5)
Subway	0.0465***	−0.00397	0.0511***	0.0470***	0.0494***
	(0.00366)	(0.0292)	(0.00349)	(0.00353)	(0.00349)
Subway × dist_center	0.00166***				
	(0.000529)				
Subway × I(2nd–3rd ring)		−0.0640*			
		(0.0365)			
Subway × I(3rd–4th ring)		0.112***			
		(0.0329)			
Subway × I(4th–5th ring)		0.0476			
		(0.0295)			
Subway × I(5th–6th ring)		0.0972***			
		(0.0296)			
Subway × I(outside 6th ring)		−0.0394			
		(0.0318)			
Subway × lnPropMgtFee			−0.0117***		
			(0.00305)		
Subway × Age				−0.000992***	
				(0.000169)	
Subway × Size					−0.000335***
					(0.0000534)
Control variables	Yes	Yes	Yes	Yes	Yes
Station fixed effects	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes
Station-month trend	Yes	Yes	Yes	Yes	Yes
N	85,539	82,489	85,539	85,539	85,539
Adjusted R^2	0.839	0.841	0.839	0.839	0.839

Source: Made by the authors.
Notes: Neighborhood-level clustered standard errors in parentheses: $***p < 0.01$, and $*p < 0.1$.

Column (2) shows that the rent appreciation caused by subways is wave-shaped in spatial distribution, and it is even negative within the 3rd ring road. This may be explained as the relative traffic advantage within the 3rd ring road being weakened with the expansion of the subway network, as the coverage rate of the subway system in this area is high enough at the beginning of the period. Therefore, there may be a siphon effect of rental demand from the core area to the periphery area due to the reduction of the gap in transportation convenience, which changes the spatial distribution of housing rents. The rent appreciations of subway stations in the 3rd–4th ring area and 5th–6th ring area are significantly 11.2 and 9.73 percentage points higher than that in the area within the second ring road, while the rent appreciations in 4th–5th ring area and outside the 6th ring area are 4.76 and 3.94 percentage points higher, respectively, but not statistically significant. This wavy distribution of rent appreciation is in line with the theoretical prediction of urban economics on the spatial distribution of market potential of single-center cities (Lucas and Rossi-Hansberg, 2002). Column (3) indicates that the property costs of neighborhoods negatively moderate the impact of subway stations on housing rents, i.e. the upscale neighborhoods (corresponding to high property costs) are affected less by subways. This is contrary to the conclusion of Bowes and Ihlanfeldt (2001), and the results indicate that the improvement of the public transportation system can narrow the gap between different neighborhoods to a certain extent. Column (4) shows that building age can negatively moderate the impact, i.e. the older houses are affected less by subways. This may be because the newly constructed neighborhoods are generally far away from the city center, and this moderation effect reflects the spatial heterogeneity to some extent. Column (5) indicates that house area can negatively moderate the impact, i.e. the bigger houses are affected less by subways. This can be explained as small houses become more popular in the rental market as the rent rises due to the opening of surrounding subway stations, under budget constraints.

4.6. *Limitations*

There are still some limitations in this study. We must admit that subway is only one of many factors that affect housing rent, and we cannot completely exclude the influence of other factors on the conclusion of this paper. The empirical study is based on the housing rent data collected from a real estate agency in Beijing, whether the data is representative and whether these conclusions can be generalized to other cities need further verification. In addition, although using the progressive difference-in-difference methods to eliminate the influence of other factors, we still face some endogenous problems, e.g. the non-randomness of subway line and stations planning. In future research, non-parametric estimation and other methods can be used to analyze the distribution of housing values around subway stations in more detail. Information such as geological structure of cities can be used to construct instrument variables to better eliminate endogenous problems.

5. Conclusion

The rapid expansion of cities is often accompanied by the increase in commuting costs, and developing public transportation system represented by subways is an important means to alleviate congestion and reduce commuting costs. As a public good that significantly improves the travel convenience of residents along the lines, subways increase the accessibility of public transport system and reduce the travel time and cost of residents to other destinations, thus improving the residential value. However, most of the existing literature focus on the impact of subways on house prices, and seldom consider the impact on house rents, which can better reflect residential values than the former. In addition, there is no agreement on the influence range of subway stations in the literature, and it is also unclear whether the announcement of subway planning can cause rent appreciation. We empirically study these problems based on the long-term, fine-grained, and accurate data and make up for the research gap in this field.

Using the historical transaction data of a leading real estate agency from 2011 to 2020 and relevant subway data in this period matched by spatial and time information, we employ empirical methods such as progressive DID to identify the impact of subway network expansion on housing rents. The results show that the reduction of the distance to the nearest subway station by 1 km increases the rent per unit area by 2.32% and the total rent by 2.72%, which implies an average rent appreciation of about 5%. Another identification strategy shows that the impact range of the opening of subway stations on the surrounding residential rent is about 1.5 km, and the average rent appreciation within the range is 5%, which is consistent with the baseline result. There is a non-linear relationship between the rent appreciation and the distance to subway stations, i.e. the rent appreciation first increases and then decreases with the increase of the distance. Furthermore, adding a line to non-transfer stations increases the rent by 10% for houses 1.5–2 km away from the stations and thus improves the influence range of the stations. The dynamic effect analysis shows that the impact of subway stations on housing rents continues to increase in the first two years after the opening of the stations, and the long-term impact is about 6%. The test using the samples along an uncompleted line shows that the announcement of subway planning has a statistically insignificant short-term positive impact on housing rents, i.e. there is a weak transmission mechanism from housing price to rent only in the short term after the announcement of the planning. The analysis of observations far away from subway stations confirms the existence of the siphon effect on the rental market, i.e. the rent of housing far away from the new subway stations reduces because of the opening of the stations. The further the distance, the greater the depreciation. Lastly, heterogeneity analysis shows that houses far away from the city center are averagely affected more by subways, but the more elaborate regression indicates a wave-shaped relationship between the rent appreciation and the distance to the city center. As for heterogeneity in neighborhood and house characteristics, on average, houses with a large area in upscale and old neighborhoods are affected less by subways.

The results of this paper have rich practical significance and policy implications: First, opening stations and adding lines can effectively improve the accessibility of the subway network and enhance the residential value of the surrounding housing. The subway network construction should be orderly promoted in areas with low station coverage but high population density. Second, attention should be paid to the planning of subway stations and lines and short-interval stations should be avoided. The study shows that a closer station has no significant impact on residential value for houses within the influence range of the existing subway stations. Third, great importance should be attached to the connectivity of the subway network so as to increase the accessibility by weaving different lines into a network, as the study shows that transfer stations have a greater degree and range of impact on residential value.

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