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Subway Opening, Traffic Accessibility, and Housing Prices: A Quantile Hedonic Analysis in Hangzhou, China

Haizhen Wen [1,2], Zaiyuan Gui [1,2], Chuanhao Tian [2,3,*], Yue Xiao [1,2] and Li Fang [4]

1 Department of Civil Engineering, Zhejiang University, Hangzhou 310058, China; ningduwhz@hotmail.com (H.W.); guizy@zju.edu.cn (Z.G.); xiaoyuexy@zju.edu.cn (Y.X.)
2 Center for Real Estate Studying, Zhejiang University, Hangzhou 310058, China
3 School of Public Administration, Zhejiang University, Hangzhou 310058, China
4 Department of Urban and Regional Planning, Florida State University, Tallahassee, FL 32306, USA; kfang@umd.edu
* Correspondence: tch@zju.edu.cn

Received: 22 April 2018; Accepted: 27 June 2018; Published: 30 June 2018



Abstract: Most existing studies empirically investigated the impact of rail transit on housing prices using the traditional hedonic price model, which is based on ordinary least squares (OLS). This method can estimate only the average implicit prices of housing characteristics and may ignore possible heterogeneous impacts of rail transit at different housing price levels. As a useful supplement to OLS regression, quantile regression can measure how implicit prices of explanatory variables vary across different price levels, thereby providing a comprehensive picture of the relationship between housing characteristics and prices. By using Hangzhou, China as an example, this study adopts the traditional hedonic price model and quantile regression model to investigate the capitalization effect of a new subway line on housing prices. Empirical results suggest the significant impacts of accessibility to subway stations. The average housing price within 2 km of the station is 2.1% to 6.1% higher than those outside. We also find that the impacts of the subway differ significantly across the distribution of housing prices, wherein the absolute value of estimated coefficients increased from 0.023 for the 15th quantile to 0.086 for the 95th quantile. The subway opening strengthens the capitalization effect of traffic accessibility. The absolute value of price elasticity increases from 0.044 to 0.053, and the range of influence is expanded from 1500 m to 2000 m.

Keywords: rail transit; housing price; capitalization; hedonic price model; quantile regression; accessibility to subway stations

1. Introduction

The development of the urban rail transit system has been thriving over the last decade, and many cities in China adopted the urban rail transit system as their main transport mode. By the end of 2015, 44 cities implemented rail transit plans and 26 of them already constructed rail transit systems. Existing literature shows that urban rail transit systems can impose positive and negative impacts on housing prices. On the one hand, the rail transit provides improved accessibility and reduced commuting costs to properties along the route. Consequently, the benefits of accessibility and convenience will be capitalized into the housing prices of nearby property [1,2]. The premium in housing prices induced by rail transit measures the rate of capitalization. In previous studies, scholars often use some synonyms as alternatives to capitalization, such as value appreciation [3], price premiums [4], and economic benefits [5]. On the other hand, the construction of the rail transit generates noise and pollution problems. The negative impacts during the construction period may

not affect property values in the long run, but do have an effect in the short run [6,7]. In addition, high population movement around stations may also cause security concerns during the operation period [8,9]. Therefore, the influence mechanism of rail transit on housing values should be examined to realize the sustainable development of urban rail system.

Hangzhou presents an interesting case for many reasons. As the capital of Zhejiang Province, the total economic output of Hangzhou in 2015 ranked ninth among the 36 capital cities in China, and its average annual GDP growth was 10.2%. Since the housing reform in 1998, Hangzhou has a dynamic urban real estate market. The average housing price appreciated, in real terms, by at least 10% every year between 1999 to 2010, outpacing the growth rate of many western countries even during their property heyday, which is called the 'Hangzhou Phenomenon' and has attracted widespread attention from scholars. Another feature of the Hangzhou is that Subway Line 1, which began construction on 28 March 2007 and opened on 24 November 2012, is the first rail transit service and the main line of the urban rail network in Hangzhou. After several years of operation, data from a variety of sources were made available to examine the influence of Subway Line 1. Based on price data from 2011 to 2015 in the Hangzhou housing market, this study attempts to address the following questions: (1) Does Subway Line 1 have a significant impact on housing price? If so, what is the extent and spatial scope of this impact? (2) Did the capitalization effect of the subway experience a remarkable change during the construction and operation periods? (3) How do the effects of the subway vary across various levels of housing prices before and after the subway opened? Compared with existing literature, the contributions of the present study are mainly reflected in two aspects:

(1) A quantile regression model is employed to estimate the impact of the subway on various levels of housing prices. Previous studies often adopted the OLS regression to investigate the influence of the urban rail transit because houses are heterogeneous goods [10–12]. However, this method can only gauge the conditional mean effect of the rail transit on housing prices, because it assumes that effects of the rail transit are constant on high-and low-priced houses. In addition, OLS regression is sensitive to outliers and efficiency may be significantly reduced for non-normal errors. As a useful supplement to OLS regression, quantile regression can identify the implicit prices of the rail transit for each level of housing prices and is robust to the outliers caused by sample selection bias [13]. Moreover, evidence on the heterogeneous effect of the rail transit on housing prices across high-, middle-, and low-priced houses is lacking. In this study, we employ the quantile regression technique to investigate the heterogeneous impacts of subway accessibility at different housing price levels and provide new evidence, unlike those presented in existing literature.

(2) This study uses a comprehensive dataset to investigate the influence of a new subway line on housing prices before and after subway opening. A number of studies emerged following the development of the urban rail transit in many Chinese cities [5,6,14–19], many of which estimated the spatial impact range and extent. However, due to difficulties in obtaining data, only a few studies tracked the changing trend of impacts on real estate prices over time. Ye and Cai [18] and Nie et al. [6] investigated the capitalization effect of rail transit in Shanghai and Shenzhen based on time series data. The development of the urban rail transit in Hangzhou was relatively slow. Gu and Jia [20] analyzed anticipated benefits of a new subway line during the announcement phase. Their results showed that the value appreciation effect of the subway on houses in the vicinity of stations began to manifest as early as 2005 when the plan for the line was approved. Based on housing data during the construction period (2010–2012) and the operation period (2013–2015), this study sets up hedonic price models to analyze and compare the impacts of rail transit in different time periods. The results will provide new empirical evidence to fill research gaps and provide references for similar studies.

The rest of this study is organized as follows: The second part provides a review of related studies on the capitalization of urban rail transit accessibility. The third part outlines data sources, definitions of variables, and model specifications. The fourth part provides the empirical results, and the fifth presents the conclusion.

2. Literature Review

Over the last two decades, the impact of rail transit on housing prices has become an important topic of study given the accelerated pace of rail transit construction throughout the world. Although literature in this field is well established, the relationship between rail transit accessibility and house values remains very confusing. Bowes and Ihlanfeldt [10] indicated that urban rail transportation can impose positive and negative effects on housing prices. They concluded the rail transit provides a superior means of transport alternative to driving in reducing commuting costs and mitigating traffic pressure. The improved accessibility provided by the rail transit can also optimize the land use pattern around stations and improve commercial, entertainment, and cultural infrastructure, thereby promoting the development of the economy and society. In terms of negative effects, Bowes and Ihlanfeldt [10] identified noise and pollution experienced by nearby residents during prolonged construction periods. High population movement around stations may attract criminal activity. Therefore, the effect of rail transit on housing values is very complicated.

Numerous previous studies found that urban rail transit benefits house values. For example, Bajic [21] examined the effects of the Spadina subway line in Toronto. The empirical results indicated that the increased accessibility and reduced commuting costs were capitalized in housing prices. So et al. [22] found that subway accessibility to transportation is a crucial factor of housing prices in Hong Kong. In Charlotte, North Carolina, Billings [23] found a price premium of 11.3% for condominiums and 4.0% for single-family properties within one mile of the rail station. The analyses of Seoul Metro Line 5 [24] and Toronto [25] also identified positive gains in housing values. However, a few studies reached different conclusions. For example, Pan [26] suggested that the depreciation of housing values within 0.25 mile of a station mainly because of attendant noise after three years of light rail opening. In addition, a small number of studies shows no significant difference in housing values for some properties in Miami [27], Atlanta, and Washington, D.C. [28].

Previous studies always used housing market data to establish hedonic price models for empirical analysis. In theory, a house can be seen as a heterogeneous good, and its price depends on a bundle of individual characteristics, which include location, neighborhood, and structure characteristics [29,30]. As an important extrinsic amenity, the urban rail transit plays a key role when house buyers make decisions. Naturally, the benefits of traffic facilities and services are capitalized into housing values [9,31–34]. Benjamin and Sirmans [35] studied the railway in Washington, D.C. and found that the rental value of an apartment was expected to increase by 2.5% for every 0.1 mile approaching the nearest station. Hess and Almeida [36] suggested that each foot decrease in distance resulted in an increase of $2.31 in property values. Typically, accessibility is measured by the straight-line distance from the property to the rail transit station [10,11,26,37,38]. These studies directly applied the distance variable into estimated models to obtain price elasticity, semi-elasticity, or marginal price for traffic accessibility then assessed the average capitalization effect of the rail transit. In most cases, this method can meet the study requirements.

Scholars also realized that the impact of the rail transit have a certain spatial scope. However, no uniform standard exists for the influence scope of the rail transit in previous studies. A meta-study by RICS [39] found that the scope of influence is approximately 1000 m for residential areas and 400 m for commercial areas in most cases, but may go up to 2000 m and 1200 m for these two type of areas in some cases. Cervero and Duncan [31] discovered that the influence range of the rail system in Diego County, California was 500 m to 800 m. Weinberger [40] revealed that the scope of influence on housing rental values in Santa Clara County, California was 1.2 km. Ko and Cao [41] reported that the premium effect of a light rail transit on commercial property values extended to about 0.9 miles away from stations in Minneapolis. Other studies directly established a certain range around rail transit stations as the affected area based on previous results, such as 0.7 km [42], 0.5 miles [43], and 1 mile [2,44,45].

By conducting studies in some major cities in China, scholars recently agreed that the urban rail transit yielded positive effects on housing prices and the effects diminished with the increase

in distance from the station. Wang [17] discovered that value appreciation effects of the rail transit were limited to within 1 km to 1.5 km from stations in Shanghai. Liu et al. [46] discovered that the influence scope of Metro Lines 1 and 2 in Nanjing was 1.5 km. Xu et al. [4] conducted a study with 676 residential property units along the rail line in Wuhan and found that the rail transit had a 16.7% price impact within 100 m and an 8.0% impact in the range of 100 m to 400 m. Zhang [5] performed an empirical analysis on Metro and Light rails in Beijing and showed that influence ranges were 1600 m and 800 m, respectively. Using hedonic price models, Dai et al. [14] analyzed the premium effect of rail transit on surrounding houses and found that changes of housing prices were sharper around transfer stations than those around non-transfer stations. Specifically, housing prices would rise 96.5 yuan per m^2 around a transfer station and 27.4 yuan per m^2 around a non-transfer station when distance from a station was reduced by 100 m.

In recent years, assessing dynamic changes of the capitalization effect over time is drawing increased attention from scholars. As rail transit projects go through different periods, such as the announcement period, construction period, and operation period, the property value impact can differ at each stage [37,47–50]. A typical study conducted by Henneberry [51] on the Supertram in Sheffield, England showed a slight decrease in surrounding property price when the line was in the construction stage. The anticipation of disruption during the construction stage may account for this phenomenon. However, the negative effect disappeared after the opening of this system. Similar studies conducted by Yan et al. [7] and Nie et al. [6] demonstrated that property value impacts of rail transit were negative during the construction period, but shift to positive at the operation period. In other cases, the positive anticipation of building rail transit infrastructure would be capitalized into property values [52–56]. For example, Mcmillen and McDonald [3] systematically assessed the impact of the Chicago's Midway Rapid Transit Line on housing values from 1983 to 1999. Their results demonstrated that the expected benefit of this new line was capitalized into housing values before the line opening in 1993. The key finding of the study was that value appreciation changed from 11.7% to 19.4% after the opening of rail system. Agostini and Palmucci [37] showed that the price of apartment increased 4.1–7.9% after the construction of the Santiago metro system was announced and 3.9–5.4% after the location of the stations was identified. Loomis [49] found that the price appreciation induced by San Juan metro system during the construction phase was different from the operation phase. Similar studies in the context of China are limited due to the short history of the free housing market of China and difficulties in obtaining data. Empirical evidence about the temporal effect of the urban rail transit has mainly concentrated on some metropolises, such as Beijing [57], Shanghai [18], and Shenzhen [6]. Table 1 summarizes a set of empirical studies on the effect of rail transit on property values.

Table 1. Summary of previous studies about the transit impacts on property value.

Author	Location	Tansit Type	Accessibility Variable	Size of Study Area	Key Results
Henneberry [51]	Sheffield, England	T	Straight-line distance	Not indicate	Property value impact of Supertram was negative during the construction period, but disappeared after the opening of the system.
Nie et al. [6]	Shenzhen, China	M	Shortest distance to the nearest station	1 km	Property value impact of MRT was negative during the construction period, but shifted to positive after the opening of the system.
Yan et al. [7]	Charlotte, (NC), USA	L	Network distance	1 mile	Property value impact of LRT was negative during the construction period, but shifted to positive after the opening of the system.
Nelson and Mccleskey [11]	Atlanta, USA	H	Straight-line distance	1.25 miles	Positive impacts of rail transit system proximity on property values.
Bowes and Ihlanfeldt [10]	Atlanta, USA	M	Straight-line distance	3 miles	Single-family houses within a quarter mile from stations sold for 19% less than houses beyond three miles.
Mcmillen and Mcdonald [3]	Chicago, USA	M	Distance to the nearest metro station	1.5 miles	Property value appreciation range changed from 11.7% during construction period to 19.4% around the operation period.
Hess and Almeida [36]	Buffalo, (NY), USA	L	Straight-line and network distance	0.5 mile	Property value increased in high-income station areas, but decreased in low-income station areas.
Mathur and Ferrell [38]	San Francisco, USA	L	Straight-line distance	3 miles	Positive effects of single-family values found within half a mile radius of the Ohlone Chynoweth TOD.
Agostini and Palmucci [37]	Santiago, Chile	M	Straight-line distance	1 km	Property value increased between 4.1% and 7.9% after construction was announced and between 3.9% and 5.4% after the location of the stations was identified.
Billings [23]	Charlotte, (NC), USA	L	Travel distance	1 mile	Property values were 4.0% higher for single-family properties and 11.3% higher for condominiums than outside aone mile radius of LRT stations.
Pan [26]	Houston, USA	L	Straight-line distance	3 miles	The opening of the line had positive effects on property values; Negative impacts are associated with properties located within a quarter mile of stops.
Dubé et al. [9]	Montreal, Canada	C	Walking distance and car driving time	Not indicate	Housing prices were higher within 1500 m than outside the 1500 m radius.
Zhang [5]	Beijing, China	B, L, M	Distance to the nearest station	1 mile	The impact zone for MRT can extend to more than one mile from stations but only to half a mile for LRT.
Liu et al. [46]	Nanjing, China	M	Straight-line distance	2 km	Positive impacts are found for houses located within 1.5 km to stations.
Xu et al. [4]	Wuhan, China	M	Road network and straight-line distance	1 km	Property value increased 16.7% for the 0–100 m core area and approximately 8.0% within the 100–400 m radius.
Dai et al. [14]	Beijing, China	M	Distance to the nearest station	2 km	Positive effects found; the influence scope of a transfer station on property values was 1200–1400 m, while that of the non-transfer station was within 1000 m.
Zhong and Li [58]	Los Angeles, USA	M, L	Distance to the nearest station	3 miles	Proximity to mature rail transit stations was positive for multi-family property values, but negative for single-family properties; multi-family property values were higher within 1600 m than their counterparts located beyond 1600 m.

Transit Type: B = bus rapid transit, C = commuting rail, H = heavy rail transit, L = light rail transit, M = metro rail transit, T = tram line transit.

Most prior studies on rail transit impacts used the traditional OLS regression method, which focuses on conditional mean effects on housing prices. Evidence on the heterogeneous effects of the rail transit on housing prices across high-, middle-, and low-priced houses is still lacking. As a useful supplement to OLS regression, quantile regression produces a complete description of the impact across the entire distribution of housing prices and is robust to non-normal random errors [59,60]. This method has been widely used in the field of social sciences and some scholars have recently tried introducing it into the field of real estate [61–65]. For example, Kang and Liu [66] investigated the influence of the 2008 financial crisis on housing prices at different quantiles of the price distribution in Taiwan. They found that high-priced properties were more affected than low-priced properties. Compared with the existed literature on real estate field, there has been limited empirical research concerning public transit effects on housing values at different price levels. Only Wang et al. [67] estimated the rental effect of metro stations on apartments with property rents data between December 2012 and January 2013 in Shanghai. However, this study can be improved by extending study period to investigate the dynamic influence mechanism of metro line on property rents. In order to fill this research gap, we adopt the quantile regression model to analyze impacts of a subway on various levels of housing prices, thereby assessing how buyers of high-priced houses value the rail transit differently from buyers of low-priced houses. We also examine the effects across different time periods and distance segments for each point of the price distribution, thereby providing an improved explanation of real-world phenomenon and depicting the relationship between subway and housing prices.

3. Data and Model

3.1. Study Area and Data Sources

This study focuses on the capitalization effect of Hangzhou Subway Line 1 on housing prices during its construction and operation phases. Subway Line 1 provides the first subway service to Hangzhou, which was announced in June of 2005 by the State Council of China. This line began construction on 27 March 2007 and opened on 24 November 2012. The houses in our sample are from six districts which constitute the main urban areas of Hangzhou: Xihu, Binjiang, Xiacheng, Shangcheng, Gongshu, and Jianggan, because Subway Line 1 travels through several municipal districts in Hangzhou (Figure 1). Xihu District was positioned as the recreational business district (RBD) of Hangzhou by the local government in 2007. Due to the superior natural amenities, such as the West Lake and Xixi Wetland in this district, there exists some expensive residential areas. The traditional CBD is located in Xiacheng District, whereas the new CBD (Qianjiang New City) is gradually becoming mature in Jianggan District. As for Shangcheng district, the government positioned it as the central activity zone (CAZ). Binjisng District is a recent development area, and the Gongshu District was once an industrial base of Hangzhou. Table 2 provides a description of housing prices in each district, taking 2015 transaction data as an example. The mean price of houses in six districts ranges from 161,42.620 Yuan/m^2 to 23,383.046 Yuan/m^2, indicating that houses located in Xihu District enjoy the highest average price and houses in Binjiang District have the lowest average prices. Additionally, as can be seen from the map, there is no community distributed in the vicinity of the five stations which are located at the northeast section of Subway Line 1 (from the East Railway Station to East Bus Station). The reason is that during the period from 2011 to 2015, a large number of urban villages were located in this area and the houses in urban villages cannot be traded in the real estate market. To be specific, the urban village is a unique phenomenon in large Chinese cities and is a product of China's rapid urbanization and rural migration recently [68]. Thus, the five stations are not included in our study.

Table 2. Descriptive statistics of housing prices in 2015 (Yuan/m^2).

District	Mean	Minimum	Maximum	Std. Deviation
Xihu	23,383.046	11,957.656	40,360.580	6245.878
Xiacheng	21,121.221	13,021.148	39,228.508	4105.430
Shangcheng	21,116.857	14,760.147	34,234.477	3867.221
Jianggan	20,147.465	9251.887	34,350.520	5162.274
Gongshu	17,503.769	11,014.712	34,005.770	3296.209
Binjiang	16,142.620	11,010.741	25,214.473	3034.882

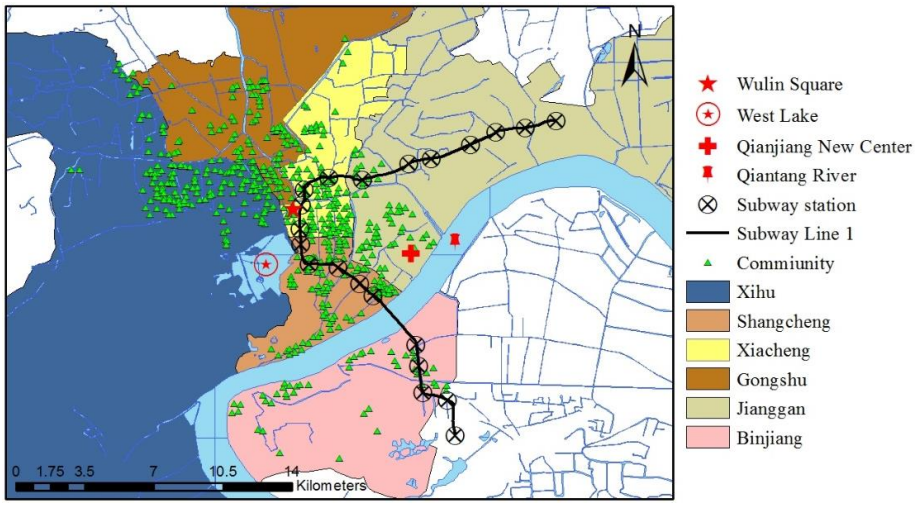


Figure 1. Map of the spatial distribution of housing communities and Subway Line 1.

This study uses housing communities as the basic analysis unit. Housing communities are located within the urban area and connected by roads in China. These communities are often built by a single real estate developer, with varying basic infrastructure and public services. The data comes from three main sources. The housing price data from 2011 to 2015 are gathered from the Hangzhou Real Estate Administration. To make the data comparable, this study utilizes only multi-layer and high-rise housing data to eliminate the effect of high-priced housing, such as villas and townhouses. Moreover, we excluded community samples that had extreme values on area. The neighborhood characteristic data, such as external environment quality, education facilities, security, etc., are obtained through a field survey involving 660 housing communities. Then, an electronic map is used to measure three location variables. Using the measuring distance function, we can obtain the distance from the housing community to the nearest subway station, West Lake, Wulin Square, and Qiantang River. The proximity variable is also coded with the electronic map. We use a dummy variable to evaluate a university within 1 km from the community as 1 and that outside 1 km as 0.

In accordance with the opening date of Subway Line 1, we divide the entire database into two time periods: the construction period (2011–2012) and the operation period (2013–2015). Based on the report of Hangzhou second-hand house price index, which covered the transaction data from 2007 to 2015 (see Appendix A). We discovered that before April 2010, the second-hand house price index increased from 100 to 250.87 (January 2007 was the base period), and since then it has entered a stable period with some minor fluctuations. Therefore, we select the housing price data from 2011 to 2015 as the sample of this study. After removing samples that have missing or extreme values on variables, 2652 valid data samples are finally obtained. The descriptive statistics and quantiles of variables are reported in Table 3. The quantile values of housing price presented in Table 3 are average values of the prices associated with a 5% confidence interval around a specific quantile point. For instance, the housing price associated with 0.1 quantile point is 12,491.621 Yuan. A 5% confidence interval of housing price around 0.1 quantile point is from 11,651.818 Yuan to 13,097.392 Yuan. Meanwhile, for houses with prices in this interval, the average value of distance to subway station is 4.118 km.

Table 3. Descriptive statistics and quantiles of variables, 2562 samples.

	Minimum	**Maximum**	**Mean**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Housing price	9251.887	40,360.580	21,549.933	12,491.621	15,557.850	18,625.190	21,662.192	24,698.702	27,854.164	31,133.921	34,120.748	37,229.013
5% conf.				11,651.818	14,721.326	17,807.810	20,918.030	24,038.97	27,145.031	30,317.252	33,458.140	36,516.098
interval				13,097.392	16,243.774	19,347.658	22,467.880	25,572.516	28,692.322	31,794.818	34,871.150	37,952.434
Distance to subway	0.105	10.339	2.809	4.118	4.537	2.877	2.654	2.009	1.760	1.798	1.725	1.815
Distance to Wulin Square	0.350	12.790	4.631	9.978	7.448	4.677	4.201	3.167	2.782	2.654	3.394	3.094
Distance to West Lake	0.300	13.100	4.096	8.941	6.485	4.347	3.486	2.921	2.729	2.074	2.062	2.349
Distance to the Qiantang River	0.095	16.532	5.995	5.056	7.121	6.3447	5.544	5.442	6.066	6.357	4.983	6.840
External Environment quality	1	5	3.120	2.907	3.164	3.210	3.040	3.083	3.094	3.167	3.462	3.044
Inner environment quality	1	5	3.210	3.372	3.199	3.121	3.124	3.224	3.236	2.867	3.46	3.304
Transportation convenience	1	5	3.090	1.837	2.289	2.853	3.231	3.682	3.670	3.867	3.846	3.870
Security	1	5	3.590	3.698	3.356	3.448	3.628	3.654	3.686	3.500	3.640	3.609
Education facilities	1	4	3.130	2.721	2.685	3.005	3.215	3.292	3.434	3.533	3.269	3.609
Nearby universities	0	1	0.600	0.209	0.438	0.541	0.626	0.677	0.793	0.800	0.731	0.783
Building age	1	37	14.130	9.767	11.637	14.924	14.890	15.125	13.972	15.667	13.846	14.957

3.2. Variable Selection

When applying the hedonic price model, the selection of explanatory variables is a key step in setting up the hedonic price model. Subway accessibility is the primary variable examined in this study. First, we adopt the straight-line distance from housing communities to the nearest subway station to analyze the overall impact on housing prices. Based on the finding that the impact scope of the rail transit on residential property values is around 1000 m in most cases [9,14,46,69], but can go up to 2000 m [39,53,70], we divide communities into five categories (0–500 m, 500–1000 m, 1000–1500 m, 1500–2000 m, and beyond 2000 m) according to their distance to subway station to explore whether the rail transit impact changes at different distance segments. Explanatory variables can also be classified into three categories [31,71], namely, location, neighborhood, and structural variables. On the basis of previous studies on the Hangzhou housing market conducted by Wen, Bu, and Qin [72], Wen, Jin, and Zhang [73], and Wen, Xiao, and Zhang [74], three location variables, six neighborhood variables, and one structural variable are chosen as control variables.

Wulin Square is the traditional CBD (central business district), West Lake is the center of the urban landscape, and Qianjiang New City is the new CBD, located on the bank of the Qiantang River. From the aspect of location features, this study selects the distance between the community center and West Lake, Wulin Square, and the Qiantang River as location variables. Six districts are used as dummy variables to identify their fixed effects, which result from different policies and public services. Neighborhood variables refer to various environmental factors and auxiliary service facilities around communities, which reflect the convenience of people's lives. According to the demand of home buyers for natural landscapes, travel, and education, six other variables are considered: external environment quality, inner environment quality, transportation convenience, nearby universities, educational facilities, and security. Building age is selected as structural feature. The study also includes dummy variables of Y_{2011}–Y_{2015}, accounting for effects of macro factors, such as macro-control policy and inflation, which may influence housing prices. Table 4 presents the description, quantization, and expected sign of these variables.

Table 4. Variable description, quantization, and expected sign.

Variable	Variable Definition and Quantization	Expected Sign
Distance to subway	Straight-line distance between the community center and the nearest subway station (km)	-
D_1	1 if the distance to subway is within 500 m; 0 otherwise	+
D_2	1 if the distance to subway is within 500–1000 m; 0 otherwise	+
D_3	1 if the distance to subway is within 1000–1500 m; 0 otherwise	+
D_4	1 if the distance to subway is within 1500–2000 m; 0 otherwise	+
Distance to West Lake	Straight-line distance between the community center and the coast of West Lake (km)	-
Distance to Wulin Square	Straight-line distance between the community center and Wulin Square (km)	-
Distance to the Qiantang River	Straight-line distance between the community center and the coast of the Qiantang River (km)	-
External environment quality	Park, mountain, river, lake, green space within 1000 m from the community, each item is scored with 1, total is 5	+
Inner environment quality	Environmental quality inside the community, including greening condition, sanitary condition, air quality and quiet degree, is divided into 5 degrees: quite bad, bad, common, good, very good, scored as 1–5, respectively	+
Transportation convenience	Transportation conditions around the community, Measured by total number of bus routes within 1000 m of the community, is divided into 5 degrees: quite poor, poor, common, good, and very good, scored as 1–5, respectively	+
Security	Security conditions inside and outside the community, is divided into 5 degrees: quite bad, bad, common, good, and very good, scored as 1–5, respectively	+
Education facilities	A high school, junior high school, elementary school, and kindergarten facility within 1000 m of the community is each scored as 1, with a total of 4	+
Nearby universities	1 if a university or college within 1000 m, 0 otherwise	+
Building age	The age of the building (year, transaction years minus actual built years)	-
Xihu	1 if the community is in Xihu district; 0 otherwise	?
Gongshu	1 if the community is in Gongshu district; 0 otherwise	?
Xiacheng	1 if the community is in Xiacheng district; 0 otherwise	?
Shangcheng	1 if the community is in Shangcheng district; 0 otherwise	?
Jianggan	1 if the community is in Jianggan district; 0 otherwise	?
Y_{2011}–Y_{2015}	1 if the house was procured at time t (in years); 0 otherwise, where t = 2011, 2012, . . . , 2015	?

+, - and ? represent positive effect, negative effect, and uncertain effect on housing price, respectively.

3.3. Empirical Model Specification

To investigate the capitalization effect of the subway on housing prices, hedonic price models are established with data in three time periods: 2011–2015, 2011–2012, and 2013–2015. Based on OLS regression and quantile regression methods, 12 models are set to explore this empirical issue. Models 1–6 are the basic models and models 7–12 are the quantile regression models.

(1) Basic model

Traditional hedonic price models are applied as basic models. The dependent variable and continuous independent variables are adopted into logarithmic form, whereas class variables and dummy variables are adopted into linear form. OLS estimated results are used as a benchmark and comparison for subsequent analyses. First, subway distance is introduced into the models to gauge the overall effect of its accessibility on housing prices. Basic models 1–3 are defined as follows:

$$\mathrm{LnP} = \beta_0 + \beta_1 \mathrm{LnD} + \Sigma \alpha_i X_i + \gamma_j Y_j + \varepsilon, \quad (1)$$

where P is the housing price; D is the distance of a community from the subway station; X_i are the set of housing characteristics; Y_j are the time dummy variables that represent the year the house was procured; α_i, β_0, β_1, γ_j are the coefficients to be estimated; and ε is an error term.

Housing communities are then divided into five areas according to their distance from the subway station. Communities that are more than 2 km away from a station serve as the reference category to analyze changes of capitalization effects in distance segments. Models 4–6 are designed as follows:

$$\mathrm{LnP} = \beta_0 + \beta_m D_m + \Sigma \alpha_i X_i + \gamma_j Y_j + \varepsilon, \quad (2)$$

where D_m are the dummy variables of distance interval, and the remaining variables are the same as in Equation (1).

(2) Quantile regression model

Effects of the subway may vary widely across the entire distribution of housing prices. The conventional mean-based approach is insufficient to capture the heterogeneity of housing prices. Thus, to differentiate heterogeneous impacts on high, medium, and low-priced houses, quantile regression is employed to optimize the basic models. Models 7–9 are defined as follows:

$$\mathrm{LnP} = \beta_0 \tau + \beta_1 \tau \mathrm{LnD} + \Sigma \alpha_i \tau X_i + \gamma_j \tau Y_j + \varepsilon, \quad (3)$$

where τ represents a quantile point in the distribution; $\alpha_i \tau$, $\beta_0 \tau$, $\beta_1 \tau$, $\beta_m \tau$, $\gamma_j \tau$ are the coefficients to be estimated.

The principle of Models 10–12 is similar to Model 7–9, with the following expression:

$$\mathrm{LnP} = \beta_0 \tau + \beta_m \tau D_m + \Sigma \alpha_i \tau X_i + \gamma_j \tau Y_j + \varepsilon \quad (4)$$

4. Results and Discussion

4.1. Results of Basic Models

(1) Overall accessibility effect of the subway on housing prices

Models 1–3 are traditional hedonic price models. The distance from the subway is utilized to measure the overall effect of its accessibility on housing prices. The regression coefficients are estimated through the OLS method and the results are reported in Table 5. Results of the ANOVA test suggest the models are valid with the 1% significance level for F values. Models 1–3 have adjusted R^2 values of 0.693, 0.715, and 0.681, respectively, which suggest that the independent variables of these models can explain about 70% of the variation of the dependent variable and indicate that every model has a good fit.

Table 5. Regression results of models 1–3.

	Model 1 (2011–2015)			Model 2 (2011–2012)			Model 3 (2013–2015)		
	Unstandardized Coefficients		Standardized Coefficients	Unstandardized Coefficients		Standardized Coefficients	Unstandardized Coefficients		Standardized Coefficients
	Coef.	*p*-Value	Beta	Coef.	*p*-Value	Beta	Coef.	*p*-Value	Beta
(Constant)	10.106 ***	0.000		10.012 ***	0.000		10.190 ***	0.000	
Ln(Distance to subway station)	−0.049 ***	0.000	−0.211	−0.044 ***	0.000	−0.194	−0.053 ***	0.000	−0.225
Ln(Distance to Wulin Square)	−0.057 ***	0.000	−0.169	−0.048 ***	0.004	−0.147	−0.059 ***	0.000	−0.172
Ln(Distance to West Lake)	−0.204 ***	0.000	−0.543	−0.206 ***	0.000	−0.565	−0.207 ***	0.000	−0.548
Ln(Distance to the Qiantang River)	−0.090 ***	0.000	−0.429	−0.084 ***	0.000	−0.411	−0.092 ***	0.000	−0.436
External environment quality	0.013 ***	0.001	0.046	0.019 ***	0.001	0.070	0.009 **	0.064	0.032
Inner environment quality	0.056 ***	0.000	0.233	0.056 ***	0.000	0.243	0.054 ***	0.000	0.221
Transportation convenience	0.007 **	0.007	0.041	0.011 ***	0.009	0.061	0.005	0.135	0.030
Nearby Universities	0.028 ***	0.000	0.061	0.030 ***	0.001	0.068	0.028 ***	0.000	0.062
Education facilities	0.006	0.101	0.021	0.004	0.467	0.014	0.007	0.137	0.025
Security	−0.005	0.187	−0.019	−0.003	0.639	−0.010	−0.007	0.191	−0.025
Ln(Building age)	−0.068 ***	0.000	−0.181	−0.057 ***	0.000	−0.183	−0.086 ***	0.000	−0.193
Xihu	0.509 ***	0.000	1.005	0.490 ***	0.000	0.997	0.517 ***	0.000	1.010
Gongshu	0.335 ***	0.000	0.530	0.360 ***	0.000	0.586	0.318 ***	0.000	0.499
Xiacheng	0.244 ***	0.000	0.422	0.283 ***	0.000	0.505	0.220 ***	0.000	0.379
Shangcheng	0.146 ***	0.000	0.252	0.183 ***	0.000	0.322	0.122 ***	0.000	0.210
Jianggan	0.238 ***	0.000	0.343	0.265 ***	0.000	0.398	0.224 ***	0.000	0.319
Y2012	−0.067 ***	0.000	−0.118	−0.070 ***	0.000	0.160			
Y2013	−0.010	0.232	−0.017						
Y2014	−0.078 ***	0.000	−0.139				−0.066 ***	0.000	−0.136
Y2015	−0.088 ***	0.000	−0.156				−0.073 ***	0.000	−0.150
Adjusted R^2	0.693			0.715			0.681		
F	289.836 ***			150.095 ***			184.390 ***		

***, **, and * represent the 1%, 5%, and 10% significance levels, respectively.

Three models are estimated for time periods of 2011–2015, 2011–2012, and 2013–2015, with coefficients of subway distance variables at −0.049, −0.044, and −0.053, respectively. Significance levels are all below 1%, which indicates that the subway affects housing prices significantly. These coefficients represent the impact of subway accessibility on housing price for every one percent change in distance from the station. For example, during construction and operation phases, every 1% decrease in distance from the subway brings about a 0.049% increase in housing price. Similarly, in Models 2 and 3, the coefficients indicate that every 1% decrease in distance raises housing prices by 0.044% during the construction period compared with 0.053% during the operation period. These results show that the value-added effect during the operation period is greater than during the construction period. This finding is coherent with conclusions of previous studies [3,75] that rail transit impact follows certain rules; that is, the anticipatory benefits of a new subway line begin to be capitalized into housing prices before subway opening. Nevertheless, due to noise and pollution during the building process of the rail transit system, the positive capitalization effects associated with the operation period are usually larger than those associated with the construction period.

Moreover, estimated coefficients of other independent variables are generally statistically significant at less than the 10% level with expected signs. Distance to West Lake, distance to Wulin Square, distance to the Qiantang River, interior environment quality, surrounding environment quality, and nearby universities also significantly influence housing prices. This finding is coherent with the conclusion of early studies on the real estate market in Hangzhou [72–74,76]. Since the regression coefficients represent the price elasticity and semi-elasticity of housing characteristics, the influence degree of each characteristic on housing prices cannot be compared directly. However, the standardized coefficients (beta) are obtained after standardizing all variables (Z-scores). They are comparable and the absolute value of them can be used to rank the influence degree. Taking Model 1 as an example, the influence degree of the nine characteristic variables which affects housing prices are significantly different. Specifically, the absolute value of beta of the West Lake distance is the greatest (0.543), while the transportation convenience variable has the smallest influence degree on housing prices (0.041). In addition, the absolute value of beta of the distance to the subway station is 0.211, which ranked fourth among the nine variables. This reveals that people's willingness to pay a price premium generated by the subway station is relatively strong.

(2) Distance heterogeneity of the subway affects housing prices

In Models 4–6, we use dummy variables D_1–D_4 to represent subway accessibility in place of linear distance variables to gauge the heterogeneous impacts of the subway in various distance segments. Similar to Models 1–3, Models 4–6 are estimated for time periods of 2011–2015, 2011–2012, and 2013–2015. Regression results are summarized in Table 6. The adjusted R^2 of Models 4–6 are 0.683, 0.707, and 0.676, respectively. Significance levels are lower than 0.001, which indicate that all models are effective and have good explanatory capabilities. Most variables are statistically significant and can pass the 10% significance level test with expected signs.

Table 6. Regression results of models 4–6.

	Model 4 (2011–2015)			Model 5 (2011–2012)			Model 6 (2013–2015)		
	Unstandardized Coefficients		Standardized Coefficients	Unstandardized Coefficients		Standardized Coefficients	Unstandardized Coefficients		Standardized Coefficients
	Coef.	*p*-Value	Beta	Coef.	*p*-Value	Beta	Coef.	*p*-Value	Beta
(Constant)	10.115 ***	0.000		10.048 ***	0.000		10.194 ***	0.000	
D_1	0.061 ***	0.000	0.075	0.035 *	0.066	0.044	0.077 ***	0.000	0.095
D_2	0.053 ***	0.000	0.095	0.034 **	0.027	0.064	0.064 ***	0.000	0.115
D_3	0.052 ***	0.000	0.075	0.031 *	0.066	0.045	0.064 ***	0.000	0.093
D_4	0.021 *	0.056	0.026	−0.010	0.543	0.044	0.039 ***	0.006	0.048
Ln(Distance to Wulin Square)	−0.085 ***	0.000	−0.251	−0.081 ***	0.000	−0.249	−0.087 ***	0.000	−0.256
Ln(Distance to West Lake)	−0.200 ***	0.000	−0.532	−0.202 ***	0.000	−0.556	−0.201 ***	0.000	−0.531
Ln(Distance to the Qiantang River)	−0.089 ***	0.000	−0.426	−0.081 ***	0.000	−0.393	−0.093 ***	0.000	−0.442
External environment quality	0.010 ***	0.008	0.036	0.016 ***	0.007	−0.013	0.006	0.208	0.022
Inner environment quality	0.058 ***	0.000	0.239	0.057 ***	0.000	0.059	0.055 ***	0.000	0.228
Transportation convenience	0.007 **	0.015	0.038	0.010 **	0.013	0.019	0.004	0.254	0.023
Nearby universities	0.025 ***	0.000	0.054	0.026 ***	0.005	0.059	0.025 ***	0.002	0.054
Education facilities	0.008 **	0.049	0.026	0.005	0.344	0.057	0.009 *	0.086	0.029
Security	−0.008 **	0.039	−0.030	−0.006	0.328	0.246	−0.010 **	0.048	−0.038
Ln(Building age)	−0.071 ***	0.000	−0.189	−0.059 ***	0.000	−0.022	−0.090 ***	0.000	−0.203
Xihu	0.481 ***	0.000	0.948	0.448 ***	0.000	−0.188	0.497 ***	0.000	0.973
Gongshu	0.312 ***	0.000	0.493	0.323 ***	0.000	0.914	0.303 ***	0.000	0.476
Xiacheng	0.222 ***	0.000	0.385	0.252 ***	0.000	0.529	0.203 ***	0.000	0.351
Shangcheng	0.153 ***	0.000	0.263	0.186 ***	0.000	0.451	0.133 ***	0.000	0.228
Jianggan	0.251 ***	0.000	0.361	0.277 ***	0.000	0.329	0.237 ***	0.000	0.338
Y_{2012}	−0.065 ***	0.000	−0.116	−0.067 ***	0.000	0.417			
Y_{2013}	−0.009	0.276	−0.016			−0.155			
Y_{2014}	−0.077 ***	0.000	−0.137				−0.066 ***	0.000	−0.137
Y_{2015}	−0.086 ***	0.000	−0.153				−0.074 ***	0.000	−0.154
Adjusted R^2	0.683			0.707			0.676		
F	241.115 ***			122.727 ***			154.692 ***		

***, **, and * represent the 1%, 5%, and 10% significance levels, respectively.

In Model 4, regression coefficients of D_1–D_4 are 0.061, 0.053, 0.052, and 0.021, respectively, which indicate that communities within 500 m of a subway station are 6.2% more expensive than those beyond 2000 m, and they also enjoy the highest premium. Appreciation rates demonstrate a slight decline at 5.3% and 5.2% within ranges of 500–1000 m and 1000–1500 m, respectively. In terms of properties located within 1500–2000 m of a station, the value-added effect on housing prices remains statistically significant, but the appreciation rate drops to a highly reduced magnitude of 2.1%. In Model 5, D_1–D_4 have price semi-elasticities of 0.035, 0.034, 0.03, and −0.010, respectively. Accordingly, price appreciation rates for D_1–D_4 during the construction period are 3.6%, 3.5%, 3.1%, and −1%, respectively. Price appreciation rates for D_1–D_4 during the operation period are 8.0%, 6.6%, 6.6%, and 4.0%, respectively. Similar to Model 4, the price appreciation effect of the subway on housing price during the construction and operation periods decreases with increasing distance from the station. The changing trend of the impact is similar. However, during the construction period, influence on communities located within 1500–2000 m of a station was not significant. This result suggests that the average spatial range of the subway impact on housing prices during the construction period is 1500 m. Moreover, the regression coefficients of D_1–D_4 in the operation period are significant at 5%, which indicates that the subway impact range expanded after the opening of the subway line.

Figure 2 shows that changing trends of price appreciation ratios in construction and operation periods are similar and decline with increasing distance. Changes in the appreciation effect of housing prices also have various sensitivities in different distance segments. When distance between the community and the subway station exceeds 1500 m, housing prices have reduced sensitivity to the change in distance. For example, in the operation period, the appreciation rate of houses located within 1500–2000 m of a station is lower than those within 1000–1500 m. Therefore, appreciation rates of housing prices located within 1500 m of the subway station decrease slowly with increasing distance. In particular, the appreciation ratios of the spatial ranges of 500–1000 m and 1000–1500 m are almost consistent. The probable reason is that people are generally willing to pay for the price premium generated by the subway station proximity of within 20 min of walking time at a walking speed of approximately 4–5 km/h. When the distance exceeds this threshold, the willingness of people to pay for subway accessibility will diminish. Therefore, the price premium within the distance of 1500–2000 m will be reduced considerably, and the subway will have little, or even no, significant effect on housing prices in this spatial segment.

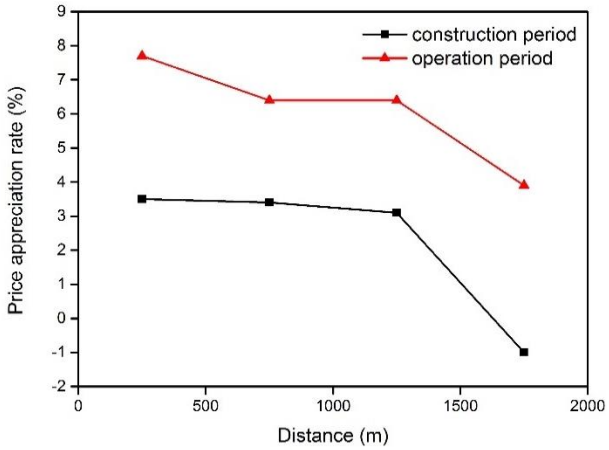


Figure 2. Distance heterogeneity of the subway that affects housing prices.

4.2. Results of Quantile Regression Models

In traditional hedonic price models, OLS regression can obtain only the average impact of characteristics on housing prices. The implicit assumption that the impact of a specific explanatory variable on high-, medium-, and low-priced houses is consistent. However, this assumption may not

hold true in reality. Therefore, to overcome the limitations of OLS regression, Models 7–12 use quantile regression to examine the impact of Subway Line 1 for different quantiles of housing price distribution. The regression coefficients of subway distances are shown in Tables 7 and 8.

Table 7. Quantile regression results of Models 7–9.

	Model 7 (2011–2015)		**Model 8 (2011–2012)**		**Model 9 (2013–2015)**	
	Coef.	***p*-Value**	**Coef.**	***p*-Value**	**Coef.**	***p*-Value**
OLS	−0.049 ***	0.000	−0.044 ***	0.000	−0.053 ***	0.000
q05	0.008	0.484	0.015	0.392	0.014	0.269
q10	−0.007	0.507	−0.002	0.894	−0.010	0.442
q15	−0.023 **	0.023	−0.030 **	0.009	−0.021 **	0.027
q20	−0.038 ***	0.000	−0.033 **	0.002	−0.038 ***	0.000
q25	−0.042 ***	0.000	−0.035 ***	0.000	−0.045 ***	0.000
q30	−0.044 ***	0.000	−0.038 ***	0.000	−0.046 ***	0.000
q35	−0.040 ***	0.000	−0.034 ***	0.000	−0.044 ***	0.000
q40	−0.041 ***	0.000	−0.041 ***	0.000	−0.044 ***	0.000
q45	−0.044 ***	0.000	−0.042 ***	0.000	−0.050 ***	0.000
q50	−0.050 ***	0.000	−0.039 ***	0.000	−0.047 ***	0.000
q55	−0.048 ***	0.000	−0.044 ***	0.000	−0.049 ***	0.000
q60	−0.054 ***	0.000	−0.050 ***	0.000	−0.057 ***	0.000
q65	−0.058 ***	0.000	−0.058 ***	0.000	−0.060 ***	0.000
q70	−0.065 ***	0.000	−0.070 ***	0.000	−0.069 ***	0.000
q75	−0.067 ***	0.000	−0.070 ***	0.000	−0.074 ***	0.000
q80	−0.073 ***	0.000	−0.073 ***	0.000	−0.073 ***	0.000
q85	−0.069 ***	0.000	−0.073 ***	0.000	−0.077 ***	0.000
q90	−0.079 ***	0.000	−0.078 ***	0.000	−0.080 ***	0.000
q95	−0.086 ***	0.000	−0.099 ***	0.000	−0.074 ***	0.000

***, **, and * represent the 1%, 5%, and 10% significance levels, respectively.

The results of Model 7 indicate that apart from the 5th and 10th quantiles, subway distance variables are significantly related to housing prices with negative signs. In other words, subway distance has no significant effect on low-priced houses, but significantly raises the price of medium- and high-priced houses. The effects of distance variables also demonstrate heterogeneity across quantiles. When $\tau \geq 0.15$, subway distance has a significant positive effect on housing prices, and implicit prices present a clear upward trend from the 15th to 95th quantiles. For instance, the elastic coefficient of the subway distance variable at the 15th quantile is −0.023, whereas that at the 95th quantile is −0.086. This result shows that subway accessibility yields a far greater impact on high-priced communities than on medium and low-priced communities. The existence of the subway may be raising housing prices directly and remarkably because most high-priced communities are located in the city center and are close to Subway Line 1. As to conditions before and after the opening of Subway Line 1, regression results of Models8 and 9 are consistent with those of Model 7. In other words, capitalization effects of the subway show a rising trend as housing prices increase in conditional quantiles. In addition, price appreciation effects during the operation period are greater than those during the construction period at most quantile points. For example, for every one percent decrease in distance from the subway station at the median point, communities show a 3.9% increase in prices during the construction period and a 4.7% increase during the operation period. This finding indicates that the opening of the subway can enhance its capitalization effect.

Table 8. Quantile regression results of Models 10–12.

	Model 10 (2011–2015)				**Model 11 (2011–2012)**				**Model 12 (2013–2015)**			
	D_1	**D_2**	**D_3**	**D_4**	**D_1**	**D_2**	**D_3**	**D_4**	**D_1**	**D_2**	**D_3**	**D_4**
OLS	0.061 ***	0.053 ***	0.052 ***	0.021 *	0.035 *	0.034 **	0.031 *	−0.010	0.077 ***	0.064 ***	0.064 ***	0.039 ***
q05	−0.085 ***	−0.082 **	−0.051 **	−0.052 **	−0.081 ***	−0.063 **	−0.039	−0.040	−0.093 **	−0.106 **	−0.060 *	−0.059 **
q10	−0.046 *	−0.040 **	−0.034 *	−0.034 **	−0.073 **	−0.056 **	−0.057 **	−0.040 *	−0.016	−0.025	−0.009	−0.020
q15	−0.034	−0.017	−0.030 **	−0.031 **	−0.029	−0.024	−0.033	−0.020	−0.020	−0.003	−0.013	−0.014
q20	−0.010	0.010	−0.020 **	−0.008	0.013	0.002	−0.019	−0.004	−0.005	0.012	−0.011	0.007
q25	0.034	0.034 **	0.001	0.024 *	0.021 ***	0.006	−0.017	0.011	0.027	0.038 **	0.010	0.030
q30	0.028	0.028 *	0.010	0.018 *	0.020	0.001	−0.003	0.012	0.030	0.046 ***	0.023	0.028
q35	0.031	0.026 **	0.019	0.019 *	0.027	0.018	0.011	0.008	0.042 *	0.042 **	0.037 *	0.026 *
q40	0.032	0.028 *	0.029 **	0.016	0.020	0.019	0.027	0.009	0.057 **	0.049 ***	0.050 **	0.033 **
q45	0.047 **	0.039 **	0.042 **	0.018	0.022	0.016	0.022	0.002	0.063 **	0.054 ***	0.062 **	0.037 **
q50	0.063 ***	0.057 ***	0.063 ***	0.025 *	0.027	0.030	0.036	−0.003	0.076 ***	0.063 ***	0.070 ***	0.037 **
q55	0.071 ***	0.062 ***	0.072 ***	0.025 **	0.038	0.0045 **	0.050 *	0.004	0.099 ***	0.077 ***	0.085 ***	0.045 **
q60	0.081 ***	0.076 ***	0.079 ***	0.035 **	0.035	0.051 **	0.048 *	0.001	0.103 ***	0.083 ***	0.092 ***	0.052 **
q65	0.088 ***	0.079 ***	0.081 ***	0.034 **	0.045	0.050 **	0.041	−0.004	0.118 ***	0.097 ***	0.106 ***	0.057 **
q70	0.098 ***	0.083 ***	0.089 ***	0.036 ***	0.049	0.044 **	0.040	−0.007	0.133 ***	0.101 ***	0.113 ***	0.059 **
q75	0.099 ***	0.074 ***	0.079 ***	0.035 **	0.071 **	0.060 **	0.057 **	0.000	0.131 ***	0.099 ***	0.111 ***	0.069 **
q80	0.109 ***	0.080 ***	0.090 ***	0.040 **	0.121 ***	0.070 **	0.068 **	−0.001	0.103 ***	0.082 **	0.087 **	0.051 *
q85	0.102 ***	0.076 ***	0.083 ***	0.035 *	0.106 **	0.056 **	0.047	−0.016	0.127 ***	0.076 ***	0.089 **	0.051 **
q90	0.118 ***	0.070 **	0.104 **	0.018	0.114 **	0.076 ***	0.070 **	−0.023	0.135 ***	0.075 ***	0.129 ***	0.054
q95	0.137 ***	0.085 ***	0.138 **	0.030	0.166 **	0.093 **	0.112 **	−0.017	0.137 ***	0.065 **	0.152 ***	0.050

***, **, and * represent the 1%, 5%, and 10% significance levels, respectively.

Model 10 further describes the impact of subway on housing prices across quantiles in each distance segment. The coefficients of D_1–D_4 show that the subway has a significant negative effect on housing prices for the cheapest communities within the 10th percentile, and a positive impact on communities above the 25th percentile. Nevertheless, in the basic model based on the OLS regression, positive impacts on residential prices are obtained in each distance segment. By comparing results of the OLS and quantile regressions, we find that OLS results overestimate impacts relative to low quantiles and under-estimate those for high quantiles, thereby producing biased results.

In general, coefficients of D_1–D_4 depict a climbing trend of change in different quantiles. For instance, the coefficients of D_1 increased from 0.047 at the 45th quantile to 0.137 at the 95th quantile. With regard to a specific quantile point, value appreciation ratios decrease with increasing distance from a station. For example, coefficients of D_1–D_4 at the 75th quantile are 0.099, 0.074, 0.079, and 0.035, respectively, which indicate that the subway capitalization effect demonstrates a downward trend with increasing distance. This finding is in line with results obtained from basic models.

Regression results of Models 11 and 12 suggest that impacts of the subway on housing values during the operation phase are generally larger than that during the construction period. Similar to results of Model 10, effects of the subway in these models increase as housing prices rise in conditional quantiles. In each quantile point, impacts of the subway also experience a downward trend with increasing distance. The estimated coefficients in Model 11 are statistically insignificant from the 15th quantile to the 50th, which indicate that the subway does not affect the value of low and medium-priced houses during the construction period. By contrast, from the 75th quantile to the 95th, estimated coefficients of D_1–D_3 are significant below 5%. This result suggests that housing prices are noticeably influenced by the subway when housing prices are high, and that the spatial scope of the influence is 1500 m. In the operation period, the subway yields a notable value appreciation effect at the 35th quantile and above. Moreover, the influence scope is 2000 m from the 35th quantile to the 85th and 1500 m at the 90th and 95th quantiles. These results show that the impact scope of the subway on high-priced houses is greater than on medium-priced houses. In other words, home buyers of high-priced houses show increased willingness to live near subway stations than buyers of low- and medium-priced houses.

5. Conclusions

This study employs a large sample of housing data from 2011–2015 in Hangzhou to examine the capitalization effects of Subway Line 1 on housing prices before and after the subway opening. Based on the hedonic price model, OLS regression and quantile regression methods are employed to quantitatively measure the impact of subway accessibility on housing prices. The empirical results show the following.

(1) The subway produces a significant impact on housing prices, and accessibility effects vary at different distance intervals. During construction and operation periods, housing prices are negatively related to subway distance, that is, every 1% decrease in subway distance results in a 0.049% increase in housing price. The value-added effect diminishes gradually with increasing distance. Specifically, houses within 500 m of a subway station enjoy the highest premium (6.2%). The appreciation rate experiences a sharp decline (2.1%) when the distance exceeds 1500 m.

(2) The opening of the subway enhances the capitalization effect of subway accessibility. The subway has a significant and positive impact on housing prices in the construction and operation phases. First, the price elasticity of the distance variable increases from 0.044 during the construction period to 0.053 during the operation period. Second, the influence range of the subway also expanded from 1500 m to 2000 m. Finally, the percentage gain in housing prices during the operation period is higher than that during the construction period in each distance segment.

(3) The subway exhibits a heterogeneous capitalization effect across different houses of low, medium, and high prices. The quantile regression model further verifies results obtained from basic hedonic price models. Moreover, the quantile regression model also reveals that the subway produces

evidently distinct impacts at different housing prices. The price elasticity (absolute value) of the subway distance exhibits a rising trend in conditional quantiles. Results indicate that medium- and high-priced communities are highly sensitive to rail transport accessibility. The effects of the subway in each distance segment also rise as housing prices increase in conditional quantiles. This finding suggests that the price premiums of medium- and high-priced houses are remarkably greater than that of low-priced houses.

(4) The quantile regression model provides us with valuable information that cannot be obtained from the OLS regression and reveals the complex impacts of housing prices before and after the opening of the subway. From quantile regression results, we find that buyers of high-priced houses have different rail transit preferences from buyers of low-priced houses, thereby resulting in heterogeneity of the capitalization effect of the subway. By depicting the changing trend of implicit prices across the entire housing price distribution, quantile regression can comprehensively estimate subway impacts and reveal behavioral differences among home buyers at different price levels.

Through an empirical study of the Hangzhou real estate market, this study analyzes changes in the capitalization effect before and after the opening of a new subway line. The results of this study can serve as a reference for the government to formulate relevant policies:

(1) Strengthen the comprehensive development of land supply around subway stations. As an important development line and passenger corridor to the city, Hangzhou Subway Line 1 will promote the value of real estate around the station and affect the functional planning and layout of urban space. Drawing from the relevant conclusions of this study, the land around the station should implement comprehensive and high-intensity developments and give full play to the agglomeration function. Thus, the station area will form a functional area integrating public transportation, residential properties, commercial facilities, and office facilities, and then reflect the economic and social benefits of the urban rail transit.

(2) Consider the potential for low-priced housing gentrification and avoid negative effects. Public transport is one of the important factors that influence the home purchasing decisions of people. The empirical analysis of Hangzhou Subway Line 1 finds that medium- and high-priced housing markets are sensitive to subway accessibility. Buyers of medium- and high-priced houses show a notable willingness to pay to live near a subway station. Hence, potential exists for the gentrification of low-priced houses surrounding the stations. Policymakers should fully consider this potential situation. In urban construction, policymakers should continue to improve urban infrastructure, ensure the supply of affordable housing, and formulate corresponding policies to secure housing affordability for the low-income population.

Finally, this study has two limitations and we consider them as future research directions. First, this study focuses on the impact of subways on housing prices with the quantile regression model, and does not consider the spatial effects, such as spatial autocorrelation and spatial heterogeneity. In general, spatial econometric models can improve the effectiveness and robustness of the hedonic price model, and have been widely used by scholars. The Moran's I indices in this study are small (0.162, 0.193, 0.182, 0.230, and 0.215 from 2011 to 2015, respectively), so we adopted the quantile regression model, and obtained robust results. How to combine the spatial econometric model and quantile regression model to study the capitalization effect of subway accessibility, which is worthy of further study. Second, when we use community-level data to set up models, the modifiable areal unit problem (MAUP) deserves our attention. The average housing prices of the communities are used in our study, and MAUP may be caused by different scales and shapes of communities. In future studies, we could consider working with basic units, optimal zoning, and performing sensitivity analyses to avoid MAUP issues.

Author Contributions: Conceptualization, H.W. and C.T.; Methodology, H.W.; Software, Z.G. and Y.X.; Validation, H.W., Z.G. and Y.X.; Formal Analysis, H.W. and Z.G.; Investigation, H.W. and Z.G.; Resources, H.W.; Data Curation, H.W. and Z.G.; Writing-Original Draft Preparation, H.W. and Z.G.; Writing-Review & Editing, H.W., Z.G., L.F. and Y.X.; Visualization, Z.G.; Supervision, H.W.; Project Administration, C.T.; Funding Acquisition, C.T.

Funding: This study was funded by National Social Science Foundation of China [grant number 17BJY224] and Zhejiang Provincial Natural Science Foundation of China [grant number LY18G030002]. All errors remain are our own.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

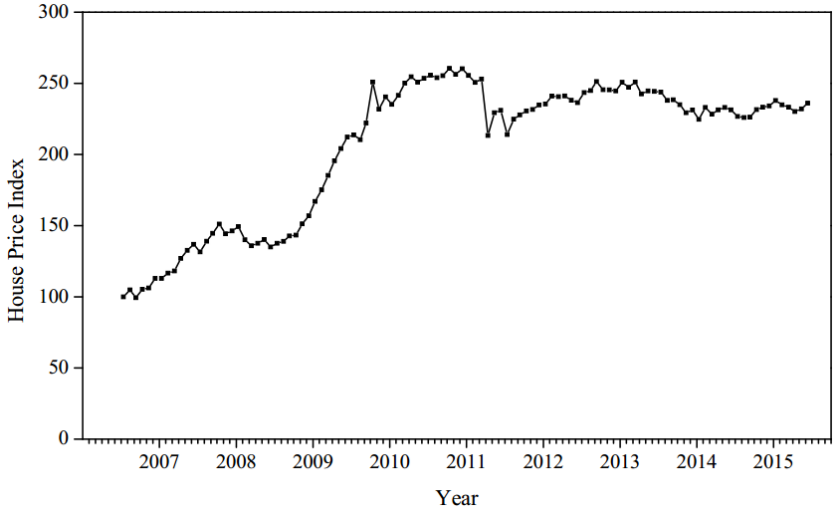


Figure A1. Hangzhou monthly House Price Index from 2007 to 2015.

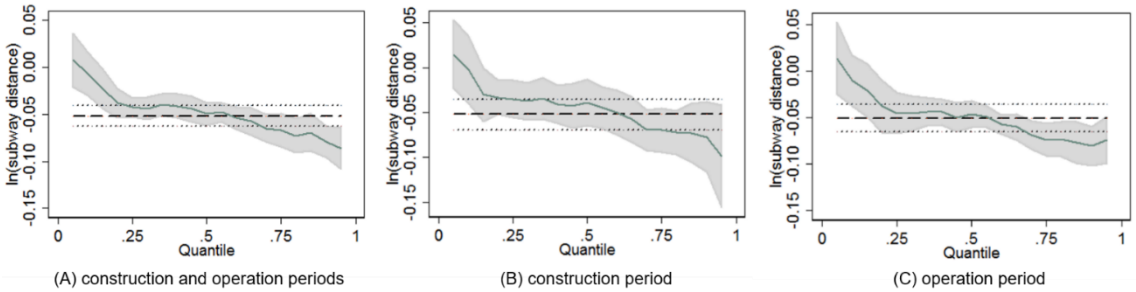


Figure A2. Quantile regression results for subway distance.

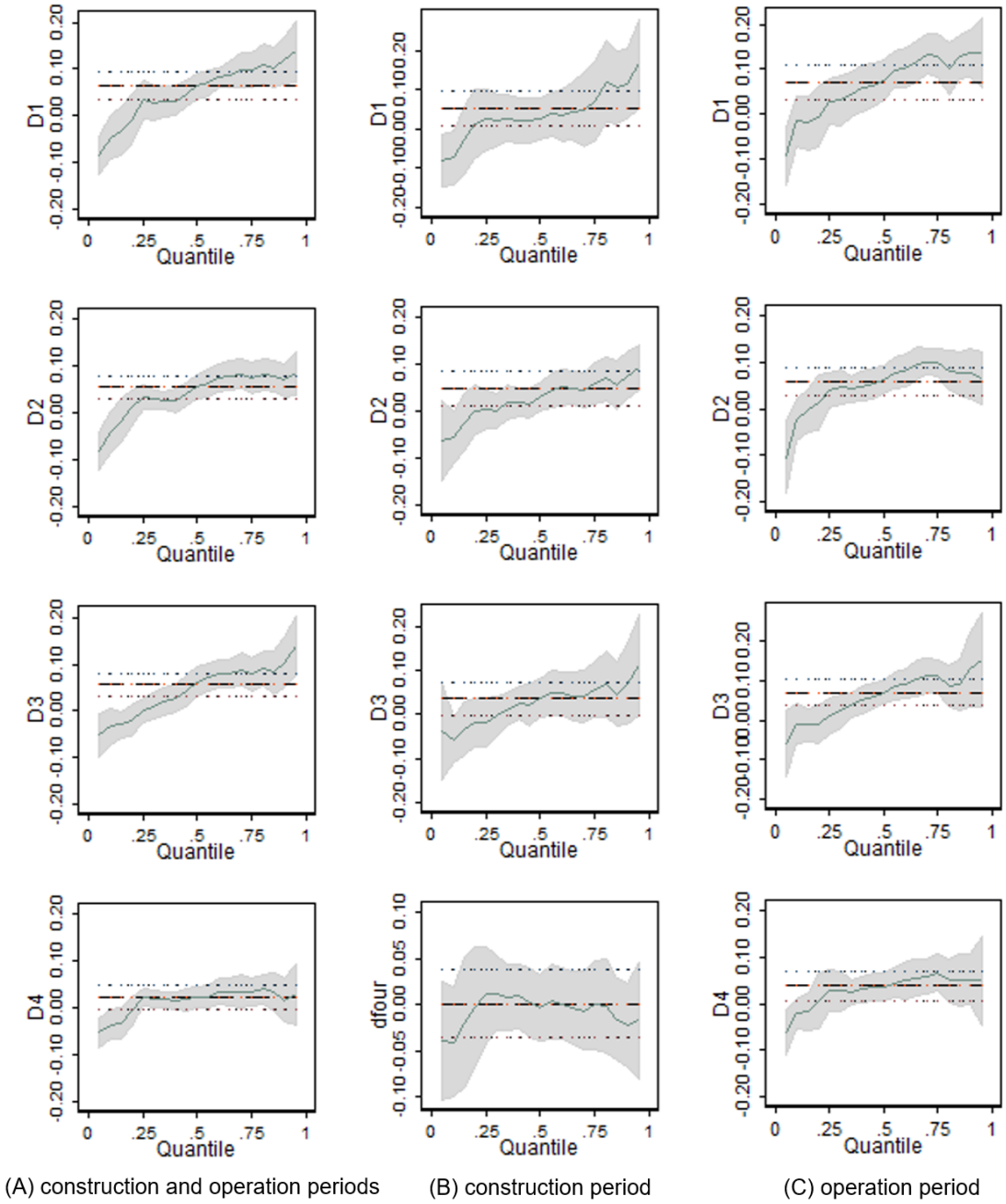


Figure A3. Quantile regression results for D_1–D_4.

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