

## Transit Premium and Rent Segmentation: A Spatial Quantile Hedonic Analysis of Shanghai Metro

### Abstract

When measuring the betterment effect of public transit, most of the existing econometric research tends to use residential property price data and to focus on the conditional mean rather than the conditional variance in terms of the implicit price premium paid for access to public transit. However, because property sale price partly reflects speculation on future capital gains, it sheds little light on the renters' willingness-to-pay for living near public transportation facilities, let alone the variation in rent premium for transit proximity. We in this paper employ a spatial quantile hedonic regression method to gauge the rental impact of metro stations on a large sample of two-bedroom-one-bathroom (2b1b) apartments across 2,575 residential complex communities (or “*xiaoqu*” in mandarin Chinese) in Shanghai, China, as observed between December 2012 and January 2013. We find: a) a community's geographic adjacency to the nearest Shanghai Metro station tends to correlate positively with the *xiaoqu*'s average asking rent of 2b1b apartments, indicating a significant rent premium for transit proximity; b) although the transit premium fluctuates across the different rent levels, the variation is statistically insignificant, suggesting no evidence of transit-induced segmentation of the local private residential rental market. Apart from its policy implications, this paper demonstrates a US-China comparative perspective and a novel spatial quantile regression approach to test the segmentation effect of mass transit in a dynamic urban housing market.

(Keywords: public transit, rent premium, segmentation, Shanghai Metro)

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## 1. Introduction

There is a general consensus in the literature about the betterment effect of public transit with regard to the nearby urban residential properties, as the positive externalities of transportation infrastructure are known to be capitalized in property price (Bowes and Ihlanfeldt, 2001, Debrezion et al., 2011, Hess and Almeida, 2007, Ryan, 1999). However, relatively fewer transportation studies have managed to differentiate between the uplift of property value due to actual improvement in transport accessibility versus the real estate investors' speculation on future capital gains through transit-induced property value appreciation. Such differentiation is important according to Poterba (1984), because a typical renter consumes housing as a necessity good, while an investor sees it as an income-generating capital asset, hence their different degrees of willingness-to-pay for living near public transit.

Distinguishing between the two types of betterment mechanism is not only necessary in theory, but can also address some practical policy problems. For example, a series of empirical studies based in the US have identified the gentrification effect of public transit on the local housing markets (Lin, 2002, Immergluck, 2007, Kahn, 2007), especially in a sense of displacing low-income households who used to rent cheap properties but, after new transit development, may experience even steeper rise in asking rents than those who live in more expensive properties (Pollack et al., 2010, 2011). Does this transit-induced gentrification problem observed in American cities also exist in China? How to test the variance in transit premium across the different segments (i.e., cheap vs. expensive properties) of the local rental market within an urban China context? We intend to address the both questions through this research.

In this paper, we analyze the per square meter asking rents of two-bedroom-one-bathroom (2b1b) apartments across 2,575 residential complex communities (or “*xiaoqu*” in mandarin Chinese) observed between December 2012 and January 2013 in Shanghai, China, based on each *xiaoqu*'s geographical proximity to its nearest Shanghai Metro station. Our data choice is for several reasons. First, Shanghai features a booming residential property market, both in terms of the sales and rental sectors, wherein the demand for housing continues to exceed the supply (Chen and Jin, 2015). Under this market condition, observed asking prices and rents are found to approximate what are actually agreed in the market (Feng and Wu, 2015: p.379). Second, it is readily clear, by comparing Figures 1 and 2, that the movement of private apartment asking rent index in Shanghai is much smoother than the corresponding trend in condo resale price. Rent is thus a more stable dependent variable than sale price when assessing Shanghai Metro's contribution to property value based on cross-sectional transaction data collected at a fixed point of time. Third, the latest Shanghai Census finds that most ordinary local working-class families live in two-bedroom apartments sized between

80 and 100 square meters (Yang et al., 2015: 30). This type of property is also most frequently observed in our sample dataset, representing a predominant share of the private rental market in Shanghai. How the transit proximity premium of Shanghai Metro affects the average as well as the variance in the rents of two-bedroom apartments is not only relevant to our research, but also of broader policy interest in terms of how to supply affordable housing for the majority of working population in Shanghai (Chen et al., 2010).

To investigate the theoretical and practical issues aforementioned, we apply a spatial quantile hedonic approach **in this study**. After adjusting for spatial autocorrelation, we find that a community's average asking rent for 2b1b apartments tends to rise by circa 0.4 % when the *xiaoqu* is every 100 meter closer to the nearest Shanghai Metro station. However, even though the transit proximity premium of Shanghai Metro appears to vary between different quantile points on the rent distribution (i.e., from the cheapest 10% to the most expensive 10% asking rents), the volatility is statistically insignificant, suggesting no evidence of rent segmentation caused by the transit premium paid for adjacency to Shanghai Metro stations.

The remainder of this paper is organized as follows. The succeeding section reviews the literature on transit-induced gentrification of the urban housing markets in America. The Chinese background of this study regarding Shanghai Metro and the local private residential rental market are introduced next. The design of this research is presented afterwards, alongside the setup of our spatial quantile hedonic regression model. We report and discuss the model results before concluding the paper with directions of future research.

## **2. Public Transit and Gentrification of Urban Housing Markets in America**

Although “gentrification” is a multifaceted concept encompassing the demographic, economic, socio-political and even cultural aspects of urban life, a major indicator of urban gentrification is the rising home value and housing cost as a result of neighbourhood upgrading and infrastructure improvement (Palen and London, 1984). A series of studies have identified the gentrification effect of transit development in American cities by focusing on the local housing market dynamics. For instance, Lin (2002) found that residential properties within half-a-mile radius of urban transit stations saw a 20% higher rate of value appreciation than those farther away in Northwest Chicago between 1975 and 1991. Kahn (2007) identified similar evidence in Boston and Washington D.C. by studying the correlation between rail transit investment and home price movement across 14 American cities between 1970 and 2000. In another study, Immergluck (2007) discovered that even the announcement of a new rail line's construction plan in Atlanta had an analogous value-uplifting impact on the local residential property market.

While rise in property value is often seen as a desirable outcome of transit-led gentrification, it has serious displacement implications for the urban poor. In the same paper on Atlanta, Immergluck (2007: p.1743) lamented that “Lower income renters, whose new leases are likely to reflect higher tax assessments and higher property values, will almost certainly experience some pressure towards displacement”. A similar sentiment was shared by Pollack et al (2010, 2011), who pointed out that transit-served metropolitan areas in America contain a disproportionately larger share of rental housing stock and higher concentration of low-income renter population. More attention should thus be diverted from property price to rent data, especially with respect to “how a new transit station can set in motion a cycle of unintended consequences in which core transit users—such as renters and low income households—are priced out in favor of higher-income, car-owning residents who are less likely to use public transit for commuting” (Pollack et al., 2010: p.1).

Empirical studies by Baum-Snow et al. (2005) and Glaeser et al (2008) confirm that the urban poor in America are relatively more dependent on public transportation for mobility, which may explain why, after transit development, the rents of nearby cheaper properties can rise even faster than their more expensive counterparts. From another perspective, this finding also resonates with Smith’s (1987) seminal “rent gap” theory of gentrification, *viz.*, cheaper properties occupied by lower income residents in many American inner-city neighbourhoods actually feature a larger potential in terms of ground rent uplift as a result of capital improvements, which include, but are not limited to, investment in transport infrastructures.

Compared with the US-based literature on transit-led housing market gentrification, there has been limited empirical research concerning this topic in China. Zheng and Kahn (2013) is one of the few examples which interpret the betterment effect of public transit investment on local home prices as a sign of urban gentrification in Beijing, China. However, as in the US, less is known about the rental market impact of transit development in Chinese cities. We argue in the next section that this information is much needed given China’s unique housing market structure.

### **3. Public Transit and Private Residential Rental Market in Shanghai**

China has a dynamic urban housing market. Average home price in the five large Chinese cities – Shanghai, Beijing, Shenzhen, Hangzhou, Chengdu – had appreciated, in real term, by at least 10% every year between 2003 and 2010, outpacing the growth rate in America even during its property heyday between 1995 and 2006 (Wu et al, 2012: p. 532). Another feature of the Chinese housing market is that rise in land value accounts for a large share of home price inflation – estimated, for example, to be over 60% for Beijing in 2010 – leading to very high price-to-rent ratios across major cities in the country, implicating widespread speculations on future capital gains through land value appreciation (Wu et al., 2012: pp. 537 - 539).

Figures 1 and 2 illustrate respectively the increase in nominal resale and rental prices for private condominium apartments in Shanghai between January 2006 and January 2015 (CREIS, 2016).<sup>1</sup> It is readily clear that the resale prices have increased much more rapidly than rental values.

Figure 1: Re-sale Price Index for Condominiums in Shanghai, 2006-2015



Source: China Real Estate Index System (CREIS) and fdc.fang.com

Figure 2: Rental Price Index for Condo Apartments in Shanghai, 2006-2015



Source: China Real Estate Index System (CREIS) and fdc.fang.com

<sup>1</sup>China Real Estate Index System (CREIS) calculates both the resale and rental price indexes based on observed sample asking prices. The average per square meter condo resale price in Beijing observed in December 2014 has a benchmark index value of 1000. Likewise, the average per square meter apartment rental value in Beijing, December 2015, is indexed as 1000 as the rental benchmark. Since the units of resale and rental price indexes are different, we present the trends of both indexes separately in Figures 1 and 2 to illustrate the degree of fluctuation within the respective case. For more information please refer to <http://fdc.fang.com/index/ErShouFangIndex.html>

Like elsewhere, public transit plays an important role in China's urban housing market. Much of the speculated land value uplift in China is attributable to the local governments' investment in transportation infrastructures, especially intra-city light rails (Wang and Baddeley, 2015). In Shanghai, for example, 13 rapid-transit intra-city metro lines have been developed since 1995, reaching an aggregate system length of 437 km early 2013, roughly equivalent to the size of London's nearly 200-year old underground system (Shanghai Metro, 2013).

By analysing the resale prices of 503 condo apartments in 2007, Pan and Zhang (2008: p.24) estimated the resale value of a typical condo unit in Shanghai to rise by an average of 1.1% for being every 100 meter closer to the nearest metro station. However, this estimation involves a potential measurement problem, because observed property sale price relies partly on homebuyer's expectation about future capital gains when reselling the property, while a property's actual use value, according to Poterba (1984, 1992), needs to be assessed by calculating the "imputed rent" a homeowner would pay for an equivalent unit in the local private rental market. In this vein, the transit proximity premium identified by Pan and Zhang (2008) may be less associated with the actual land value lifted by Shanghai Metro, but more attributable to the general speculations in the Shanghai housing market, especially given the widening gap over time between the resale price in Figure 1 and private rental value in Figure 2.<sup>2</sup>

In a similar spirit, Chong et al. (2014) maintain that residential rent is a better predictor of household wage income than property sale price. Comparing the monthly rents of small, medium versus luxury condo apartments across Hong Kong, Shanghai and Taipei between January and March 2011, Chong et al (2014) find residential rents to well reflect relative household income levels in all of the three cities, mainly because the time value of commuting as a measure of shadow wage turns out to be strongly and positively correlated with the observed rent data. In other words, higher income households tend to rent more expensive apartments, while lower income households tend to take cheaper ones.

Notwithstanding the price and income differentiation within the local rental market, Chen and Jing (2015) find renters in Shanghai as a whole tend to earn significantly less income and are also less likely to possess a car than the local homeowners. The lack of private vehicles restricts the renters' residential location choice to where exist more public transit facilities, a finding in resonance with that by Glaeser et al. (2008) and Pollack et al. (2010, 2011), who saw a similar phenomenon in American cities.

Nevertheless, if transit-led housing market gentrification in America has a tendency to price-out low-income renters by raising the rents of cheaper properties more quickly than those of the more expensive properties, would a similar rent

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<sup>2</sup> The price-rent gap further widened in February 2016, when Shanghai witnessed a drastic 21% rise in average property sold price compared with the same period in 2015, even though the local rent level remained stable (Bloomberg News, 2016)

segmentation effect also exist in the case of Shanghai? How to test the varying impact of Shanghai Metro on the different segments (i.e., cheap vs. expensive properties) of the local residential rental market? In the next section, we undertake to set up a spatial quantile hedonic model to explore the both research questions.

#### 4. Hypotheses, Data and Methods

Based on the existing literature, we employ a spatial quantile hedonic approach, adapted from Liao and Wang (2012), to estimate both the average and variance in transit proximity premium for Shanghai Metro as reflected in the local private rental market. Our research hypothesis is twofold: a) Adjacency to Shanghai Metro is assumed to have a positive effect on the average asking rent, indicating an overall significant rent premium for transit proximity; b) the rent premium for access to Shanghai Metro is supposed to vary between different rental price levels, with the rents of cheaper properties being more sensitive or elastic to transit proximity, reflecting a segmentation effect of transit proximity on asking rents.

Data for our analysis are collected by one of the coauthors based in Shanghai at the Leixury Real Estate Market Research and Consulting Co., Ltd (referred to as Leixury hereafter). Leixury obtained a large volume of asking rents of residential properties between December 2012 and January 2013 from two largest rental advertising websites in China (<http://www.haozu123.com> and [www.fang.com](http://www.fang.com)). Within the raw sample, two-bedroom-one-bathroom (2b1b) condo apartments appeared to be the most frequently observed and thus the most typical type of rental units in Shanghai, which is consistent with a key finding from the latest Shanghai Census (i.e., 6<sup>th</sup> Census in 2010), that most local working-class families tend to live in two-bedroom apartments sized between 80 and 100 square meters (Yang et al., 2015: 30). To control the heterogeneity effect of different property types on the asking rents, a subsample only containing 2b1b condos was further selected, after removing outlier observations showing rents per square meter above or below the average for more than three standard deviations. These 2b1b apartments were then grouped into 2,575 residential complex communities (or *xiaoqu* in mandarin Chinese). For every *xiaoqu*, the asking rents of all the 2b1b condos observed therein was averaged by their aggregate floorage in square meter, essentially producing a rental value index for each of the 2,575 communities.

Leixury also collected the specific longitudes and latitudes of 236 metro stations, on top of the locations of 46 state-owned major hospitals, 531 parks and 159 primary and middle public schools within the municipal boundary of Shanghai, in addition to the year when each community had initially been built and the percentage of green space within every *xiaoqu*. The centroid of the People's Square in downtown Shanghai was recorded as the urban center (see Figure 3). In Table 1, the distance measured in  $v_3$ ,  $v_4$ ,  $v_5$ , and  $v_6$  is, respectively, the Euclidean distance from an observed apartment complex community to the nearest hospital, metro station, park and school.  $v_7$  gauges the Euclidean distance from each observed community to the

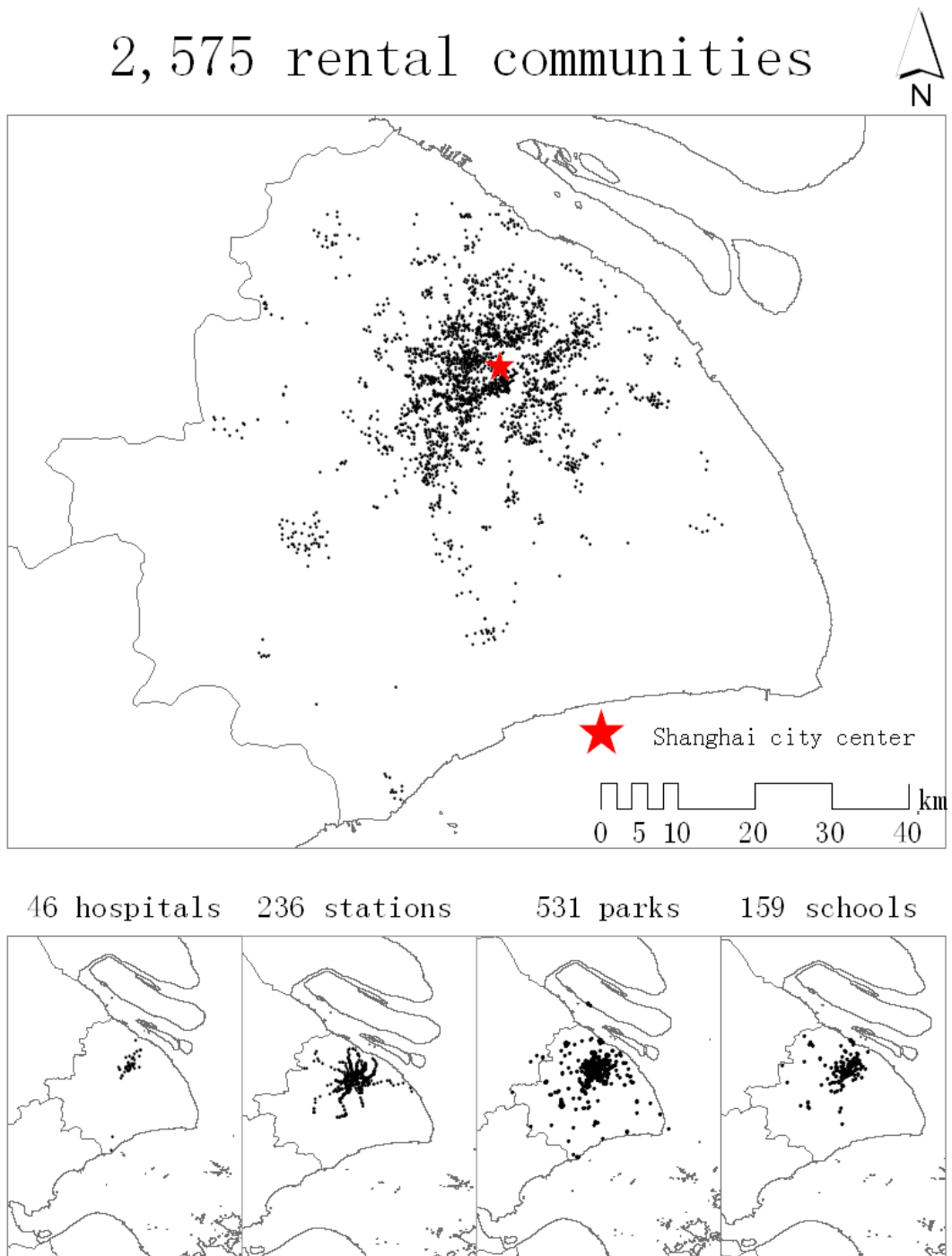
People's Square as the urban center in Shanghai. In the context of this research,  $v_4$  is treated as target variables while  $v_1$ ,  $v_2$ ,  $v_3$ ,  $v_5$ ,  $v_6$  and  $v_7$  as control variables.

Table 1: Descriptive Statistics (sample size: N = 2,575)

variable	definition	mean	std dev
$r$	average yearly asking rent per square meter (in rmb)	551.942	228.942
$v_1$	age of community (in years)	11.827	5.998
$v_2$	percentage of green space within community	35.39%	9.87%
$v_3$	Euclidean distance to the nearest hospital (in meter)	4626.900	5494.231
$v_4$	Euclidean distance to the nearest metro station (in meter)	1532.811	2807.477
$v_5$	Euclidean distance to the nearest park (in meter)	1095.014	1182.977
$v_6$	Euclidean distance to the nearest school (in meter)	2075.010	3086.680
$v_7$	Euclidean distance to Shanghai city center (in meter)	10691.617	8020.467



Figure 3: Sample Observations in the Study Area



Following Heikkila et al (1989), we define a Cobb-Douglas function of asking rent,  $r$ , as per equation (3), which involves seven independent variables (i.e.,  $v_1 \dots v_7$ ), each corresponding to an observed housing attribute included in Table 1. Equation (4) can be further log-transformed into a multivariate linear regression form as illustrated by equation (5), wherein  $b_k = \frac{\partial r / r}{\partial v_k / v_k}$  (for  $k = 1, 2, \dots, 7$ ) by mathematical definition and  $b_k$  measures the change by percentage in  $r$  given every 1% of shift in  $v_k$ .<sup>3</sup>

$$r = b_0 \prod_{k=1}^{n=7} v_k^{b_k} \quad (4)$$

$$\log(r) = b_0 + b_1 \times \log(v_1) + b_2 \times \log(v_2) + \dots + b_7 \times \log(v_7) + \varepsilon \quad (5)$$

Figure 4 illustrates the extent of spatial autocorrelation, measured by univariate Moran's  $I = 0.37$ , for the observed asking rents as the dependent variable. Moran's  $I$  ( $-1 \leq I \leq 1$ ) gauges the degree of spatial association:  $I = 1$  when the geographical correlation is perfectly positive;  $I = -1$  for perfectly negative correlation;  $I = 0$  if there is no spatial interdependency (Anselin, 1988). As the rent data are clearly spatially autocorrelated according to Figure 4, we specify a spatial weight matrix,  $W$ , to geographically weight the observed asking rents. The weight  $w$  in equation (6) is generated by the spatial weight matrix function in equation (7), while  $\lambda$  in equation (6) can be interpreted in the same way as Moran's  $I$ . Since  $w \times \log(r)$  is a spatially endogenous factor, equation (5) requires a two-stage estimation procedure, whereby the first stage predicts the value of  $w \times \log(r)$  as a linear function of  $\log(v_k)$  ( $k = 1, 2, \dots, 7$ ) plus their first-order spatially weighted values, given the spatial weight matrix  $W$  (LeSage, 1999).

$$\log(r) = b_0 + \lambda \times w \times \log(r) + b_1 \times \log(v_1) + b_2 \times \log(v_2) + \dots + b_7 \times \log(v_7) + \varepsilon \quad (6)$$

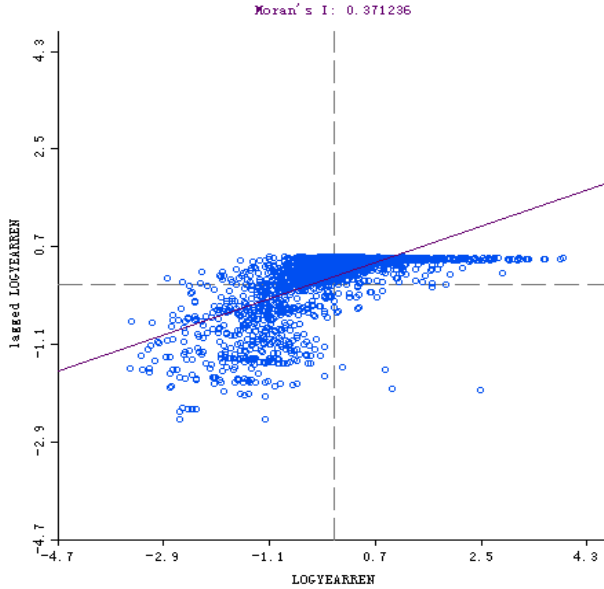
As an element of  $W$ ,  $w_{j,m}$  in the spatial weight generate function (7) measures the impact of rental value on location  $j$  with respect to the value on location  $m$ , if  $j$  is within 1000 meters of  $m$ .  $S_{m1000}$  counts the total number of rental communities observed within 1000 meters of  $m$ . Each of those nearby (ie  $\leq 1000m$ ) observations is hypothesized to have an equal impact on the rental value at location  $m$ . Rental observations farther than 1000 meters away are assumed to have no impact on  $m$ . We define the spatial weight matrix,  $W$ , in this way, mainly because we consider 1000 meters a reasonable walking radius within which two residential communities may be seen as mutual substitute goods. This hypothesis about  $W$  is testable by estimating  $\lambda$  in equation (6). If  $\lambda$  turns out to be significant, there is empirical evidence for the spatial pattern characterized in equation (7).

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<sup>3</sup> For  $v_2$  on the percentage of green space within a community,  $b_2$  measures the change in  $r$  given the relative change in that percentage. For example, if a community originally with 25% green coverage now sees a rise to 50%, the relative change is  $(50\% - 25\%) / 25\% = 100\%$ .

$$w_{j,m} = \begin{cases} \frac{1}{\sum S_{m_{1000}}}, & \text{if } \sum S_{m_{1000}} \neq 0 \text{ and } j \text{ is within 1000 meters of } m; \\ 0, & \text{otherwise ;} \end{cases} \quad (7)$$

Figure 4: Spatial Correlation of Observed Asking Rents



Liao and Wang (2012) demonstrate that a linear hedonic spatial lag model such as equation (6) can be regressed back both to the conditional mean and to the different conditional quantile points. While they use observed house prices as the response variable, we in this paper conduct a spatial hedonic estimation of asking rents by following the instrumental variable quantile regression (IVQR) algorithm devised by Chernozukov and Hansen (2006) on Matlab as a programming software platform.

$$\int_{\log(r)_{\min}}^{\log(r)_q^i} K(\log(r))d \log(r) = i/q \quad (8)$$

Essentially, we undertake linear programming to solve the integral equation (8) in reference to  $\log(r)_q^i$ , given a kernel density function  $K(\log(r))$ , where  $i$  ( $i = 1, 2, \dots, q$ ) stands for the  $i^{\text{th}}$  quantile on the conditional distribution of  $\log(r)$  if the distribution is divided into a total of  $q$  equal intervals. Note that the Matlab-based algorithm by Chernozukov and Hansen (2006) assumes  $K(\log(r))$  to be Gaussian and follows Powell's (1986) kernel density estimation method to calculate the asymptotic standard errors for the quantile coefficients.

## 5. Model Results

### 5.1 Logistic versus Spatial Hedonic Regression Results

We firstly compare in Table 2 the results of logistic regression versus the outcomes of a two-stage hedonic linear regression which includes a spatial lag as per equation (6). The logistic regression results appear to be rather robust, because the spatial lag model generates very similar coefficient estimates, although  $\lambda = 0.021$  and is significant with 99% level of confidence. We also run a post-hoc Moran's  $I$  test in GeoDa, which shows Moran's  $I = 0.046$  for the residuals of log-log regression (see Figure 5) versus Moran's  $I = 0.043$  for the residuals of the spatial hedonic model (see Figure 6). These results seem to suggest that, by including a number of distance-based control variables, the logistic regression itself has alleviated the spatial correlation of the observed asking rents to a large extent (i.e.,  $0.37 \rightarrow 0.046$ ), while the spatial lag further reduces the autocorrelation by a minor albeit significant degree (i.e.,  $0.046 \rightarrow 0.044$ ).

Table 2: Logistic and Spatial Hedonic Regression Results (Sample Size: N = 2,575)

Variable	Log-Log			Spatial Lag	
	coefficient	standardized coefficient	VIF	coefficient	standardized coefficient
constant:	9.422*** (0.082)			9.198*** (0.101)	
$\log(v_1)$ : community age	-0.040*** (0.010)	0.055	1.101	-0.044*** (0.010)	-0.061
$\log(v_2)$ : greenness	0.044*** (0.016)	0.036	1.015	0.043*** (0.016)	0.035
$\log(v_3)$ : hospital	-0.117*** (0.007)	-0.346	2.751	-0.113*** (0.007)	-0.336
$\log(v_4)$ : metro station	-0.061*** (0.006)	-0.160	1.664	-0.058*** (0.006)	-0.153
$\log(v_5)$ : park	-0.032*** (0.007)	-0.071	1.403	-0.030*** (0.007)	-0.067
$\log(v_6)$ : school	-0.035*** (0.007)	-0.093	1.888	-0.034*** (0.007)	-0.091
$\log(v_7)$ : urban center	-0.140*** (0.012)	-0.254	3.137	-0.135*** (0.012)	-0.245
$w \times \log(r)$ : weighted rent				0.021*** (0.006)	0.056
R square (adjusted R square)	0.584 (0.583)			0.590 (0.588)	
F-test ( <i>df</i> )	2575 (7)			2575 (8)	
<i>p</i> -value	0.000			0.000	

\*  $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$ ; standardized error in the parentheses below each corresponding coefficient.

Figure 5: Spatial Autocorrelation of the Residuals of Log-Log Regression

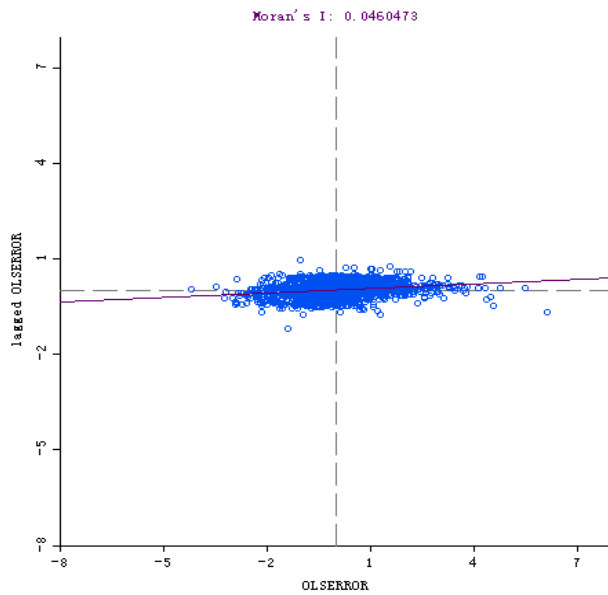
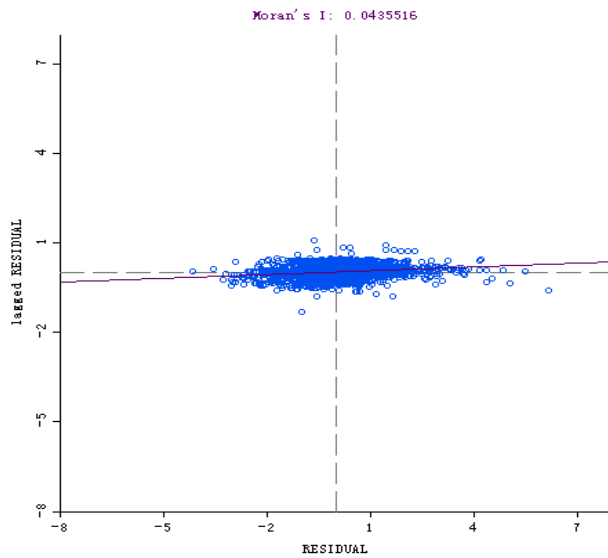


Figure 6: Spatial Autocorrelation of the Residuals of Spatial Lag Model



The signs of all of the coefficients in Table 2 are consistent with the general intuitions: Asking rent tends to rise for a newer apartment complex community with a higher proportion of internal green space and located closer to hospital, metro station, park, school, and the Shanghai city center. Standardized coefficients suggest that the distances to the hospital ( $v_3$ ) and city center ( $v_7$ ) tend to have the largest impact on asking rents, followed immediately by the distance to the nearest metro station ( $v_4$ ) as our target variable. VIF (Variance Inflation Factor) for the logistic model shows little sign of multicollinearity, except for the slightly higher correlation between the distance to the hospital ( $v_3$ ) and that to the city center ( $v_7$ ), reflecting a fact that the hospitals are more centrally located, as also illustrated in Figure 3.

In terms of the target variable  $v_4$ ,  $b_4 = -0.058$  (after controlling the spatial effect) indicates that, for a typical apartment complex community in Shanghai, the average asking rent of its 2b1b condos would only rise modestly though significantly by circa 2.9 %, even if the community’s Euclidean distance to the nearest Shanghai metro station is somehow halved. As the mean distance from an apartment complex to the nearest metro station is about 1,533 meter according to Table 1, the rental value of an average community is expected to rise by about 0.4% for every 100 meter closer the nearest metro transit. Overall, this result is aligned with general findings of other China-based empirical research: Residential property value is significantly correlated with albeit inelastic to transit proximity (Xu and Zhang, 2016).

#### 4.2 Quantile Regression Results

Does the transit proximity premium of Shanghai Metro vary between different rent segments in the local rental market? Table 3 sheds some intriguing lights on the issue. Compared with the communities containing more expensive 2b1b apartments, the 25% cheapest *xiaoqu* seems to witness the largest marginal contribution by being close to the Shanghai metro stations ( $b_4 = -0.061$ ). Specifically, for every 1% of decrease in distance to the nearest metro station, the cheapest 25% rental communities show an average of 0.061% increase in the asking rents, vis-à-vis 0.054% and 0.055%, respectively for the communities at the 50% and 75% quantile point on the conditional distribution of  $\log(r)$ .

However, after we follow Giuliano et al (2010: 3121) and conduct a Wald’s Chi-squared test regarding the equivalence of quantile coefficients, we find no statistically significant variance in  $b_4$  across the three quantile points in asking rent. In fact, in Table 4, only the coefficients for community age ( $b_1$ ) and for distance to the nearest hospital ( $b_3$ ) seem to show significant difference between the 75% quantile point versus the 50% and 25% quantile points, respectively.

Table 3: Quantile Spatial Hedonic Results

Variable	25% in $\log(r)$		50% in $\log(r)$		75% in $\log(r)$	
	coefficient	asymptotic std error	coefficient	asymptotic std error	coefficient	asymptotic std error
constant:	8.825***	0.138	9.009***	0.127	9.531***	0.139
$\log(v_1)$ : community age	-0.025*	0.013	-0.035**	0.012	-0.090***	0.013
$\log(v_2)$ : greenness	0.037*	0.021	0.046**	0.020	0.042*	0.021
$\log(v_3)$ : hospital	-0.068***	0.010	-0.085***	0.009	-0.141***	0.010
$\log(v_4)$ : metro station	-0.060***	0.009	-0.054***	0.008	-0.055***	0.009
$\log(v_5)$ : park	-0.036***	0.009	-0.026**	0.009	-0.018*	0.009
$\log(v_6)$ : school	-0.037***	0.009	-0.034***	0.008	-0.027***	0.009
$\log(v_7)$ : urban center	-0.157***	0.017	-0.153***	0.016	-0.134***	0.017
$w \times \log(r)$ : weighted rent	0.035***	0.008	0.028***	0.007	0.013*	0.008

\*  $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$

Table 4: Comparing Quantile Coefficients using Wald Chi-Squared Test

Variable	25% vs 50% in $\log(r)$		25% vs 75% in $\log(r)$		50% vs 75% in $\log(r)$	
	$\chi^2(1)$	Sig.	$\chi^2(1)$	Sig.	$\chi^2(1)$	Sig.
constant:	0.9626		12.9919	***	7.6864	***
$\log(v_1)$ : community age	0.3195		12.5000	***	9.6645	***
$\log(v_2)$ : greenness	0.0963		0.0283		0.0190	
$\log(v_3)$ : hospital	1.5967		26.6450	***	17.3260	***
$\log(v_4)$ : metro station	0.2483		0.1543		0.0069	
$\log(v_5)$ : park	0.7469		2.2284		0.3951	
$\log(v_6)$ : school	0.0621		0.6173		0.3379	
$\log(v_7)$ : urban center	0.0294		0.9152		0.6624	
$w \times \log(r)$ : weighted rent	0.4336		3.7813	*	1.9912	

\*\*  $p < 0.1$ ; \*\*\*  $p < 0.05$ ; \*\*\*\*  $p < 0.01$  for  $\chi^2$  with  $df = 1$ ; see Giuliano et al (2010: 3121) for the detailed calculation method

Using Matlab, we manage to repeat the same analysis featured in Tables 3 and 4 on quantile points other than 25%, 50% and 75% on the conditional distribution of  $\log(r)$ .<sup>4</sup> Among all of the eight independent variables (i.e.,  $v_1$  to  $v_7$ , plus  $w \times \log(r)$ ), only four of them (i.e.,  $v_1$ ,  $v_3$ ,  $v_5$  and the spatial lag) display statistically significant variance in the corresponding coefficients on the whole conditional distribution of  $\log(r)$ . Other variables such as  $v_4$  (i.e., distance to metro station) show no significant volatility across the rent segments.

## 5. Discussion

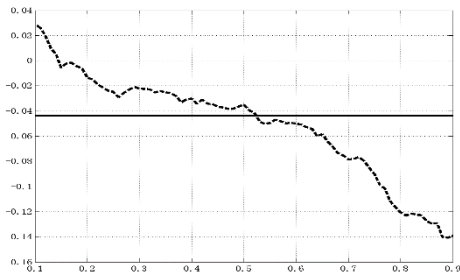
### 5.1 Rent vs Price Premium for Transit Proximity in China

Our spatial quantile hedonic analysis based on the asking rent data from Shanghai firstly confirms the existence of a modest albeit significant rent premium for the transit proximity to Shanghai Metro. While this result conforms to the general findings in the related literature (Xu and Zhang, 2016), the estimated premium (i.e., +0.4%/100m) appears to be considerably less than the according figure (i.e., +1.1%/100m) reported by Pan and Zhang (2008) in a similar study on Shanghai Metro. The estimation gap can certainly be attributed to the two different datasets collected at two different points of time. However, another possible explanation is that the condo resale data used by Pan and Zhang (2008), unlike our rent data, involves generic simultaneity between the observed condo resale price and the speculated inflation of property value because of transit proximity (Poterba, 1984, 1992). This kind of speculation can be particularly strong in China's urban housing markets, given the very low rent-to-price ratio across the major Chinese cities (Wu et al, 2012).

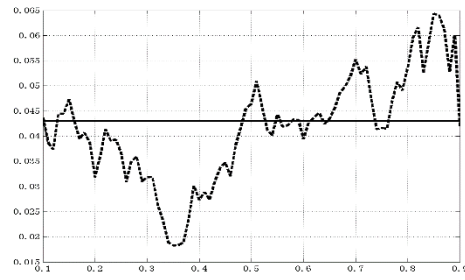
<sup>4</sup>A quantile spatial hedonic regression based on the IVQR algorithm is run in Matlab with regard to every percentile from 10% to 90% (i.e., 81 percentile points in total) on the conditional distribution of  $\log(r)$ . Coefficient estimates tend to be insignificant for extremely low or high percentiles.

Figure 7: Coefficient Estimates by Quantile Points

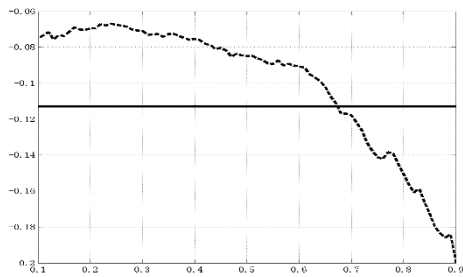
(1): Community Age ( $\chi^2 = 969.04^{***}$ )



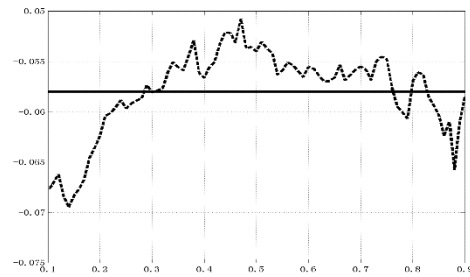
(2): Greenness ( $\chi^2 = 44.16$ )



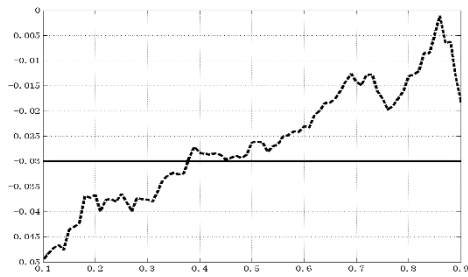
(3): Distance to Hospital ( $\chi^2 = 525.84^{***}$ )



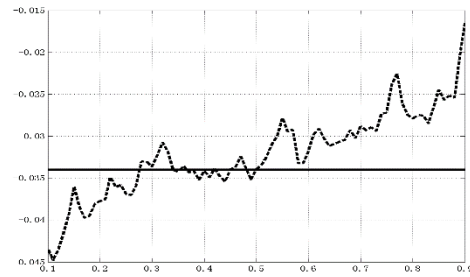
(4): Distance to Metro Station ( $\chi^2 = 30.32$ )



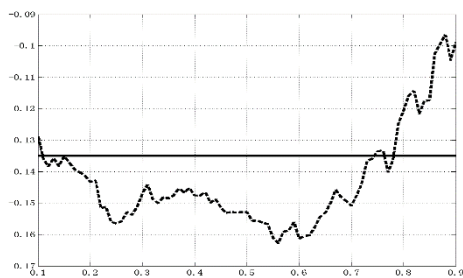
(5): Distance to Park ( $\chi^2 = 184.08^{***}$ )



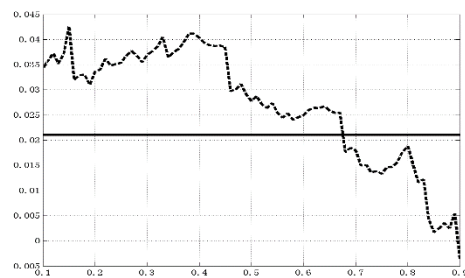
(6): Distance to School ( $\chi^2 = 54.08$ )



(7): Distance to Urban Center ( $\chi^2 = 45.52$ )



(8): Spatially Lag ( $\chi^2 = 164.40^{***}$ )



Notes:

- a) coefficient estimates on the vertical axis
- b) quantile points on the horizontal axis;
- c) dashed line based on estimates by quantile spatial hedonic regression;
- d) solid line based on estimates by mean hedonic regression with a spatial lag
- e) \*  $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$  for  $\chi^2$  with  $df = 80$



## 5.2 Transit Premium and Rent Segmentation in Shanghai

Within the Shanghai private rental market of 2b1b condo apartments, we observe no significant variation in terms of the rent premium for transit proximity to Shanghai Metro, even though Figure 7(4) appears to show steeper rise in asking rents for the circa cheapest 30% and most expensive 20% 2b1b apartment complexes. In other words, there is no statistical evidence to support the claim that the rents of 2b1b apartments in Shanghai have become more segmented or differentiated because of their relative distance to the nearest metro stations.

While the above result seems to differ from the findings by Immergluck (2007) and Pollack et al. (2011) regarding light-rail induced housing market gentrification in American cities, the difference is perhaps attributable to a couple of local factors in Shanghai. First, renters in Shanghai tend to have more homogeneous socioeconomic status than their American counterparts. A dominant proportion of the 2b1b condo renters in Shanghai are working-class families who cannot yet afford to buy local properties (Chen and Jin, 2015). However, many migrant workers who earn even less income in Chinese cities are often not included in the private residential rental market, because the lowest-income migrants usually reside in informal settlements (Webster et al., 2016). In this vein, the homogenous working-class renter population in Shanghai may exhibit an overall similar willingness-to-pay for access to Shanghai Metro, which can explain the lack of variation in the estimated rent premium for transit proximity.

Another potential explanatory factor is the higher cost of driving in Shanghai and other East Asian cities. For example, according to Chong et al (2014), even though the apartment rents in Shanghai and Hong Kong are both found to be highly correlated with wage income, “most people in Hong Kong and Shanghai travel to the CBD by public transportation, since private motor vehicle ownership in these two cities is relatively low due to expensive and limited parking spaces in the CBD, high gasoline taxes and import duties on motor vehicles” (Chong et al., 2014: p.181). In other words, local people’s commuting mode choices tend to be independent of their property values.

## 5.3 Intellectual and Methodological Contributions

Whether new transit development would segment the local housing market and lead to neighborhood gentrification has received considerable academic attention in America (Lin, 2002, Kahn, 2007, Immergluck, 2007, Glaeser et al., 2008, Pollack et al., 2010, Pollack et al., 2011). From a comparative perspective, we argue that the same problem is also research worthy in China, given the mutually involved transport equity and housing affordability issues.

By analyzing a large set of residential rental market data from Shanghai, we demonstrate a spatial quantile hedonic regression approach to test the segmentation effect of transit premium. Although our model results suggest a lack of statistical evidence regarding Shanghai Metro’s segmentation effect on the local condo

apartments' asking rents, we showcase, especially through Figure 7, that the results of conventional hedonic regression-back-to-the-mean can be further calibrated by testing the variation in the betterment effect of public transit on residential properties at different price levels. Given the ubiquitous price-based segmentation of the real estate market, spatial quantile hedonic analysis could generate relatively more comprehensive and robust empirical estimations, whether in America, China or elsewhere.

## 6. Conclusion

Employing a spatial quantile hedonic regression approach, we in this paper assess the betterment effect of metro stations with respect to the per square meter average asking rents of two-bedroom-and-one-bathroom (2b1b) apartments across 2,575 residential communities in Shanghai, China, based on empirical data observed between December 2012 and January 2013. We find key evidence in twofold: a) a community's geographic adjacency to the nearest Shanghai Metro station tends to correlate positively with the *xiaoqu's* average asking rent of 2b1b apartments, indicating a significant albeit modest rent premium for proximity to Shanghai Metro; b) while the proximity premium seems to fluctuate across the different rent levels, the variation is statistically insignificant, suggesting no evidence of transit-induced rent segmentation. While confirming a general principle of modern urban economics that improved transportation access tends to raise property value, the results of our study also reflect the local housing market conditions in terms of low rent-to-price ratio and the local renters' relatively similar degrees of willingness-to-pay for access to public transit.

In addition to the US-China comparative perspective of our research, we put forward a couple of methodological considerations relating to the measurement of transit access premium using housing market data. First, we point out that assessments based on property price data may misestimate transit premium, because property price, unlike rent data, involves speculation on future capital gains which cannot be explained only by improved accessibility due to investment in public transportation facilities. Second, we demonstrate a spatial quantile hedonic regression approach, which tends to generate more robust and comprehensive transit premium estimates than the conventional back-to-the-mean hedonic pricing method. Our future research is intended to further refine the existing rent-based spatial quantile hedonic appraisal method by including more control variables such as the number of parking spots, local population and job density, etc, the lack of which admittedly limit the predictive power of our current model. We also hope to collect data regarding actual agreed rents, which reflect the renters' willingness-to-pay more precisely than the asking rents we adopted in this study as a proxy.

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