INTERNATIONAL REAL ESTATE REVIEW

2010 Vol. 13 No. 2: pp. 190 – 217

Submarket, Heterogeneity and Hedonic Prediction Accuracy of Real Estate Prices: Evidence from Shanghai

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This paper contributes to the literature by examining how much the prediction accuracy of real estate prices could be improved by applying hedonic equations at suitably defined disaggregate levels and incorporating directional heterogeneity of distance gradients. We build our empirical analysis on a large-scale database of real estate projects sold between 2005 and 2007 in Shanghai. Our analysis suggests that the Shanghai real estate market is a complex aggregate and taking into account submarket and directional heterogeneity in hedonic regressions could provide considerable benefits in improving the precision of real estate price predictions.

Keywords

Hedonic analysis; Prediction accuracy; Submarket

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1. Introduction

Real estate prices in Shanghai and other major cities in China have continued to soar in the past few years. With the rising importance of the Chinese economy in the world, the booming Chinese real estate market has attracted escalating attention from global observers. However, compared to a large volume of institutional and descriptive studies about Chinese housing policy reforms and macro real estate market development (Deng 2005; Quan, 2006, for example), there are still limited empirical literature on the micro structure of real estate prices in Chinese cities. Rare examples include Yang (2001) and Zheng and Kahn (2008)'s study on Beijing, Jim and Chen (2006)'s study on Guangzhou, Kong et al. (2007)'s study on Jinan, and Chen & Hao (2008)'s study on Shanghai. But so far, no studies have demonstrated the relative prediction precision efficiency gain from using hedonic techniques in mass property appraisal in China.

This paper has a two-fold purpose. First, this paper aims to provide knowledge of the key determinants of real estate prices in Shanghai. At the same time, it attempts to examine how much the prediction accuracy of real estate prices could be improved by applying hedonic equations at suitably defined disaggregate levels and incorporating directional heterogeneity of distance gradients.

Ways to improve the accuracy of real estate price predictions are always a central topic in the real estate literature (Goodman and Thibodeau, 2003). To achieve this goal, the key challenge is to model the impacts of locational attributes on real estate prices and usually this type of work proceeds with hedonic approaches. Recently, increasingly more researchers have thrown doubts on the validity of the ordinary least squares (OLS) regression which is the standard estimation method in the hedonic approach (Bao and Wan, 2007). Two key understanding assumptions of OLS, residuals should be independent from each other (no serial correlation, $E\left(\varepsilon_i \varepsilon_j\right) = 0$) and the variances of residuals should be equal to all (homoscedasticity, $E(\varepsilon_t)^2 = E\left(\varepsilon_j{}^2\right) = e^2$), are often found violated when applying OLS regressions in the massive appraisal for real estate prices.

Researchers have pointed out that OLS residuals over space tend to be non-random and show a strong pattern of *spatial dependence* due to nearby properties which often have similar building characteristics and are affiliated with identical locational and neighbourhood amenities (Basu and Thibodeau, 1998; Dubin, 1998; Goodman and Thibodeau, 2003). For the causes of heteroscedasticity in OLS estimation residuals, while it is said that a primary reason is the age of dwelling (Stevenson,2004), several other factors are found to be important too.

The violation of no serial correlation assumption would lead coefficient estimates of parameters to be inefficient and the presence of heteroscedasticity would produce incorrect values of coefficients estimated. To correct these biases, recently, there have been many spatial statistical attempts to incorporate spatial dimension of real estate data; one is the spatial autoregressive lag (SAR) model, which includes spatially lagged dependent variables as explanatory variables in the model (Can,1992; Can and Megbolugbe, 1997). This bears a close resemblance to the autoregressive (AR) process in a time series analysis. The second is the spatial error model (SEM), where the focus is to model the spatial autocorrelation of real estate price OLS equation residuals (Dubin,1992). The third is the so-called location models, which incorporate geographical coordinates or other spatial indicators that identify the absolute locations of properties as explanatory variables in the model (Case et al., 2004; Tu et al., 2007). Despite large variations over these approaches, the ultimate goal is the same: to ensure that the residuals over space would not exhibit any non-random patterns.

Although the applications of spatial econometrics and geo-statistical methods have made impressive progress during the last decade, a recent paper by Bourassa et al. (2007) however suggests that the gains of prediction accuracy from including suitably-defined submarket indicators in OLS equations can be larger than those employing sophisticated spatial econometric specifications. The authors suggest that their finding has great practical implications, as standard hedonic equations adapted with submarket dummy variables are by far easier to implement than spatial statistical methods. This conclusion carries to the issue of heteroscedasiticy too. It has been suggested that applying hedonic models at a submarket, which has a much greater level of homogeneity than the city level, will exhibit great reduction of heterosecdascity (Stevenson, 2004).

In addition, usually the literature assumes a uniform price gradient pattern in any direction outward from the city center. However, this is hardly true in real life. For example, Soderberg and Janssen (2001) examine the real estate market in Stockholm and find an asymmetric price gradient. Cameron (2006) suggests that allowing for directional heterogeneity in distance profiles would improve the precisions of hedonic property value models.

Thus, this paper contributes to the literature by examining how much the prediction accuracy of real estate prices could be improved by applying hedonic equations at suitably defined disaggregate levels and incorporating directional heterogeneity of distance gradients. The rest of this paper is organized as follows: Section 2 presents a brief description of the Shanghai real estate market; Section 3 gives the conceptual and empirical framework of our analysis; Section 4 introduces the data and econometric model; Section 5 contains our empirical results; and finally, Section 6 provides the concluding remarks.

2. Background: The Real Estate Market in Shanghai

The Chinese real estate market has experienced rapid growth and fast transformations over the last two decades. Notably, the Chinese real estate market is developing under a relatively unique policy context. Shortly after the new Chinese government was established in 1949, private ownership of residential property in the urban areas was nearly extinguished (Chen et al., 2003). Until 1998, most urban residents in China were housed by the welfare housing system in which the government, or state-owned enterprises, produced and allocated housing almost free of charge (Quan, 2006). Few Chinese people at that time would have thought about owning their homes. In March 1998, the welfare housing system was abolished in a sudden reform by Prime Minister Zhu Rongji as an essential component of economic stimulus package plan against the 1997 Asian financial crisis. With a private homeownership that roared from nearly zero to currently more than 70% in the urban area in such a short period (Chen et al., 2009), China's experience in developing the real estate market is perhaps one of most amazing stories among its economic miracles.

Undoubtedly, Shanghai is one of the best places to learn about the Chinese real estate market. For many decades, Shanghai was the largest industrial center in China and its sheer population size stands out among China's major cities. By the end of 2008, Shanghai's population had exceeded 18.88 million and the population density in the urban area was about 7174 person per square kilometer (Shanghai Statistics, 2009). Starting in the 1990s, Shanghai witnessed exponential growth in both residential and commercial real estate development. Since the early 1990s, Shanghai has been the largest real estate market among all mainland Chinese cities and prosperity in the new century further cemented Shanghai's top position. In 2008,[1] total real estate sales in Shanghai was 192 billion RMB in terms of trading value and 23.39 million sqm in terms of sold floor area; both were the largest among all mainland Chinese cities and accounted for 7.65% and 3.55% of the national total, respectively. The average nominal price of all types of real estate sold in Shanghai during 2008 was 8195 RMB/sqm, 215% of the national average and second only to Beijing's 12,418 RMB/sqm among provincial-level units.

Among all mainland Chinese cities, the Shanghai real estate market is arguably the most open to the world and the most competitive. At the end of

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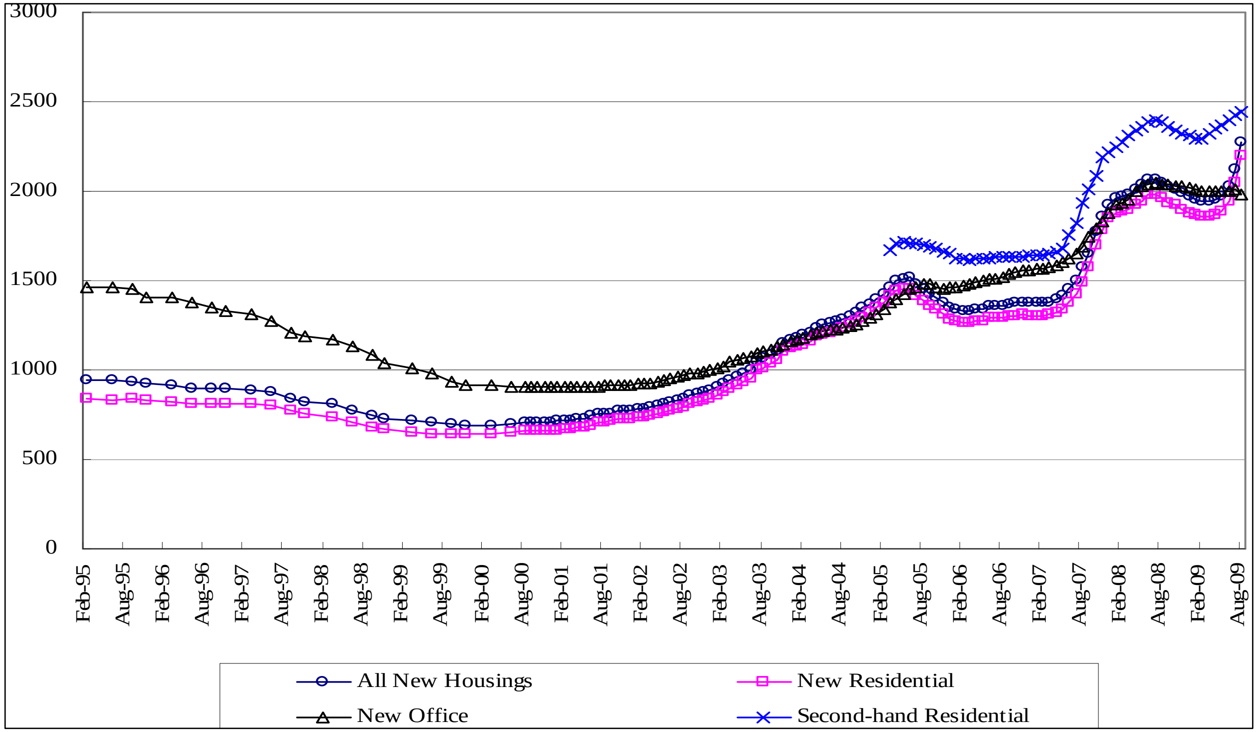
[1] In 2008, the share of Shanghai's population and GDP in the national total were 1.4% (3.1% in urban population) and 4%, respectively (China Statistics Yearbook, 2009).

2008,there were 3898 real estate developers(including 614 overseas developers) active in the Shanghai real estate market and provided jobs to 92,555 employees, among which 23% worked for overseas developers.

Although Shanghai is by far the leading business center in China, the residential real estate market was dominated by residential real estate development, generating roughly 85% of total actual property sales in terms of both trading value and sold floor area. According to the Shanghai Statistics Bureau, by the end of 2008, the home-ownership rate had risen to more than 77% among Shanghai's permanent residents. About half of Shanghai home-ownership was due to the privatization of welfare housing in the late 1990s and the rest due to own market purchases. It is notable that during the short period of 2004-2008, the proportion of households who became home-owners through privatization fell by 5.1 percentage points, whilst the proportion that purchased housing from the market rose rapidly by more than 10 percentage points. By 2008, more households had become home-owners by purchasing housing from the market than those who had done so through privatization. For the period 1999-2008, a sum of 222 million sqm of new residential real estate were sold on the Shanghai market, which implies that roughly 2 million units of apartments had been purchased since 1999 and 200,000 units on average per year. As in many advanced economies, the second- hand residential property market has been flourishing in Shanghai in recent years.

With a golden decade between 1999 and 2008, the average nominal price of first-hand residential real estate in Shanghai rocketed from 3102 RMB/m^2 to 8182 RMB/m^2, achieving 164% of net growth within 10 years. There are people who argue that the fundamental strength of the Shanghai economy, alongside the growing availability of mortgage credit and historically low interest rates, drives this phenomenon. For example, the average annual nominal disposable income per capita in Shanghai increased from 10,932 RMB to 26,675 RMB for the same period and the growth volume was 144%, just a little less than that of residential property prices. Furthermore, at the end of the 1990s, the mortgage business was a still new thing in China, but now it is very common among households; by the end of 2008, the outstanding volume of mortgage loan in Shanghai exceeded 291.5 billion RMB, which was about 18 times of that in 1999. In addition, for most of the period of 1999-2008, the long-term mortgage interest rate was stable and kept around 6%. However, quite a number of researchers and newspaper columnists attributed speculative funds, from both domestic and overseas, as the major reason for the volatile upswing of real estate prices. Anyway, the fast growth of residential property prices has led to massive dissatisfaction among the public, especially those who live on low incomes (Chen et al., 2009). However, this paper focuses on the micro determinants of real estate prices in Shanghai and an examination of whether and how much the property prices contain a bubble component is left to future research.

Figure 1 Shanghai ZF Monthly Housing Price Index (1995.02 - 2009.05)



Note: ZF (ZhongFang) real estate price index is compiled by *China Real Estate Price Research College* and computed for each major city in China. Although not quality-adjusted, it is still well-recognized as a leading indicator of the China real estate market.

3. Conceptual and Empirical Framework

3.1 Hedonic Price Model

In the literature, there are several statistical methods that empirically analyze real estate price. However, indisputably, the most popular one is the hedonic framework that has been developed since Rosen (1974), which is now widely applied in both the academic community and industry (OECD, 1997; Malpezzi, 2005).

In Rosen (1974), housing is treated as a composite commodity in the sense that its market value is dependent on the vector of its characteristics (Lancaster, 1966). The theory of hedonic price functions laid down the theoretic foundation for the analysis of differentiated goods and each individual characteristic can be implicitly priced. Commonly, characteristics that are important to the market value of housing are classified into three categories: 1) structural attributes, i.e. building material, floor space, number of bedrooms and bathrooms, inner structure, age of dwelling, floor level, direction, and outside appearance; 2) neighbourhood attributes, i.e. dwelling maintenance and management service, parking, safety, surrounding parks and leisure facilities, composition of neighbours in terms of ethnic, racial, age, educational background; 3) locational attributes, i.e. distance to central business district (CBD), travel and shopping convenience, and accessibility to subway/underground and public transportation systems.

One primary purpose of the paper is to first find out the key determinants of real estate prices in Shanghai and then assess their relative importance. Indubitably, location attributes are widely regarded as the most important determinants of cross-sectional variations in real estate prices. In many cases, the distance to the CBD alone accounts for a very large fraction of variations in real estate prices. This is exactly what the classic model of the bid-rent curve of housing prices predicts for a monocentric city (Alonso, 1964; Muth, 1969).

Although the economic theory outlined by Rosen (1974) provides a general framework for the analysis of housing prices through hedonic price functions, the theory has not yet provided standard guidelines on empirical issues, such as the choice of functional form and selection of particular housing characteristics to be included in the hedonic price function (Epple, 1987). A long list of functional forms has been proposed and tested, which include parametric and non-parametric approaches (Meese and Wallace, 1991). However, recent discussions on the identification of hedonic price functions show that this issue is still open for further discussion (Ekeland et al., 2004). Maybe the most exciting breakthrough in hedonic price work during the last few decades is the increasing interest and growing application of newly developed spatial econometric techniques (Wihelmsson, 2002). However, spatial econometric analysis requires very detailed data and is technically complicated; as we were constrained by limited data access to dwelling-level information as well as the inability of our GIS software to compute all relative distances of sample observations at the time of writing, we had to ignore the issue of spatial effects in this paper. In our ongoing extended work, we plan to fulfil this gap.

It is common in the literature to consider the following model where the selling prices of housing unit are related to observable information about their physical attributes and transaction dates:

$$\log P_{it} = X_{it}\beta_{it} + D_{it}\gamma_{it} + \varepsilon_{it} \tag{1}$$

In this formulation, P_{it} is the price of housing i at time t, X_{it} is the observable characteristics of housing i at time t, D_{it} is the vector of time dummies. Correspondingly, β_{it} is the implicit hedonic price parameter of characteristics X_{it} and γ_{it} represents the time intercept coefficient. Considering the time period of the sample studied in this paper is not long, only 2 years, we choose to apply a simple formulation of regression (1) where the vector of the hedonic price coefficient is assumed to be time-invariant. This assumption is quite reasonable since it is not very likely that the location effect would substantially change within just a 2 year time frame.

3.2 Submarket and Spatial Heterogeneity

Most empirical models have conceptualized a metropolitan area as a single unified market and the coefficients of housing attributes are held constant, which means each observed attribute is assumed to have one unique marginal price. However, the primary characteristic of housing is its heterogeneity. Especially due to the spatial immobility of housing, *there are no two identical houses in the world.* House prices are influenced by a variety of land, structural, proximity, neighborhood and regional attributes. For this reason, various methods have been designed to challenge this assumption and presented so that the marginal price of housing attributes may vary according to particular systematic patterns (Anselin, 1988). A number of housing market studies have used the spatial expansion method which recognizes that functional relationships may not be constant, but vary over space and explicitly allows parameter estimates to drift based on their spatial context (Can, 1990). In addition, houses are durable, infrequently traded, and short-run supplies are relatively fixed. Thus, alterations of physical features (“repackaging”) is only possible within certain limits and many neighbourhood attributes are either fixed or change slowly and infrequently over time. Spatial heterogeneity for hedonic prices is more likely to occur when household demand for a particular characteristic is price inelastic and this preference is shared by a relatively large number of potential homeowners or renters (Day, 2003). Besides, based on the hypothesis that the variability of the implicit prices of certain property and location attributes is partly linked to individual preferences, some studies have attempted to expand housing attributes with buyer characteristics, allowing the marginal price to vary with regards to household profiles (Kestens et al., 2006).

The issue of housing submarkets or market segmentation has been raised for a long time in real estate economics. Many researchers tend to believe that a metropolitan housing market might be segmented according to either dwelling characteristics (dwelling age, building material, structural type, and neighbourhood amenities, etc.) or buyer characteristics (the composition of occupant age, income, educational attainment, social class, and ethnic or racial identity) (Goodman and Thibodeau,1998). To control for these submarket effects in hedonic price equations, researchers assume that a regional real estate market is a set of submarkets that is either predefined by its nature or self-defined by research methods. Submarkets are usually predefined by administrative borders or geographical boundaries, such as those defined by real estate agents (e.g., Palm, 1978) or appraisers (e.g., Bourassa et al., 2003). Alternatively, submarkets can be post-defined by researchers in terms of the characteristics of dwellings, neighborhoods, or census units. Statistical techniques, such as principal components and cluster analysis, have been employed to group seemingly similar dwellings or neighborhoods into submarkets(Bourassa et al.,1999). However, there is some evidence to suggest that geographical submarkets are more meaningful and useful for improving the prediction accuracy of real estate prices (Bourassa et al., 2003; 2007). In other words, the use of predefined geographical submarkets can be more powerful in predicting real estate prices than complicated statistical approaches, although the latter permits “submarket” to vary from house to house. If this argument turns out to be valid, it can be of great practical importance, as a hedonic model with dummies of predefined submarkets is substantially easier to implement than spatial econometric models. In this paper, we only focus on submarket effects due to geographical attributes, and re-examine the extent of prediction improvement by applying hedonic models with submarket dummies on Shanghai real estate data.

4. The Data and Econometric Model

Usually hedonic regressions are run on individual dwelling observations. Unfortunately, we did not have sufficient good-quality data on dwelling-level prices at the moment of writing. Instead, we ran our hedonic regressions on project-level data.[2] For this reason, we have to ignore the effects of dwelling

[2] In China, individuals do not have rights to purchase land and construct dwellings themselves in the urban areas, and all commodity dwellings are built by commercial real estate developers. Real estate developers compete for land plots through bidding in auctions and a group of dwellings in one such land plot is regarded as one project. The

characteristics on real estate prices, and focus only on the effects of locational and neighborhood characteristics. Admittedly, the extent that the missing dwelling-level prices and characteristics may affect the validity of parameter estimate of locational characteristics is open to doubt. However, this is a strategy that has been used in the literature before. See for example, Bover and Velilla (2003). We will discuss this issue in detail later.

With special permission, we obtained access to a large-scale database of monthly project-level average prices from the Shanghai Real Estate Trading Center (www.fangdi.com.cn). As this price information is registered data, its quality is the most highly credible. With a period that spans from September 2005 to October 2007 and a focus only on apartment housings in the city area while dropping luxury dwellings, for example, villas and detached houses, we accumulated 12,922 observations of monthly project- average prices for 1,803 residential real estate projects; [3] that is, each project was on average, observed 7.4 times (Std = 5.9). During the sample period, however, these projects supplied only 15,954,316 sqm or 135,578 units of apartment to the market and the average construction space per apartment sold was 117.7 sqm.

Then, we supplemented the price data with a large dataset of self-measured locational and neighborhood variables for each project, including the project's distance to the CBD[4], green ratio[5], floor area ratio (FAR)[6], total floor area

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size of a real estate project may vary from tens to thousands of apartment units. In our sample, for example, the project's average total floor area was 163,664 sqm (std = 279,786, max = 3,000,000 sqm and min =2,200 sqm).

[3] In the whole sample, the mean monthly transaction per project-month observation is 10.5 units (std = 22, max = 399 and min = 1), which is apparently not normally distributed. In addition, only 48.7% of the sample observations were recorded with more than or equal to 4 units of transactions within a month and only 25.7% recorded with more than 10 units of transactions within a month, while 28.4% observations have only 1 transaction. However, we compared the regressions with all observations and those with monthly transactions less than 4 units or larger than 10 units, and found their results of coefficient estimates do not have any qualitative differences and quantitative variations are very small (we will discuss the implication of this finding in a later section.). Thus, we choose to preserve all the observations.

[4] In this paper, CBD is defined by Shanghai People's Square, where the Shanghai municipality office is located. This is the common use in the Chinese literature with regards to Shanghai real estate market.

[5] The *green ratio* is the amount of land space covered by green plants in the project. The housing-project developer can decide on this level with some discretion, but needs to announce it publicly. In China, it is widely regarded by housing buyers as an important indicator of the environmental quality of a housing project.

[6] The floor area ratio (*FAR*) is the ratio of total construction space to the land area. It indicates the density of building in the project. This ratio is stipulated as fixed by the government when the authority releases the land to market and the project developer cannot change it throughout the development.

(TFA) of the projects,[7] availability of large shopping centers, distance to the nearest subway station, and distance to the nearest large supermarket. As the two latter variables change over time, we need to measure them in the same month as the price information.

Figure 2 The Spatial Distribution of Sample Housing Projects

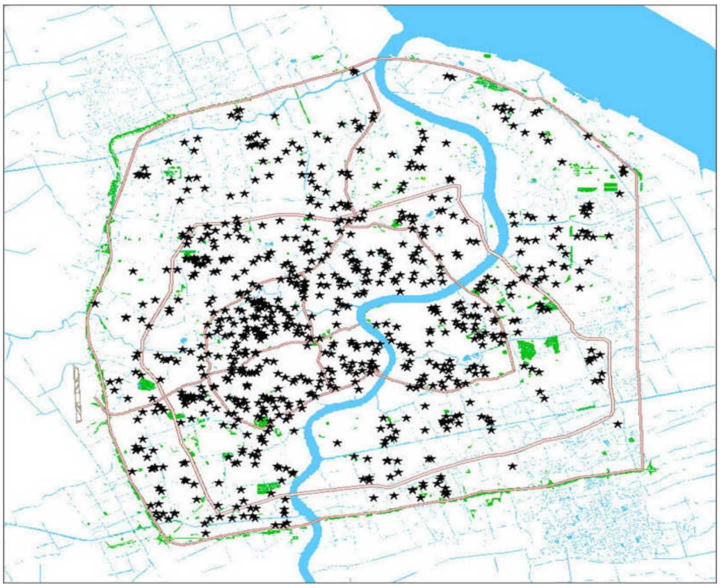


Table 1 Distribution of Projects/Observations by Rings

City Circle	Projects		Observations	
	Freq.	**Percent**	**Freq.**	**Percent**
Inner ring	567	31.45	3,880	30.03
Middle ring	552	30.62	3,937	30.47
Outside ring	684	37.94	5,105	39.51
Total	1,803	100	12,922	100

The urban area of Shanghai is known to be separated by three major rings: inner, middle and outside. See Figure 2 and Table 1 for the spatial distribution of residential real estate projects by the three rings. Table 1 suggests that there is no considerable difference of observation times of projects across the

[7] We appreciate an anonymous referee's suggestion for using this control variable. Kwok and Tse (2006) explain why estate size may matter for property prices and Leung, Ma and Zhang (2009) test this effect and find it positively statistically significant.

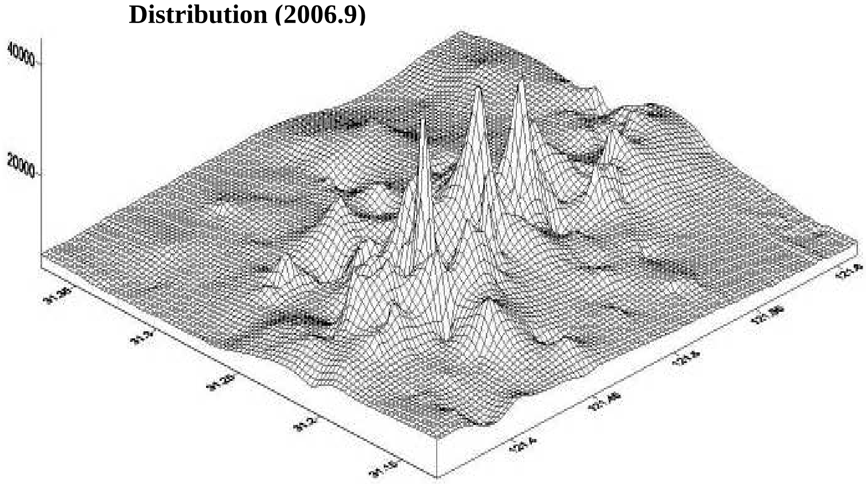
different rings. In addition, a brief description of the sample data is provided in Table 2.

Table 2 Data Description (N= 12,922, T = 26 months, G=1,803 projects)

Variable	*Meaning* (*Measured at Project Level, Monthly*)	*Mean*	*Std*	*Min*	**Max**
P	Project-average unit price, RMB/m^2	11471	4773	3043	29928
lnP	Ln(project-average price)	9.271	.383	8.021	10.307
D_CBD	Distance to CBD (km)	8.409	3.382	.463	17.958
D_ Subway	Distance to nearest subway station(km)	2.729	2.355	.045	13.030
D_Supermarket	Distance to nearest supermarket(km)	1.185	.824	.054	6.484
Shopping	Accessibility to large shopping center	.055	.228	0	1
Green	Green ratio	0.422	.082	.15	.73
FAR	Floor area ratio	2.183	.863	.21	9.5
TFA	Total floor area(10,000m^2)	16.366	27.979	.22	300

Before starting the formal econometric analysis, it will be helpful to have an intuitive impression about how the real estate prices in Shanghai are distributed by location, and especially how they decline as building distance to the CBD increases. From Figure 3, we can find that there is a very clear pattern of price gradient in Shanghai, and People's Square undoubtedly appears as the center.

Figure 3 A Three-Dimensional Display of Shanghai Real Estate Price Distribution (2006.9)



The primary econometric model used in this paper is based on the following equation:

$$\begin{aligned}\log P_{it} = \beta_0 + \beta_1 D\_CBD + \beta_2 D\_CBD^{2} + \beta_3 D\_subway \\ + \beta_4 D\_Supermarket + \beta_5 Shopping + \beta_6 Green \\ + \beta_7 FAR + \beta_8 TFA + \varepsilon_{it}\end{aligned} \quad (2)$$

where, P_{it} is the average real estate price of project i at month t (unit: RMB/m^2), D_CBD is the project's distance to the CBD, which is measured in kilometers; D_CBD^2 is the square of distance to the CBD and included in the model to capture the nonlinear relationship between price and distance to the CBD; and the meaning of other variables is explained in Table 3.

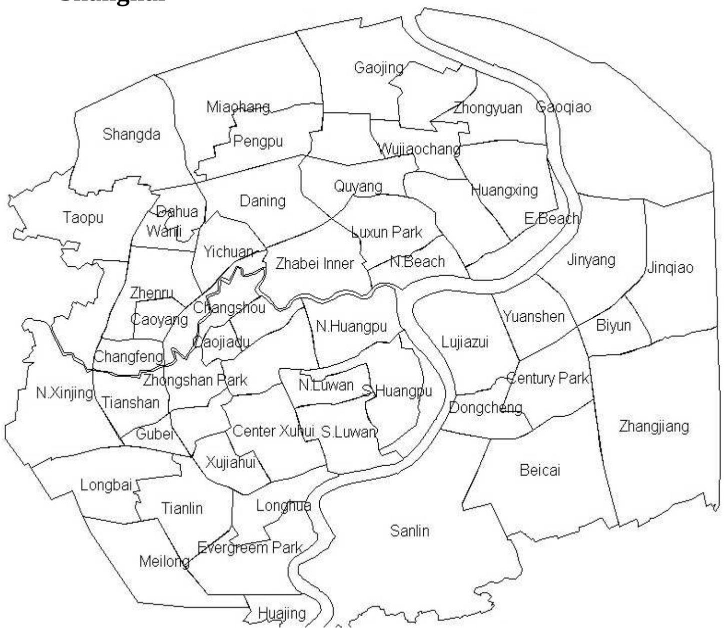
Table 3 The Definitions of Different Submarkets

Submarkets	Definitions
Building Size	Average dwelling construction space <=90 m^2 vs. those >90 m^2
City Ring	Outer Ring; Middle Ring; Inner ring
Districts	Twelve districts within the outer Ring;
Zone	85 zones defined by the land authority for the whole urban area
Direction	**East direction**: Pudong New Area; **North direction:** Yangpu district, Hongkou district, Zhabei district; **West direction:** Putuo district, north area of Jingan district and Changning district; **South direction:** Huangpu district, Luwan district, Xuhui district, Minhang district, south area of Jingan district and Changning district.

There may be concern about whether the inflation effect should be taken into account here. We assume, however, that it should not be an important issue in this paper. This is because the consumer price index (CPI) was very low during this period in Shanghai; in most times it was well below 2%. Therefore, we feel that there is not much need to deflate the nominal housing price by the CPI to obtain the real changes in housing prices. In addition, note that in all of the regressions estimated in all of the models, we control for the general time trend effect by employing a time dummy for each month.

We run hedonic regressions for the whole city as well as for four assumed categories of submarkets. The first is a submarket defined on the size of a project's average dwelling construction space area. We classify two types of projects, one is with an average dwelling construction space larger than 90 sqm and the other is smaller than or equal to 90 sqm. The second submarket is defined by the city ring (outer ring, middle ring and inner ring); the third is defined by the 12 urban districts; and the last submarket is defined by 85 zones which are used by the Shanghai land authority. Chen and Hao (2008) examine the distribution patterns of zone-level real estate prices in Shanghai in the hedonic price framework and find that the price gradient to the CBD is exactly what the classical bid-rent curve theory predicts for a monocentric city.

Figure 4 The Spatial Distribution of Zones within The Outer Ring in Shanghai



5. Empirical Results

In this paper, three quality standards are chosen to demonstrate the accuracy of the hedonic prediction. The first one is the adjusted R-squared (R^2), the second is the root mean squared error (RMSE) of the models, which is widely accepted for the measurement of prediction accuracy (Bin, 2004), and the last one is the number and the percent of true transaction housing prices which fall within a 95% confidence interval for the predicted prices.

5.1 Submarket Effect

Table 4 contains the OLS hedonic regression results with and without the four different sets of submarket dummy variables. Throughout all of the five regressions, the distance to the CBD is found to be negatively related to project-level real estate prices and highly statistically significant, while its squared term is consistently positive; this suggests that the negative impact of location disadvantage drops as property distance to the CBD increases. This is the same for the distance to the nearest subway station and supermarket. In addition, the coefficients of the project-level green ratio are consistently found positively related to project-level real estate prices. However, we found that TFA has little influence on the project-level real estate prices. The scale of the project does not seem to be a key determinant in Shanghai resident housing purchase preference. Nonetheless, a positive sign for FAR is apparently puzzling. Shanghai housing buyers prefer to live in higher density neighborhoods? This seems counter-intuitive. To investigate this ambiguity, we examined how the FAR values are spatially distributed and found that most high-FAR projects are located in the central part of the city.[8] Thus, there are reasons to believe that high values of FAR are associated with some favorable locational attributes which are unmeasured in the model. If this suspicion is true, the positive sign for FAR is kind of misleading. Nevertheless, in the subsequent section, we will re-examine the effects of FAR when the location of FAR is controlled. Finally, the impacts of distance to the nearest subway station and supermarket are found slightly different in the five regressions.

From Table 4, we can see that when more detailed submarket dummy variables are added to the OLS hedonic models, the explanatory power of the model increases: the RMSE becomes increasingly lower, the adjusted R^2 rises to a higher and higher level, and the percent of observed prices that fall into the 95% confidence bound of predicted values monotonously increases as well. The results are well consistent with expectations (Goodman and Thibodeau, 2003). Comparing these results without submarkets, we confirm that the hedonic regression with suitably-defined submarket dummies can significantly improve the accuracy of house price predictions.

Although the model with zone submarket dummies achieves the highest level of explanatory power, the highest level of an adjusted R^2 and also the lowest level of RMSE, it is not very practical or desirable to impose too many submarket dummy variables in the model when the improvement of R^2 is only moderate. For this reason, we choose the regression with district submarket dummies as our preferred model in the following analysis.

The R^2 in our regressions are between 0.5 and 0.7. These numbers are close to the common city-level results in China. For example, Zheng and Kahn (2008)'s hedonic regressions for Beijing real estate prices produce R^2 values

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[8] For example, we found that among 389 projects with a FAR value higher than 3, 64% are located in the inner ring, 24% are located in the middle ring and only 12% are in the outer ring. For 816 projects with a FAR value less than 2, only 7% are located in the inner ring, 26% are located in the middle ring and 67% in the outer ring. Such a spatial distribution of FAR, however, is consistent with the predictions of classical urban economic theories.

which range between 0.53 and 0.6. However, Leung, Cheung and Tang (2009) and Leung, Wong and Cheung (2007) report that their hedonic regressions with very detailed micro attributes for apartments in Hong Kong can, on average, attain R^2 values of 0.9. We suppose our lack of control of dwelling-level structural attributes may be the major reason for this gap.

Table 4 OLS Hedonic Estimation With and Without Different Submarkets

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
D_CBD	-0.0790*** (19.34)	-0.0785*** (19.19)	-0.0599*** (13.38)	-0.1279*** (26.70)	-0.1483*** (18.53)
D_CBD^2	0.0014*** (6.48)	0.0014*** (6.42)	0.0020*** (8.27)	0.0040*** (16.06)	0.0042*** (10.51)
D_ subway	-0.0083*** (7.20)	-0.0085*** (7.37)	-0.0110*** (9.76)	-0.0187*** (14.17)	0.0073** (2.46)
D_ supermarket	0.0128*** (3.42)	0.0127*** (3.39)	0.0079** (2.14)	-0.0191*** (5.67)	-0.0216*** (5.89)
Shopping	0.0895*** (5.83)	0.0905*** (5.87)	0.0967*** (6.54)	0.0943*** (7.37)	0.0038 (0.07)
Green	0.7003*** (19.22)	0.6890*** (18.90)	0.6617*** (18.75)	0.5545*** (17.30)	0.5418*** (15.82)
FAR	0.0803*** (14.24)	0.0812*** (14.39)	0.0725*** (13.17)	0.0175*** (3.46)	0.0022 (0.41)
TFA	0 (0.38)	0 (0.43)	0 (0.18)	0.0003*** (3.53)	0.0008*** (10.35)
_cons	9.3027*** (255.51)	9.3079*** (255.81)	9.2672*** (260.52)	9.5861*** (269.56)	9.8355*** (204.46)
Observations	12279	12279	12279	12279	12279
Adj. R-squared	0.5025	0.5031	0.5284	**0.6564**	0.7252
RMSE	0.26654	0.26638	0.25952	**0.22161**	0.19878
No of observed in 95% CI	1,178	1,201	1,276	**1,639**	2,342
% of observed in 95% CI	9.12%	9.29%	9.87%	**12.68%**	18.12%
Monthly Time Dummies	yes	yes	yes	yes	yes
Submarket Dummies	Without submarket	Building size	City Ring	Districts	Zone

Note: Robust *t* statistics in parentheses; ***stands for significance at 1% level, ** stands for significance at 5% level, * stands for significance at 10% level.

For some readers, the unavailability of dwelling-level prices and the lack of structural attributes in hedonic regressions appear much more troublesome than just smaller values of model fitness. There may be concerns about whether such missing information would produce serious omitted variable bias and affect the validity of coefficient parameter estimates for all existing control variables. However, Bover and Velilla (2003)'s work in Spain suggest that hedonic regressions with site dummies can be robust to omitted structural characteristics. In addition, as mentioned in footnote 2, most observations in our sample do not have large numbers of transactions. Thus, if the coefficients of locational attributes really depend on values of structural attributes, we have reasons to expect that regressions on observations with few transactions should exhibit different patterns of coefficient estimates with those on observations with large numbers of transactions, since the price variances of the first group should be more dominated by dwelling-level attributes than the second group. However, we did not find that. There are no vital differences in any key coefficient estimate between regressions of the two groups, both qualitatively and quantitatively. Although further formal investigations are warranted, the finding above, however, provides indirect evidence that the effects of structural attributes are largely independent of the effects of locational attributes, at least among a large-scale database of real estate property that covers the entire urban area of a mega city. If this hypothesis is true, it implies that hedonic models become easier to implement at large scale and thus will add more value in real estate appraisals. Anyhow, it appears that we may not need to worry too much about omitted variable bias in this paper.

5.2 Spatial Heterogeneity of Different Rings

In this section, we aim to examine whether and how much the marginal effects of locational and neighborhood attributes vary in different rings.

To begin, we estimate the following regression where the distance to the nearest supermarket is interacted with ring dummies, where the outer ring is used as the reference:

$$\begin{aligned}\log P_{it} &= \theta_0 + \theta_1 D\_CBD + \theta_2 D\_CBD^2 + \theta_3 D\_subway \\ &+ \theta_4 D\_subway \times Ring_{middle} + \theta_5 D\_subway \times Ring_{inner} \\ &+ \theta_6 D\_supermarket + \theta_7 Shopping + \theta_8 Green + \theta_{10} TFA + \mu_4\end{aligned} \tag{3}$$

where $Ring_i$ here stands for the dummy of each circle.

Equation (3) is just a benchmark and we can proceed to interact ring dummies with other key variables, for example, FAR and the distance to the CBD.

From column 5 in Table 4, we find that the real estate price tends to drop 1.94% when its location is one kilometer further away from the nearest subway station for the entire city. However, in column 2 of Table 5, we find that the dropping speed of price as a function of distance to the nearest subway station is much more different across the rings. It is sharpest in the outer ring, much weaker in the middle ring and almost zero in the inner ring. Adding detailed controls of FAR in column 3 of Table 5 does not change this fact. This finding can be interpreted as follows. Residents who live close to the borders of urban areas rely heavily on the subway, but those in more central parts of the city usually have much more transport options and thus have less demand for the subway. In the literature, there are arguments that the proximity to the subway station in the central part of the city are often associated with noise and crime, and thus it may not have any positive effect or in some cases, even reduce potential buyer demand for the real estate project (Bowes and Ihlanfeldt, 2001). Nonetheless, if adding more controls in locational factors, such interacting distance to the CBD with ring dummies, as columns 4-5 in Table 5 show, we would found that the proximity to the subway station is a desirable characteristic of property in the central part of the city. This is possibly because subway stations in the central part of Shanghai are often located in hotspot places with well-developed shopping environment and entertainment facilities. However, at the same time, we found the proximity to the subway station is undesirable for residents in the inner ring section of the city. This is possibly because the subway does not help much to improve commutering in the inner ring section while at the same time, the location of the subway station may not be well associated with favorable neighborhood amenities in this region. Thus, these negative externality effects of the subway, as mentioned above, dominate the positive effects of the subway in this area. These findings enrich our knowledge of the complex effect of subways on property prices.

For FAR heterogeneity in different rings, column 3 suggests that the coefficient sign of FAR is positive in the entire city. However, after interacting ring indicators with FAR, such as column 4, the coefficient sign of FAR is significantly positive only in the middle ring while becoming negative, but insignificant, in the outer ring. The sign of FAR in the inner part is positive in column 3, but becomes unclear in column 4. Similarly, after interacting the distance to the CBD with FAR as shown in column 5, the coefficient sign of FAR is insignificant. Thus, so far, we are not able to give an unambiguous conclusion of the effects of FAR on property prices in Shanghai. Although its sign appears to be positive in most cases, we still suspect that this is more due to the high correlation between the project FAR and distance to the CBD rather than its own dependent effect. Otherwise, it would be quite strange to find residents in Shanghai who prefer to live in more crowded neighborhoods. Further studies are called on this issue.

Now, we focus on the performance of price gradient. Consistent with Table 4, all models in Table 5 report negative and statistically strong signs of distance to the CBD on property prices. Based on columns 2-3, on average, one kilometer away from the CBD will induce property prices to drop around 13%. However, as suggested from the positive sign of the square of distance to the CBD, we can conclude that the price gradient is becoming flatter when moving away from the city center. Computed from the coefficient of the square of distance to the CBD, we may conclude that the declining trend of property prices will vanish to zero at locations around 13-16 kilometers to the CBD. With the exception of Pudong, locations with such a high level of distance to the CBD are almost on the city fringe in Shanghai by any direction (ref. Figure 5). In addition, as shown in columns 4-5, the speed of decline is sharpest in the middle rather than the outer ring. This is easy to understand as location will become relatively unimportant in places far away from the city center. However, compared to the outer ring, whether the speed of the decline of the price gradient is higher or lower in the inner ring is not very clear from Table 5.

5.3 The Directional Price Gradient

Usually, the hedonic literature assumes a uniform price gradient pattern in any direction outward from the city center. However, this may not be always true in real life (Yiu and Tam, 2004). For example, Soderberg and Janssen (2001) examine the real estate market in Stockholm and find an asymmetric price gradient. People familiar with Shanghai also know that the south part of urban Shanghai tends to be much more flourishing than the north part. To formally examine whether and how much the price gradient varies in different directions, we estimate the following regression where the east direction is used as the reference:

$$\begin{aligned} log\ P_{it} &= \theta_0 + \theta_1 D\_CBD + \theta_2 D\_CBD^2 + \theta_3 \left(Direction_{North} \times D\_CBD\right) \\ &+ \theta_4 \left(Direction_{North} \times D\_CBD^2\right) + \theta_5 \left(Direction_{West} \times D\_CBD\right) \\ &+ \theta_6 \left(Direction_{West} \times D\_CBD^2\right) + \theta_7 \left(Direction_{South} \times D\_CBD\right) \\ &+ \theta_8 \left(Direction_{South} \times D\_CBD^2\right) + \theta_9 D\_subway + \theta_{10} D\_subway \times Ring_{middle} \\ &+ \theta_{11} D\_subway \times Ring_{inner} + \theta_{12} D\_supermarket + \theta_{13} shopping + \theta_{14} Green \\ &+ \theta_{15} FAR + \theta_{16} TFA + \mu_5 \end{aligned} \tag{4}$$

where $Direction_i$ stands for the dummy of each direction, and $Ring_i$ stands for the dummy of each Ring.

The regression results presented in Table 6 suggest that in Shanghai, the price gradient is flattest in the south direction, significantly deeper in the west direction, and the east direction is the sharpest. The curves of the distance gradient in different direction are shown in Figure 5. Evidently, all price distance gradients are convex.[9] This finding is a very useful addition to our knowledge of the spatial distribution pattern of housing prices in Shanghai and confirms the notion that areas in the south have traditionally been more desirable to live in Shanghai. Compared to column 2 in Table 4, we can now see that controlling for directional price gradients yields significant gains in hedonic prediction accuracy.

[9] Thanks for the referee's comment that brought our attention to this issue.

Table 5 OLS Hedonic Estimation with Spatial Heterogeneity of Ring Effect

Variable	Model 1	Model 2	Model 3	Model 4
D_CBD	-0.1329*** (27.43)	-0.1234*** (17.01)	-0.1628*** (18.57)	-0.1644*** (17.34)
$(D\_CBD)^2$	0.0045*** (16.92)	0.0041*** (11.46)	0.0055*** (13.31)	0.0055*** (14.13)
D_ subway	-0.0210*** (14.77)	-0.0183*** (11.80)	-0.0102*** (6.39)	-0.0109*** (6.81)
D_ subway* Ring $_{middle}$	0.0107*** (5.52)	0.001 (0.36)	0.0191*** (5.72)	0.0046 (1.46)
D_ subway*Ring $_{inner}$	0.0188*** (4.19)	0.0134** (2.25)	-0.0269*** (3.74)	-0.0327*** (4.44)
D_ supermarket	-0.0189*** (5.58)	-0.0184*** (5.47)	-0.0203*** (5.94)	-0.0202*** (5.75)
Shopping	0.0950*** (7.40)	0.1004*** (7.72)	0.0802*** (6.24)	0.0728*** (5.59)
Green	0.5691*** (17.55)	0.5653*** (17.29)	0.5850*** (18.25)	0.5681*** (17.37)
TFA	0.0003*** (3.71)	0.0004*** (3.89)	0.0004*** (5.02)	0.0003*** (3.64)
FAR	0.0185*** (3.63)	-0.0001 (0.01)	-0.0019 (0.22)	-0.0025 (0.21)
FAR * Ring $_{middle}$		0.0264*** (5.00)	0.1017*** (9.47)	
FAR * Ring $_{inner}$		0.0205*** (2.78)	-0.0210* (1.89)	
FAR*D_CBD				0.0026* (1.93)
D_CBD* Ring $_{middle}$			-0.1097*** (14.33)	-0.0320*** (6.69)
D_CBD* Ring $_{inner}$			0.0064 (0.70)	-0.0213*** (2.79)
$(D\_CBD)^2$* Ring $_{middle}$			0.0096*** (14.97)	0.0040*** (7.98)
$(D\_CBD)^2$* Ring $_{inner}$			0.0026** (2.51)	0.0055*** (5.68)
Constant	9.5664*** (267.12)	9.5358*** (224.82)	9.7773*** (197.71)	9.7556*** (163.03)
Observations	12279	12279	12279	12279
Adj. R-squared	0.6574	0.6582	0.6713	0.6633
RMSE	.22129	.22105	.21681	.21944
No of observed in 95% CI	1,708	1,726	1,685	1,747
% of observed in 95% CI	13.22%	13.36%	13.04%	13.52%
Monthly Time Dummies	Yes	Yes	Yes	Yes
District Dummies	Yes	Yes	Yes	Yes

Note: Robust *t* statistics in parentheses; *significant at 10%; ** significant at 5%; *** significant at 1%

Table 6 OLS Hedonic Regression Results with Directional Price Gradients

	D_CBD	D_CBD^2	D_subway	D_subway × $Ring_{middle}$	D_subway × $Ring_{inner}$	D_super-Market
Reference (East)	-0.1799*** (17.33)	0.0063*** (13.09)	-0.0165*** (10.73)	0.0099*** (4.90)	0.0133*** (2.79)	-0.0191*** (5.70)
D_{North}	0.0436*** (3.72)	-0.0009 (1.61)				
D_{West}	0.0678*** (3.46)	-0.0034** (2.56)				
D_{South}	0.1027*** (6.52)	-0.0063*** (7.06)				

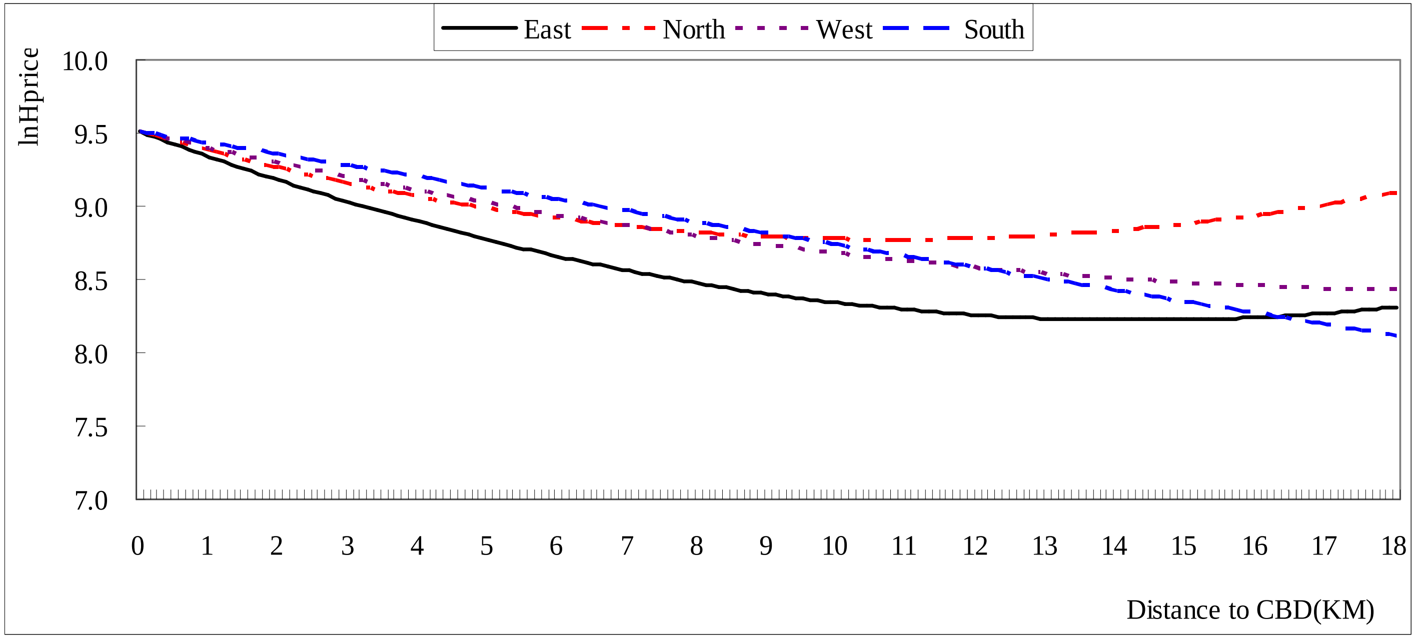
(***Extension of the Hedonic Regression***)

Shopping	Green	FAR	TFA	Cons	District Dummies	Monthly Time Dummies
0.0886*** (6.93)	0.5154*** (15.79)	0.0154*** (2.97)	0.0005*** (4.67)	9.5105*** (228.37)	Yes	Yes

Adj. R-squared = 0.6625, *RMSE* = 0.21969, 1,701 observations (13.16%) in 95%CI, *F* (52, 12226) = 557.52

Note: Robust *t* statistics in parentheses; ***stands for significance at 1% level, ** stands for significance at 5% level, * stands for significance at 10% level.

Figure 5 The Distance Gradient of Housing Prices in Different Directions in Shanghai



6 Conclusion

The ways that real estate prices vary with locational characteristics have important policy and business implications. The focus of this paper is to study the key determinants of real estate prices in Chinese cities and whether prediction accuracy could be improved when submarket dummies are added to models. In this paper, three quality standards are chosen to demonstrate the accuracy of hedonic prediction, which are an adjusted R^2, the RMSE of the models, and the number and percent of observed prices which fall within the confidence interval of predicted values.

Our hedonic regression results suggest that the project-level mean real estate price in Shanghai drops quickly as the location becomes located further away from the CBD, *ceteris paribus*. Meanwhile, we find that a shorter distance to the nearest subway station, shorter distance to the nearest supermarket, accessibility to a large shopping center, and higher green ratio substantially increase the values of real estate. Furthermore, there is also clear evidence that distinctive sub-segments exist in the housing market of Shanghai. We also find that the price gradient pattern substantially varies in different city rings and different directions outward from the city center. For example, the decline in price gradient in the north direction is much sharper than in the south direction.

With such evidence, we find a clear and substantial presence of spatial heterogeneity in the Shanghai real estate market, which indicates that the marginal prices of some housing attributes are not constant, but vary with different submarkets. Through various experiments of hedonic regressions, we confirm that the accuracy of hedonic prediction of real estate prices could be improved by adding a suitably defined submarket dummy in the models.

Nonetheless, we admit that restricted by the limitations of data and methodology used, our understanding of the micro determinants of real estate prices in Shanghai and urban China is just at the beginning level and there are many unanswered questions which need further exploration. Particularly, future studies must be based on database with reliable dwelling-level information of property prices and characteristics, and appropriate applications of spatial econometrics tools are warranted. We have been working towards that direction and hopefully will produce more fruitful results in the near future.

Acknowledgment

We thank the financial support of the National Science Foundation of China (NSFC 70601007) and Shanghai Pujiang Project for the research work of this paper. A previous version of this paper has been presented in the GCREC Beijing conference, August 2009 and comments from workshop attendants are appreciated. We gratefully acknowledge the very helpful comments and suggestions from anonymous referees and kind support from the IRER Editor. All remaining errors are, of course, our own.

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