LOCATION-DOMINANT HOUSING MARKETS:

EVIDENCE FROM BEIJING

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October 18, 2013

Abstract

This paper analyzes price tradeoffs between residential quality and location factors in the Beijing housing market. Unlike most housing markets, location factors completely dominate housing prices in this market. The main reason for this appears to be the physical size of central Beijing, where travel times between different urban activity centers are comparable to typical suburban-urban commuting times in large Western cities. To highlight these location-dominance effects, we present a comparative analysis of housing prices in central Beijing with those of the relatively smaller monocentric city of Qingdao in Eastern China. The main results of this regression analysis are to show that location accessibility factors are far more dominant in Beijing, and conversely that residential quality factors are more important in Qingdao. To further illuminate these differences, we develop a simple two-city model in which the "Big" city has multiple activity centers with travel costs comparable to typical commuting costs in the "Small" city. Here it is shown that the resulting bid-price relations between these cities are quite consistent with our empirical findings.

1. Introduction

One often hears that the three most important things in real estate are “location, location, location”. But when it comes to housing prices, there is generally some degree of tradeoff between residential quality and location. For example, the influence of location is clearly seen in New York City, where the central borough of Manhattan exhibits higher average housing prices that Brooklyn, Queens or the Bronx. But even within Manhattan, one sees significant prices variations due mainly to quality differences. Recent real estate reports show that the mean rental prices in some neighborhoods, such as SoHo and the Upper East Side, are two or three times higher than those in Harlem for the same types of housing. These differences are much more attributable to differences in housing and neighborhood quality than accessibility.

However, there is one city where “location, location, location” does ring true, namely Beijing. In contrast to New York, housing prices in central Beijing are almost invariably the highest. The main reason for this difference appears to be size. Indeed, central Beijing is about ten times larger than Manhattan, so that relative accessibility becomes more of an issue. This is perhaps seen most dramatically in suburban Beijing where prices of even the most luxurious houses are undervalued by lack of accessibility.

These differences can also be seen numerically by comparing neighborhood housing prices for Manhattan and central Beijing. In central Beijing[1], the mean of these neighborhood housing prices per square foot (in US dollars) is $419 with a standard deviation of $99; while in Manhattan[2], the corresponding mean is $2038 with a standard deviation of $1745! So even though the island of Manhattan is much smaller than central Beijing, it exhibits far greater variation in housing prices.[3]

Thus the main purpose of the present paper is to study this unique urban housing market, where city size appears to play a qualitatively different role than in typical megacities of the West, including Paris and London as well as New York. In contrast to these cities, central

[1] Data was collected for current mean prices in the 51 neighborhoods of central Beijing on the website, http://beijing.anjuke.com/, that reports housing price data for China.

[2] These figures are base on a sample of 854 individual housing sales prices in Manhattan obtained from the New York City government’s website, http://www.nyc.gov/html/dof/html/property/property_val_sales.shtml. See footnote 20 below for further discussion of this data.

[3] In relative terms, the coefficient of variation for Manhattan housing prices (0.856) is more than three times that of Beijing (0.236).

Beijing consists of multiple activity centers separated by considerable distances. In fact, commuting times typically experienced between suburbs and city centers in the West are comparable to those between alternative activity centers in central Beijing.[4]

In addition to these size differences, there is a second feature of Beijing that makes it particularly amenable for studying price tradeoffs between residential quality and location. Unlike Western cities where the measurement of residential quality (other than house size) is a challenging problem, in China there are a number of measurable attributes that are widely recognized to be reliable indicators of residential quality. With respect to housing quality itself, older houses in China are almost invariably considered to be of lower quality. In addition, since houses in China are typically grouped into walled "communities" (comparable in size to Western city blocks), those communities with higher population densities are generally considered to be of lower quality. Conversely, the presence of neighborhood green spaces (parks, gardens, etc.) generally enhances community quality. Since data on all of these attributes is widely available for cities in China, this allows price tradeoffs between location and residential quality to be more readily quantified.

But to do so, it is necessary to compare Beijing with other cities in China, rather than Western cities. Here we have chosen the city of Qingdao, which is a typical monocentric city in Eastern China. Moreover, while Qingdao is not "small" by Western standards, being roughly the same size as Paris, it is nonetheless only a quarter the size of central Beijing (Figure 2 below).

In our empirical analysis below, housing price data from these two cities is regressed on both residential quality and location variables, while treating "city" as a categorical variable. Our residential quality variables include house size and age (year of construction), as well as community population density and area of neighborhood green space. Our location variables are of two types. The primary variable for our purposes is a summary measure of accessibility to major city activity centers (in terms of travel times), designated as the *activity-accessibility index*. However, given the importance of education in Chinese culture, it is also appropriate to consider access to good high schools, designated as the *education-accessibility index*. In view of the strong collinearity between these two indices, it was necessary to run separate regressions for each. Finally, addition to these main explanatory variables, it was necessary to

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[4] For example, the rapid-transit commuting times between Newark to downtown Manhattan, and between Luton and central London, are both about 40 minutes. However, travel times on the Beijing subway between its five major city centers (discussed in section 3.1 below) are as much as one hour.

include neighborhood fixed effects in both cities to control for residual spatial autocorrelation (as discussed in Section 4.2 below)

The results for the regressions for both accessibility indices were qualitatively very similar. As expected, both location and residential quality factors were significant predictors of housing prices in all cases. But the key results of these regressions (expressed as interaction effects between "city" and the other explanatory variables) show that location is far more important in Beijing than Qingdao. Conversely, residential quality factors tend to be much less important in Beijing than Qingdao. Only the age of housing is of equal (negative) importance in both cities. These results thus provide strong support for the major hypothesis of this paper, namely that for cities with centers as large and complex as Beijing, location factors are the dominant influence on housing prices.

In the final section of the paper we attempt to illuminate this dominance effect by means of a simple one-dimensional "equilibrium bid-price" model that compares housing prices in a large city with multiple activity centers versus a smaller monocentric city. A typical example of the resulting price structures is shown in Figure 8 below. Here the larger city is assumed to have only two activity centers, at locations corresponding to each edge of the flat portion of the higher price curve shown. Since accessibility to both centers is the same for all locations between them, utility maximizing behavior leads to a constant level of equilibrium price in this central city area. This can be viewed as an extreme version of central Beijing, where the low variation in housing prices (relative to Manhattan) has reduced to no variation at all. Note also that while prices are of course higher in this central area than at the single center of the smaller city, they also fall off more quickly outside this central area. This reflects the fact that such locations are more distant from *both* activity centers, thus yielding a greater utility loss than for the monocentric city.

Before proceeding, it is of interest to relate our work to previous studies of the Beijing housing market. Most work has focused on housing policy issues in Beijing, and in particular, on those issues related to the current transition from a planned to a market economy in China (Tolley, 1991; D. Wang and Li, 2004). Somewhat closer to our own work is the study of Wang (2001), who considers the effects of this economic reform on specific housing quality variables, such as the age and layout of individual houses.

But the studies of most interest for our present purposes are those that have explicitly compared Beijing housing with other cities in China. One such study by Li (2000) compares the influence of commercialization and privatization on the housing markets in Beijing and Guangzhou (which, unlike Qingdao, is one of the largest cities in China).[5] But while this study does examine the influence of housing quality on prices in these two markets, it does not consider the influence of location. One study that does do so is by Hu and Kaplan (2001), who point out that the housing choices of wealthier residents in Beijing tend to concentrate in central Beijing and are strongly influenced by locational considerations. In this respect, our results add further support to their findings.

The remainder of the paper is structured as follows. Section 2 gives a brief overview of Beijing and Qingdao. This is followed in Section 3 with a description of the data used, together with a description of our specific residential quality and location variables. The regression analysis itself is developed in Section 4, together with a discussion of the main results. Our theoretical model is then developed in Section 5, and illustrated in terms of a numerical example. Finally, the paper concludes in Section 6 with a brief discussion of possible directions for further research.

2. Beijing and Qingdao

We begin with a brief overview of Beijing, together with the smaller city of Qingdao. Here we focus on those aspects of these two cities that are most important for the analysis to follow.

2.1 Beijing

Beijing is the capital of the People's Republic of China and one of the most populous cities in the world. In 2010, the total population within the municipal boundary of Beijing (Figure 1a) was close to 20 million. Of more interest for out present purposes is central Beijing (Figure 1a), with a 2010 population of close to 10 million. (By comparison, the 2010 population of Manhattan was about 1.5 million.) The area of central Beijing is about 230 square miles (roughly ten times the size of Manhattan). As in all major cities of China, central Beijing is composed of many traditional neighborhoods. For purposes of analysis we have combined these into 51 distinct neighborhoods, as shown in Figure 1b. Individual housing communities are much smaller than neighborhoods, and in particular, these 51 neighborhoods contain a total of about 3000 housing communities.

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[5] Guangzhou is one of the "national central cities" of China and is the fourth largest city in terms of urban population.

Figure 1

2.2 Qingdao

Qingdao is a major seaport on the east coast of China in the Shandong Province, which is nonetheless much smaller than Beijing. central Qingdao is only a quarter the size of central Beijing (Figure 2 below) with a population of about 3 million.[6] But as mentioned in the introduction, it is still larger than most urban centers in the West, such as central Paris.[7] As with Beijing, central Qingdao consists many traditional neighborhoods, which we have again combined into 22 distinct neighborhoods, as shown in Figure 2b. These neighborhoods contain a total of approximately 500 individual housing communities.

Figure 2

3. Data and Variables for Analysis

Housing price data is readily available at the community level for both Beijing and Qingdao.[8] While individual communities differ in size (roughly from around 50 to more than 1000 housing units), the housing units within each community are generally very homogeneous with respect to the attributes of interest here, namely price per square foot together with house size and age.[9] So the averages of these values can be taken to be good representatives of individual houses within these communities. The present analysis is based on averages from 2988 communities in central Beijing, and 530 communities in central Qingdao.

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[6] The politically defined municipal region of Qingdao (not shown) is almost as large as that of Beijing, and for our purposes has little practical relation to the actual urban area of Qingdao.

[7] The area of Central Qingdao is about 48 square miles, in comparison with urban Paris (including the 20 arrondissements) which is about 41 square miles.

[8] The price data for these two cities was collected at *anjuke.com*, a Chinese website that accumulates residential community information, including average housing prices and attributes of housing quality.

[9] Each community is built either by single development firms (designated as "commercial residence" communities) or by employer for workers (designated as "welfare residence" communities). In both cases, each community has a single residential committee. All these factors contribute to the homogeneity of housing units with each community.

As mentioned in the introduction, our main interest focuses on the housing-price tradeoffs between locational and residential quality variables in Beijing versus Qingdao. We now consider each of these classes of variables in more detail.

3.1 Location Variables

Recall that the major locational attributes for our purpose are in terms of access to urban activity centers and educational centers. We first consider central Beijing, where there are five major activity centers, as shown in Figure 3(a) below.

Figure 3

Among the five centers, the single biggest in terms of passenger flows (discussed below) is the central business district, "CBD"[10], located in neighborhood 23 on the map. The next two largest centers are the financial center, "Financial Street", in neighborhood 18 and the technological center, "Zhongguancun"[11], in neighborhood 5. The two smallest centers are the commercial centers, "Xidan" and "Wangfujing" in neighborhoods in 19 and 22, respectively.

To measure the accessibility of each Beijing community to these five centers, we focus on commuting times. In central Beijing the major commuting mode is public transit.[12] Since transit times are essentially constant within each neighborhood, we measure such times at the neighborhood level.[13]

3.1.1 Activity-Accessibility Index

To formalize the desired accessibility measures for both Beijing (B) and Qingdao (Q), we now let t_{ij}^{c} denote the relevant *travel time* from community i to activity center j in city,

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[10] This district is indeed referred to as the "CBD" by Beijing residents.

[11] This center is often referred to as the "Silicon Valley" of China, and is also the primary center of advanced education and research in all of China.

[12] Because of the high population density and congested street traffic, car ownership is currently restricted in Beijing. In addition, public transit is heavily subsidized to encourage ridership.

[13] To account for within-neighborhood travel times, we measure average travel time to the center of each neighborhood, based on the most appropriate mode of travel (walking, etc.) for each size of neighborhood.

$c\,(=B,Q)$.[14] For Beijing, t_{ij}^{B}, is thus the public transit time from the neighborhood containing i to the main subway station in j.[15] To gauge the relative attractiveness of each center, we also rely on passenger flows to these centers. In particular, data is available on the number commuters exiting subways at each activity center during morning rush hour. These passenger totals are taken to represent the *attractiveness*, a_j^B, of each activity center j in Beijing, as measured relative to the largest total for the CBD.[16] To construct a summary index, let n_c and N_c denote, respectively, the number of *activity centers* and *communities* in city, c.[17] In these terms, our *activity-accessibility index*, AI_i^c, for each community i in city c is defined to be:

(1) $$AI_i^c = k_c \cdot \sum_{j=1}^{n_c} \frac{a_j^c}{t_{ij}^c} \quad , \; i = 1,..,N_c \; , \;\; c = B,Q$$

where the proportionality constant, k_c, is taken to be the reciprocal of the least accessible community,

(2) $$k_c = 1/\min_i \sum_{j=1}^{n_c} \left(a_j^c / t_{ij}^c\right)$$

so that by definition, $AI_i^c \geq 1$, with $AI_i^c = 1$ for the least accessible community.

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[14] By "city" we shall always mean "Central Beijing" and "Central Qingdao", as depicted in Figure 2 above.

[15] Here it should be noted that public transit in Beijing includes both subways and buses. There are 15 subway lines with 218 stations, and in addition, there is a good bus system that covers the entire city. Commuters generally use subways whenever possible, and use buses primarily to connect with the nearest subway. So the estimated travel times used here are based roughly on shortest-time combinations of bus and subway travel from each neighborhood.

[16] The ratios of passenger totals for Zhongguancun, Financial Street, Xidan, and Wangfujing relative to the CBD are given respectively by 0.92, 0.92, 0.67, and 0.58. The relative values are also represented by the shades of gray in Figure 3(a).

[17] So for $c = B$ we have $(n_B = 5, N_B = 2988)$, and for $c = Q$ we have $(n_Q = 1, N_Q = 530)$, where the single activity center for Qingdao is shown in Figure 4(a) above.

Turning next to Qingdao $(c = Q)$, as mentioned in the introduction, this is essentially a monocentric city with single urban activity center, “Hong Kong Middle Road”, located in neighborhood 1 of Figure 4(a) below.

Figure 4

Moreover, since Qingdao is a smaller city, with a less well developed public transit system (no subway) and less congested street traffic, the major mode of travel is by private car (including personal cars and taxis). Hence commuting times are more appropriately measured here in terms of *driving time*, t_{i1}^{Q}, from (the neighborhood of) each community i to the center of neighborhood 1. Thus, by setting the attractiveness of this single center to $a_1^Q = 1$, the appropriate *activity-accessibility index*, AI_i^Q, for each community, $i = 1,..,N_Q\ (= 530)$ in Qingdao is again given by (1) and (2) with $n_Q = 1$.

3.1.2 Education-Accessibility Index

Our second measure of locational accessibility focuses on the major centers of high school education in each city. The quality of high schools in each neighborhood, j, if city c is measured in terms of the number, e_j^c, of *outstanding students* graduating from these schools. This measure differs somewhat between Beijing and Qingdao. In Beijing, e_j^B is measured in terms of the (publically available) number of students passing the pre-matriculation test for the two top universities in China, namely Peking University and Tsinghua University. But since these numbers are very small in a city the size of Qingdao, it is appropriate to broaden the class of “outstanding students”. This is accomplished with a weighting scheme in which (i) each student passing the above pre-matriculation test is given 3 points, (ii) each passing the similar test for any of the other top (C9 League) universities in China is given 2 points, and (iii) each student passing the similar test for the local Shandong University closest to Qingdao is given 1 point. The relevant education quality values, e_j^Q, for each neighborhood, j, in Qingdao in then given by the weighted number of students graduating from high schools in that neighborhood. The relative weights for each neighborhood in Beijing and Qingdao are represented by the shades of gray in Figures 3(b) and 4(b), respectively. Finally, by again using the same measures of travel times, t_{ij}^c, for each city, and letting m_c denote the number of neighborhoods with nonzero weights, e_j^c, we can define an education-accessibility index, EI_i^c, for each community, i, in city c as:

$$(3) \qquad EI_i^c = h_c \cdot \sum_{j=1}^{m_c} \frac{e_j^c}{t_{ij}^c} \qquad , \; i = 1,..,N_c \; , \;\; c = B,Q$$

where the proportionality constant, h_c, is given in a manner similar to (2) by

$$(4) \qquad h_c = 1/\min_i \sum_{j=1}^{m_c} \left(e_j^c \big/ t_{ij}^c \right)$$

again ensuring that $EI_j^c \geq 1$ with $EI_j^c = 1$ for the least accessible neighborhood.

3.2 Residential Quality Variables

Our residential quality variables are essentially of two types, namely the quality of individual houses in each community, and the local environmental quality of the community itself. We consider each of these subclasses of variables in turn.

3.2.1 Housing Quality

As mentioned in the introduction, individual houses within each community are fairly homogeneous in quality (much like individual units within condominiums in the West). As with housing prices themselves, we thus focus on representative levels of housing-quality attributes in each community. The most basic housing quality attribute is of course house size. While sizes in terms exact floor space are often not available, rough distinctions between sizes can generally be obtained from property descriptions in each community. Hence we treat house *size* as a dichotomous variable, *S*, with $S = 1$ for Beijing houses larger than 100 square meters, and similarly, $S = 1$ for Qingdao houses larger than 120 square meters. The second housing quality variable is the *age*, *A*, of each house, measured in terms of the number of years since the construction of the community (so that a community built 20 years ago yields an age, $A = 20$, for each of its housing units). Here it should again be emphasized that houses in older communities are almost invariably regarded to be of lower quality.[18]

3.2.2 Community and Neighborhood Quality

Another important attribute of each community is its density in terms of the number of housing units it contains.[19] While exact numbers are often not available, it again possible to discern from property descriptions whether or not there are more than 1000 housing units in the community. We adopt this figure as a threshold value to distinguish "high density" versus "low density" communities, and define *community density*, *D*, to be a binary variable with $D = 1$ for communities with more than 1000 units. One additional environmental attribute which influences residential quality is the presence public green spaces (parks, gardens, etc.) in the neighborhood of each community. Data is available on total *green space area*, *G*, in each neighborhood, and constitutes our final residential quality variable.

4. Regression Analysis

The basic regression models in terms of the above explanatory variables are presented in section 4.1 below. However, initial investigations of these models revealed serious spatial autocorrelation among residuals. This prompted a second phase of analysis, as detailed in Section 4.2. The final regression results are presented and discussed in Section 4.3.

4.1 Basic Regression Model

We begin by observing that there are clear differences in the distributions of housing prices between the Beijing market and US markets, such as Manhattan. As mentioned in the introduction, the most dramatic differences are in terms of the range and relative variation of these prices. This can be seen by a comparison of the histograms in Figures 5a and 5b below, where both Beijing and Manhattan housing prices have been transformed into "dollars per square foot" to allow direct comparison.

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[18] As an additional housing quality variable, we also considered the type of house, "commercial" versus "welfare" residence (as mentioned in footnote 9 above). But since "welfare" communities are almost invariably older then than "commercial" communities, this variable proved to be too correlated with age to yield any additional explanatory power.

[19] Typically communities with larger numbers of housing units allocate less public space per unit, so that the number of units indirectly reflects "density".

Figure 5

Figure 5a shows the average housing prices for the 2988 communities in central Beijing. This is compared with a smaller sample of Manhattan housing prices in Figure 5b.[20] Notice first that the price range in Manhattan is ten times that in Beijing. But even after accounting for this difference, it is clear that, unlike the typical right skewed price data shown for Manhattan, the Beijing data is much more “bell shaped”, with relatively few high outliers. This in part accounts for the smaller variation in this distribution. But it also shows that, unlike almost all housing-price regression models in the US, there is no need for a log transformation of this price data.

With these observations, our basic regression model can be formulated as follows. If in each community i of city c we let

$P_i^c =$ average price (Yuan/sqm) of housing units in i

$A_i^c =$ average age (years) of housing units in i

$S_i^c =$ average size of housing units in i ($S_i^c = 1$ for “larger” houses)

$D_i^c =$ density of housing units in i ($D_i^c = 1$ for more than 1000 units)

$G_i^c =$ area of green space (sqm) in the neighborhood of community i

$AI_i^c =$ activity-accessibility index for i

$EI_i^c =$ education-accessibility index for i

and let δ denote a *city dummy* with $\delta = 1$ if $c = Q$ and $\delta = 0$ if $c = B$, then our first regression model takes the form:

$$(5) \qquad P_i^c = \alpha_0 + \delta\,\alpha_1 + (\beta_0 + \delta\,\beta_1)\,A_i^c + (\gamma_0 + \delta\,\gamma_1)\,S_i^c + (\eta_0 + \delta\,\eta_1)\,D_i^c + (\theta_0 + \delta\,\theta_1)\,G_i^c + (\mu_0 + \delta\,\mu_1)\,AI_i^c + \varepsilon_i^c$$

In this form, the key variable coefficients for Beijing are given respectively by, $(\beta_0, \gamma_0, \eta_0, \theta_0, \mu_0)$. So the expected signs in terms of the variables above are $(-,+,-,+,+)$ .The

[20] Figure 5b shows a sample of 854 individual housing prices that is actually part of a much larger sample of house prices. These 854 samples were the only ones containing floor-space information allowing a per-sqft comparison with Beijing prices.

"interaction" coefficients, $(\beta_1, \gamma_1, \eta_1, \theta_1, \mu_1)$, indicate differences in the effects of these variables between Beijing and Qingdao. As one key example, note that for Beijing $(\delta = 0)$, the coefficient on AI_i^c is in (5) is μ_0, and that for Qingdao $(\delta = 1)$ this coefficient is now $\mu_0 + \mu_1$. So μ_1 represents the *difference* between the effects of activity accessibility on housing prices in Qingdao and Beijing. Hence, if such accessibility is more important in Beijing than Qingdao (as we hypothesize), then one would expect μ_1 to be significantly negative.

Finally, the same model using education accessibility can be constructed by simply substituting EI_i^c for AI_i^c in Model (5).

4.2 Controlling for Spatial Autocorrelation

As with all regression data for spatially contiguous units, it is imperative to check for residual spatial autocorrelation. To do so, we first constructed spatial contiguity weight matrices, W_B and W_Q, for Beijing and Qingdao neighborhoods respectively,[21] and then constructed the corresponding block-diagonal matrix, $W = diag(W_B, W_Q)$. This matrix was in turn used to construct a Moran's I test for spatial autocorrelation (based on the usual normal approximation). This test showed extremely significant autocorrelation for both models, indicating the need for modifications of Model (5) above. Here we first tried the standard Spatial Lag Model (SLM) and Spatial Error Model (SEM) formulations to control for spatial autocorrelation effects. While there was some reduction, Moran's I was still extremely significant (p-values < .0001) for both the SLM and SEM models.

After considerable experimentation, we found that spatial autocorrelation could be effectively controlled for by simply introducing neighborhood fixed effects. Then reason for this can be seen by plotting the original set of residuals for the activity-accessibility regression by neighborhoods as in Figure 6a below (where the first 51 neighborhoods on the horizontal axis are for Beijing, and the final 22 neighborhoods are for Qingdao). Here it is clear that the residual groupings in many neighborhoods are vertically shifted relative to one another, indicating that residuals are more similar within neighborhoods than between

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[21] In particular, for any pair of communities, i and j, in city $c\,(= B, Q)$ we set $W_c(i, j) = 1$ if i and j are in the same neighborhood, $W_c(i, j) = 1/2$ if i and j are in adjacent neighborhoods, and $W_c(i, j) = 0$ otherwise.

neighborhoods.[22] What this suggests is that there are important neighborhood attributes missing from our regression. Moreover, the figure also shows that these neighborhood effects are most extreme among Beijing neighborhoods, suggesting again that the importance of "location, location, location" is more evident in Beijing than Qingdao.

Figure 6

To minimize these neighborhood residual effects, our final regression models extend Model (5) by including neighborhood fixed effects for both Beijing and Qingdao. For the activity-accessibility case, this regression model takes the following form:

$$(6)\qquad P_i^c = \alpha_0 + \delta\alpha_1 + (\beta_0 + \delta\beta_1)A_i^c + (\gamma_0 + \delta\gamma_1)S_i^c + (\eta_0 + \delta\eta_1)D_i^c + (\theta_0 + \delta\theta_1)G_i^c$$
$$+ (\mu_0 + \delta\mu_1)AI_i^c + \sum_{k=1}^{51}\tau_k^B B_k^c + \sum_{k=1}^{22}\tau_k^Q Q_k^c + \varepsilon_i^c$$

where (B_k^c, Q_k^c) are indicator variables with $B_k^c = 1$ if and only if $(c = B)\,\&\,(k = i)$, and similarly, $Q_k^c = 1$ if and only if $(c = Q)\,\&\,(k = i)$.

Given the large number of neighborhood fixed effects, we employed stepwise regression to identify relevant neighborhoods, but kept all explanatory variables and interaction effects to allow full comparisons between cities. Moran tests of the new residuals produced p-values greater than 0.20 in all cases, thus confirming that spatial autocorrelation had been effectively eliminated by these fixed effects. This can be seen graphically in Figure 6b, where the fixed effects have now removed these "vertical shift" effects, yielding residuals that tend to be centered around zero within each neighborhood. [Given the large number of significant neighborhood fixed effects (more than 50 out of 73), we omit these from the regression results reported below.]

[22] This empirical finding is quite consistent with the recent theoretical result of Anselin and Arribas-Bel (2013) that spatial fixed-effect approaches are more effective that traditional spatial regression models when spatial dependencies are essentially "block diagonal" in nature.

4.3 Regression Results

Turning first to the results for Model (6) using *activity accessibility* (AI) for the key location variable, all estimates and significance levels for both explanatory variables and interaction effects are shown in Table 1 below.

Table 1

Before discussing these specific results, we start by noting that the adjusted R-square for this regression was 0.811, which is surprisingly high for any housing-price regression model. However, further investigation showed that by running the regression using only the neighborhood fixed effects, the adjusted R-square was already 0.523. So more than 50% of this housing-price variation is attributable to unobserved neighborhood effects. This of course suggests that predictive power of this model could be considerably improved by identifying and explaining these unobserved effects. But for our present purposes, the limited set of explanatory variables used here suffices to capture the major differences between housing prices in Beijing and Qingdao.

Turning now to the results in Table 1, we note first that for Beijing, all explanatory variables (A, S, D, G, AI) are very significant, and all have the hypothesized signs *except* for green space, *G*. Further investigation showed that in Beijing, green space is strongly negatively correlated with activity accessibility (-0.53). [By way of contrast, this correlation is practically zero (-0.03) in Qingdao.] So even here the tradeoff between location accessibility and residential quality is visible. In Beijing, relatively little space is devoted to parks in those neighborhoods close to (or containing) urban activity centers.

As for the important interaction effects, we see that the key interaction effect $(\delta \cdot AI)$ for *activity accessibility* is significantly negative (as hypothesized above). So even though accessibility to the single activity center in Qingdao is a positively significant predictor of housing prices, it has far less impact than in Beijing. With respect to residential quality variables, *community density* has a significantly stronger negative effect in Qingdao, and the presence of *green space* has a significantly stronger positive effect. With respect to housing quality itself, *size* has a somewhat stronger (weakly significant) positive effect in Qingdao. Only the *age* of housing has a similar effect in both cities. So on the whole it can be concluded that relative to these residential quality factors, accessibility to urban activity centers has a far more dominant price effect in Beijing than Qingdao.

Turning finally to *education accessibility* (EI), the regression results for this case are reported in Table 2 below. Here we see that these results are generally quite similar to those for activity accessibility. The only real difference is with respect to green space, *G*, where the effect is again negative for Beijing, but no longer significant. The key difference here seems to be that there is more green space around key educational institutions in Beijing than around urban activity centers. For example, there is substantial green space in and around neighbor 5 in Figure 2. Moreover, while neighborhood 5 is both an activity center (Figure 5a) and an education center (Figure 5b) for Beijing, it is far more important as an education center and contains many of the very best high schools in Beijing (as indicated by the darker shade of this area in Figure 5b).

Table 2

So in summary, we see that in both these regressions, the relative influence on housing prices of locational accessibility versus residential quality is far more dominant in Beijing than Qingdao.

5. Theoretical Model

In this final section we attempt to illuminate some of these tradeoff effects from a more theoretical perspective. To do so, we develop standard bid-price models[23] for two linear cities, a "Big City" and a "Small City", that differ in terms of the number of urban activity centers that residents frequent each day. The presence of many centers allows more activity variety, and is assumed to add to the attractiveness of city life. In the present model, the Small City is assumed to be monocentric (like Qingdao) with a single center at location, x_0, as shown in Figure 7b below.

Figure 7

The Big City is assumed (for simplicity) to have only two centers, shown at locations x_1 and x_2 in Figure 7(a). Total travel costs to these centers are smaller for locations between x_1 and x_2, so that this *center city* region, $[x_1, x_2]$, plays a role roughly similar to the high-accessibility area around the five activity centers in Beijing (Figure 3a). Movement away

[23] While prices in these models are formally "bid-rents" for land owned by an absentee landlord [as for example in Fujita (1989)], we choose to interpret these loosely "bid-prices" for housing.

from this center city in either direction increases the travel cost to *both* centers. It is these travel-cost relations that constitute the major spatial differences between the two cities. In this setting, our objective is to compare typical "equilibrium" bid prices for representative *households* living at locations such as x in Figures 7a and 7b.

5.1 The Utility Maximization Problem for Households

To do so, we start by assuming that household preferences in each city, $c \in$ {Big City, Small City}, are representable by a (log linear) *utility function*,

$$(7) \qquad u_c(z,s) = a \ln z + (1-a)\ln s + \theta_c$$

where s is the *size* of the household's residence (in square feet of floor space),[24] and z is a *composite good* (that can be taken to include other "housing quality" attributes in this model). The "elasticity" parameter, a, is assumed to satisfy $0 < a < 1$. Finally, $\theta_c \geq 0$ is taken to represent the level of *activity variety* in each city, c, where for simplicity we assume that $\theta_c = 0$ for the Small City and $\theta_c > 0$ for the Big City.

To define the relevant budget constraint for a household locating at x in city *c*, we assume that household expenditures involves daily travel costs to activity centers plus the purchase costs of commodity bundles (z,s). Following standard conventions, we treat *z* as a "numeraire" good with unit price, and let $p_c(x)$ denote the prevailing *housing price* (per square foot) at location x in city *c*.[25] To quantify commuting costs, we assume that coordinate positions are the same for both cities (as in Figure 7), and that locations x_1 and x_2 are symmetric about x_0, so that $x_0 = \frac{1}{2}(x_1 + x_2)$. For the Big City, if a household chooses to live at x, then the relevant commuting distances to activity centers are $|x_1 - x|$ and $|x_2 - x|$, respectively. At the same location in the Small City, the corresponding commuting distance to the single activity center is $|x_0 - x| = |\frac{1}{2}(x_1 + x_2) - x|$.

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[24] While the term "floor space" facilitates comparison with the empirical results above, *s* corresponds formally to "lot size" so that population densities can in principle be calculated with respect to *s* (as in footnote 27 below).

[25] Again, while $p_c(x)$ usually denotes "rent per unit of land" at *x* (Fujita, 1989), we treat this variable as "price per square foot" of housing at *x*.

Hence if the prevailing travel cost per unit of distance is denoted by t, then the relevant daily (round trip) *travel costs* for households living at location x in city c are given by:[26]

$$(8) \qquad T_c(x) = \begin{cases} 2t(|x_1 - x| + |x_2 - x|) & , \ c = \text{Big City} \\ 2t|x_0 - x| & , \ c = \text{Small City} \end{cases}$$

If the prevailing wages in city c are denoted by w_c, then the relevant *budget constraint* for a household at x in city c is given by:[27]

$$(9) \qquad w_c \geq T_c(x) + p_c(x)s + z$$

In these terms, households at each location x in city c are assumed to choose bundles (z,s) that maximize their utility (7) subject to budget constraint (9).

5.2 Bid-Price Comparisons between Cities

In equilibrium, these maximum utilities for each (identical) household must be the same at all city locations occupied. Such equilibria are identified by first determining for each possible constant utility level, u, the *bid prices*, $p_c(x;u)$, at which this utility level is exactly achieved by households at all occupied locations. Then, for a given *total population*, P, of households to be located, and a given minimum *reservation price*, p_r, for alternative land uses (typically agriculture), one can in principle identify specific equilibrium configurations in both cities [as for example in Fujita (1989)]. But since our present objective is not to analyze specific equilibrium configurations, we simply determine typical shapes for such constant-utility bid-price functions and compare them between cities. More formally, if for any given constant-utility value, u, we let the relevant *bid-price function* for city c be denoted by

[26] Note that a more realistic version of this model should include *travel time* as well, and should also allow household utility to depend on *leisure time*. But our purpose here is illustrating the basic tradeoff relations between these two cities in the simplest way.

[27] Note that commuting costs to work are implicitly included in these daily travel costs, so that for households in the Big City we do not distinguish between employment locations and other activity locations.

(10) $\quad p_c(x;u) \equiv p_c[x;a,\theta_c,T_c(x),w_c,u]$

then the exact forms of these functions can be derived, as is done in the Appendix. For our present purposes, it is enough to evaluate these functions for selected parameter values and compare them graphically. In particular, we set the relevant location values in Figure 7 to be $x_1 = -1,\ x_0 = 0,\ x_2 = 1$, and set the unit travel cost in (8) to be $t = 0.05$. Next we parameterize the utility function in (7) using $a = 0.8$ and $\theta_c = .005$ for $c =$ Big City (recalling that $\theta_c = 0$ for $c =$ Small City). Finally, given that wages tend to be somewhat higher in large cities, we set $w_c = 10$ for $c =$ Big City and $w_c = 9$ for $c =$ Small City. For these parameter choices, the bid-price functions for $u = 2$ are shown in Figure 8 below.

Figure 8

Note that these functions are actually defined over much larger domains, restricted only by budget constraints. Hence we have simply chosen a reservation price ($p_r = 0.17$) that yields reasonable "city boundaries" for the Big City and Small City.[28] The key properties of this figure for our purposes are the relative *magnitudes* and *shapes* of these functions, which are determined by the model structure above. Notice in particular that the maximum housing prices in the Big City are constant in the center city, $[-1, 1]\ (=[x_1, x_2])$. This arises from the constancy of travel costs, T_c, for c = Big City in (8) within this central region. While this constancy property is of course more extreme than in central Beijing, it is nonetheless consistent with the relatively low price variation observed in the high accessibility area around the major activity centers. Notice also that within this central region of the Big City, the total commuting cost to the two activity centers $(T_c \equiv 2)$ is seen to be approximately equal to the average commuting cost to the center of the Small City. This gives some idea of the relative *scales* of these two cities. Moreover, as shown in the Appendix, housing sizes are smallest in this center city region, and population density is highest. So, as in our regression results, location accessibility dominates residential quality considerations in this region.

[28] This model can in principle be "closed" by choosing the appropriate total population, *P*, to be the sum of the integrals of the lot-size densities in each city generated by these parameter values.

Notice also that outside this center city, housing prices in the Big City fall more sharply than those in the Small City. This again reflects the fact that movement away from the center city increases the travel costs to *both* activity centers. Notice finally that since commuting costs are relatively less important in the Small City, households achieve the same level of utility $(u = 2)$ by devoting more income to housing quality and house size. Thus, while this simple two-city model is highly stylized, it nonetheless serves to illustrate some of the location-dominant properties of the Beijing housing market relative to smaller cities like Qingdao.

6. Concluding Remarks and Directions for Further Research

In this paper we have analyzed price tradeoffs between residential quality and location factors in the housing markets of Beijing and Qingdao. The main purpose of this comparison has been to highlight the dominance of location factors in Beijing relative to most other cities. Our main hypothesis has been that this dominance results from the unusually large size of central Beijing, where travel between urban activity centers is comparable to typical suburban-urban commuting in other cities.

This raises the question of whether Beijing is unique in this regard, or whether there are other examples of such location-dominant housing markets. In China, our initial investigations suggest that Shanghai may be another possibility. Outside China, one possible candidate is central Moscow, which is even bigger in size than central Beijing. This is one direction to be explored in subsequent work.

Another avenue of exploration arises from our regression results themselves. In particular, these results show that in Beijing and Qingdao, more than half the total explained variation was accounted for by neighborhood fixed-effects. As was pointed out, this raises a next set of questions, namely how to account for these unobserved neighborhood effects. One approach would be to analyze the spatial pattern of these neighborhood coefficients (much like spatial residual analysis) to determine whether this pattern suggests more meaningful explanatory variables that might capture some of this variation. Such possibilities will be explored in subsequent work.

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Appendix: Derivation of Bid-Price Functions

To derive the relevant bid-price functions, we start by recalling the *utility functions*,

(A.1) $$u_c(z,s) = a\ln z + (1-a)\ln s + \theta_c$$

for households at locations *x* in each city, $c \in$ {Big City, Small City}, together with corresponding (equality) *budget constraints*,

(A.2) $$w_c = T_c(x) + p_c(x)s + z$$

where travel costs, $T_c(x)$, are defined for each city, *c*, by

(A.3) $$T_c(x) = \begin{cases} 2t(|x_1 - x| + |x_2 - x|) & , \ c = \text{Big City} \\ 2t|x_0 - x| & , \ c = \text{Small City} \end{cases}$$

Then for any given level of utility, *u*, the relevant *bid-price function*, $p_c(x;u)$, for each city, *c*, is obtained by solving (A.2) for $p_c(x)$ as

(A.4) $$p_c(x) = \frac{w_c - T_c(x) - z}{s}$$

and finding the commodity bundle, (z,s), that maximizes this price subject to the condition that utility, *u*, be exactly achieved, i.e.

(A.5) $$p_c(x;u) = \max_{(z,s)}\left\{\frac{w_c - T_c(x) - z}{s} : u = a\ln z + (1-a)\ln s + \theta_c\right\}$$

This can be equivalently formulated as a Lagrangian maximization problem:

(A.6) $$\max_{(z,s,\lambda)} L(z,s,\lambda) = \frac{w_c - T_c(x) - z}{s} + \lambda\left[a\ln z + (1-a)\ln s + \theta_c - u\right]$$

The first-order conditions for a maximum yield the follows results:

(A.7) $$0 = \frac{\partial L}{\partial z} = -\frac{1}{s} + \frac{\lambda a}{z} \Rightarrow z = s\lambda a$$

(A.8) $$0 = \frac{\partial L}{\partial s} = -\frac{w_c - T_c(x) - z}{s^2} + \frac{\lambda(1-a)}{s}$$

$$\Rightarrow s\lambda(1-a) = w_c - T_c(x) - z$$

$$\Rightarrow s = \frac{w_c - T_c(x) - z}{\lambda(1-a)}$$

(A.9) $$0 = \frac{\partial L}{\partial \lambda} \Rightarrow u = a\ln z + (1-a)\ln s + \theta_c$$

By (A.7) and (A.8) we see that

(A.10) $$\frac{z}{\lambda a} = s = \frac{w_c - T_c(x) - z}{\lambda(1-a)} \Rightarrow z = \frac{a}{1-a}[w_c - T_c(x) - z]$$

so that by exponentiating (A.9) and using (A.10) we obtain

(A.11) $e^{u} = z^{a}s^{1-a}e^{\theta_c} \Rightarrow e^{u-\theta_c} = \left(\frac{a}{1-a}\right)^{a}\left[w_c - T_c(x) - z\right]^{a} s^{1-a}$

$$\Rightarrow s^{a-1} = e^{\theta_c - u} \left(\frac{a}{1-a}\right)^{a}\left[w_c - T_c(x) - z\right]^{a}$$

By solving for *s*, and setting $A(a) = [(1-a)/a]^{a/(a-1)}$, we then obtain the *bid-size function*,

(A.11) $s_c(x,u) = A(a)^{-1}e^{(u-\theta_c)/(1-a)} \left[w_c - T_c(x) - z\right]^{-a/(1-a)}$

for housing choices at each utility level, *u*. Note in particular (from the negativity of the last exponent) that this bid-size function is always *increasing* in travel costs, $T_c(x)$, so that equilibrium house sizes are smallest in the center of the city where travel costs are lowest. Thus we see that there is a natural *tradeoff* between house size and accessibility.

Finally, by substituting this into (A.4) we obtain the corresponding *bid-price function*,

(A.12) $p_c(x;u) = \frac{w_c - T_c(x) - z}{s_c(x;u)} = \frac{w_c - T_c(x) - z}{A(a)^{-1}e^{(u-\theta_c)/(1-a)} \left[w_c - T_c(x) - z\right]^{-a/(1-a)}}$

$$= A(a)e^{(\theta_c - u)/(1-a)}\left[w_c - T_c(x) - z\right]^{1/(1-a)}$$

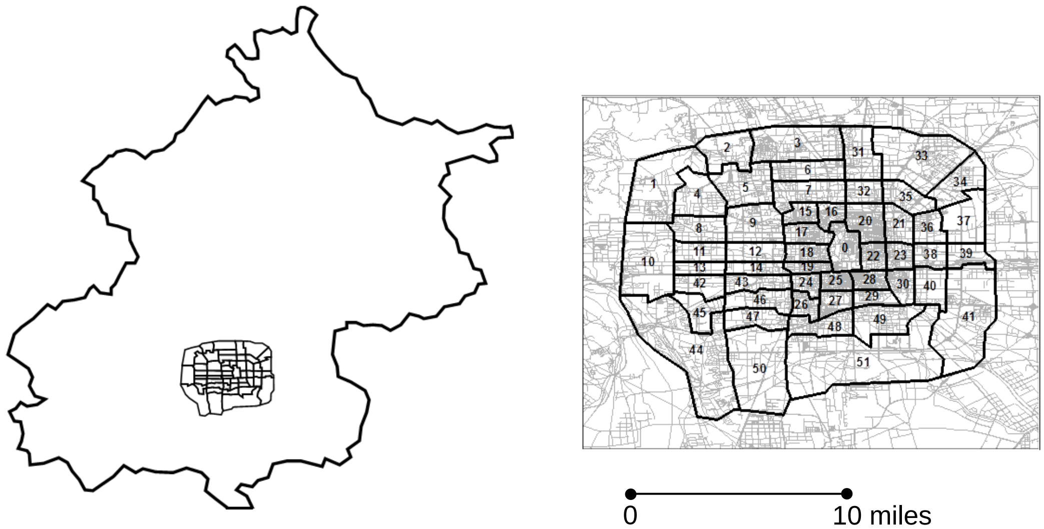
In a manner paralleling to the bid-size function above, these bid-prices are seen to be *decreasing* in travel costs, $T_c(x)$, so that equilibrium housing prices are always highest in the center of the city.

Term	Parameter	Coefficient	t Ratio	p Value
α_0	-	16964.44	31.70	<0.0001*
β_0	A	-98.70	-10.42	<0.0001*
γ_0	S	3158.10	21.77	<0.0001*
η_0	D	-702.00	-5.09	<0.0001*
θ_0	G	-2.40	-4.30	<0.0001*
μ_0	AI	3459.42	31.30	<0.0001*
α_1	δ	-11449.28	-15.06	<0.0001*
β_1	$\delta \cdot A$	-2.96	-0.08	0.9331
γ_1	$\delta \cdot S$	629.97	1.75	0.0799
η_1	$\delta \cdot D$	-1312.57	-3.52	0.0004*
θ_1	$\delta \cdot G$	4.58	6.82	<0.0001*
μ_1	$\delta \cdot AI$	-458.03	-2.55	0.0107*

Table 1. Regression Results for the Activity-Accessibility Case

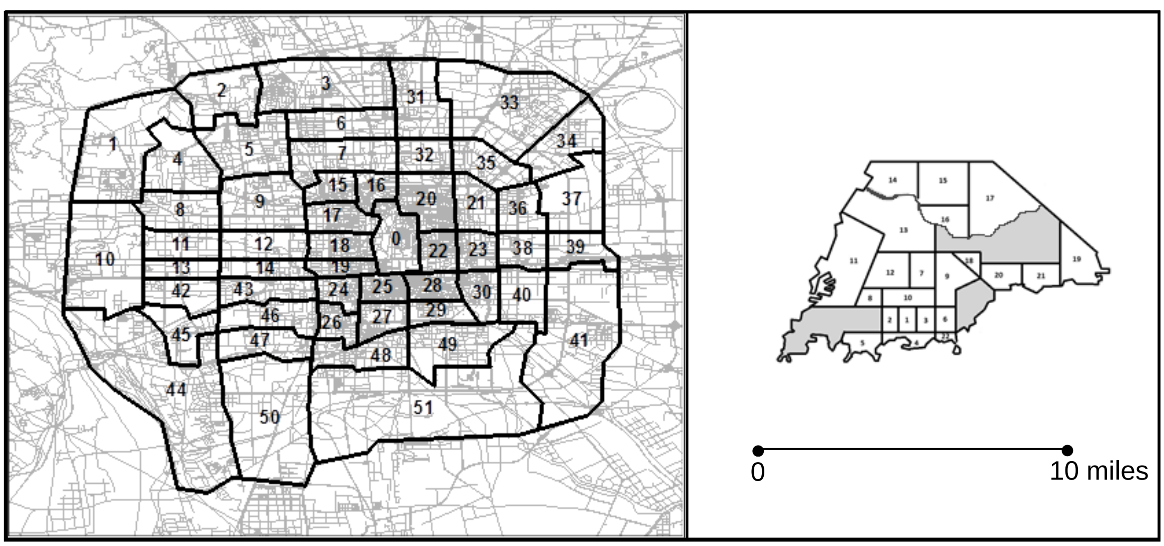
Term	Parameter	Coefficient	t Ratio	p Value
α_0	-	16822.79	42.14	<0.0001*
β_0	A	-98.98	-10.86	<0.0001*
γ_0	S	3157.19	21.72	<0.0001*
η_0	D	-706.22	-5.12	<0.0001*
θ_0	G	-0.53	-1.05	0.2917
μ_0	EI	3554.56	35.92	<0.0001*
α_1	δ	-7356.14	-7.38	<0.0001*
β_1	$\delta \cdot A$	-14.62	-0.40	0.6865
γ_1	$\delta \cdot S$	662.49	1.84	0.0653
η_1	$\delta \cdot D$	-1293.04	-3.46	0.0006*
θ_1	$\delta \cdot G$	35.36	15.55	<0.0001*
μ_1	$\delta \cdot EI$	-4472.63	-9.71	<0.0001*

Table 2. Regression Results for the Education-Accessibility Case



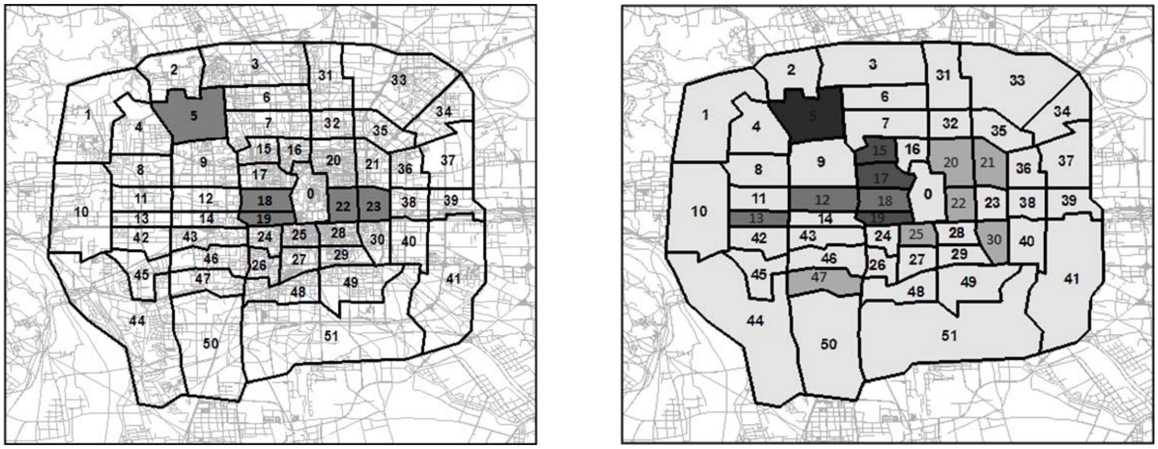
(a) The Municipal Boundary of Beijing (b) The area of Central Beijing

Figure 1. Map of Beijing and Central Beijing



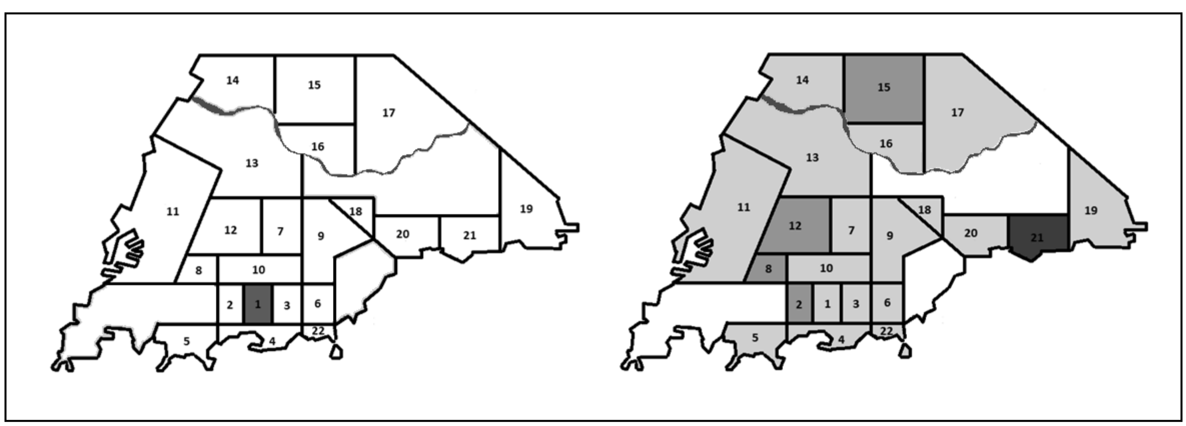
(a) The 51 Neighborhoods of Beijing (b) The 22 Neighborhoods of Qingdao

Figure 2. Comparison of Central Beijing and Qingdao



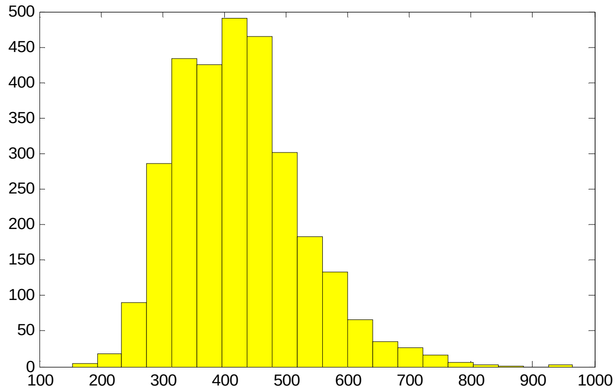
(a) Activity Centers in Central Beijing (b) Education Centers in Central Beijing

Figure 3. Activity and Education Centers in Central Beijing

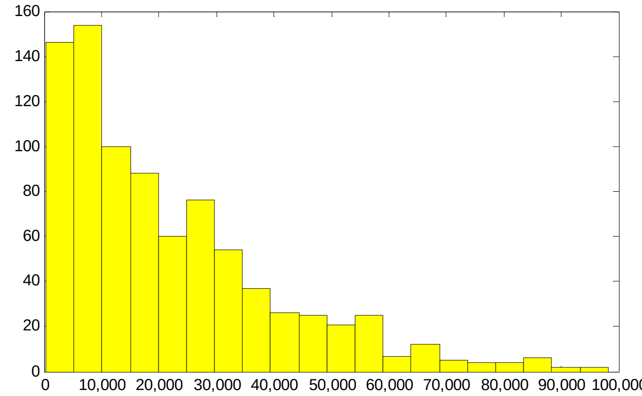


(a) Activity Centers in Qingdao (b) Education Centers in Qingdao

Figure 4. Activity and Education Centers in Qingdao

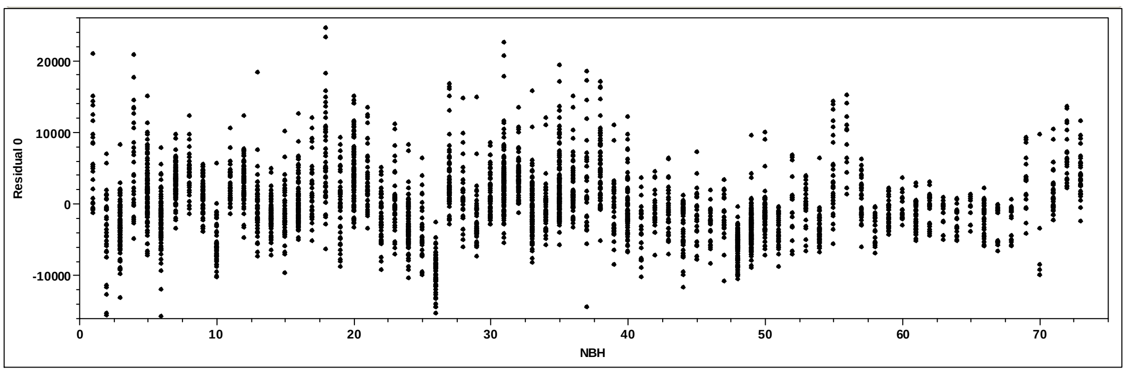


(a) Beijing Housing Prices

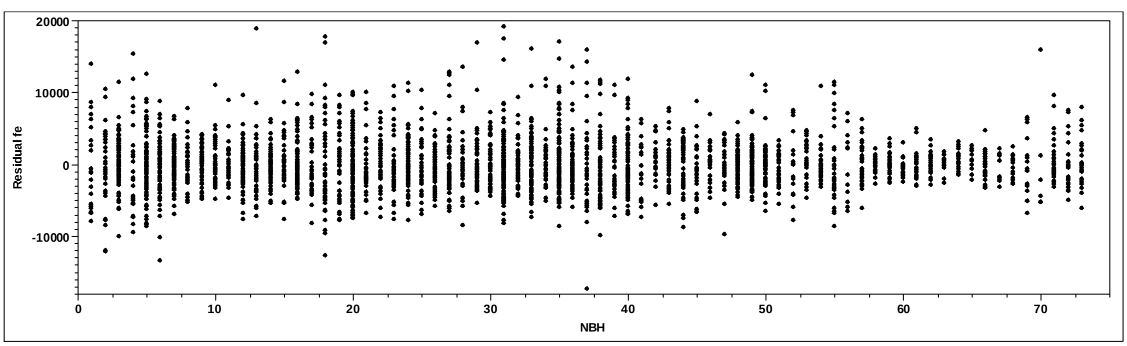


(b) Manhattan Housing Prices

Figure 5. Comparison of Beijing and Manhattan Housing Prices



(a) Initial Residual Plot by Neighborhoods in Beijing and Qingdao



(b) Final Residual Plot in the Presence of Neighborhood Fixed Effects

Figure 6. Comparison of Initial and Final Plots of Neighborhood Effects

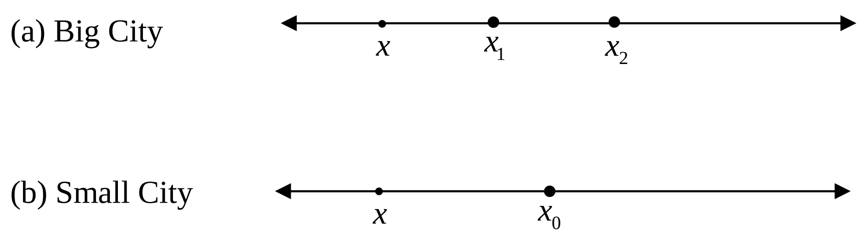


Figure 7. Comparison of Big and Small Cities

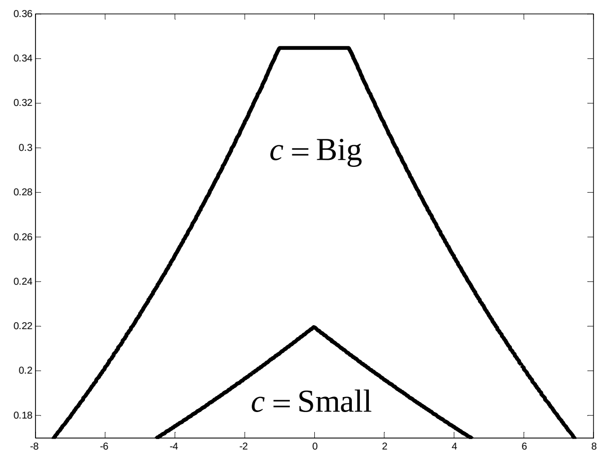


Figure 8. Comparison of Bid Price Functions, $p_c(x)$