

Siebert, Ralph; Zhou, Xiaoyan

Working Paper

The Measurement of Spatial Competition: Evidence from the Real Estate Market

CESifo Working Paper, No. 11380

Provided in Cooperation with:

Ifo Institute – Leibniz Institute for Economic Research at the University of Munich

Suggested Citation: Siebert, Ralph; Zhou, Xiaoyan (2024) : The Measurement of Spatial Competition: Evidence from the Real Estate Market, CESifo Working Paper, No. 11380, CESifo GmbH, Munich

This Version is available at:

<https://hdl.handle.net/10419/305622>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

The Measurement of Spatial Competition: Evidence from the Real Estate Market

Ralph Siebert, Xiaoyan Zhou

Impressum:

CESifo Working Papers

ISSN 2364-1428 (electronic version)

Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH

The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute

Poschingerstr. 5, 81679 Munich, Germany

Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de

Editor: Clemens Fuest

<https://www.cesifo.org/en/wp>

An electronic version of the paper may be downloaded

- from the SSRN website: www.SSRN.com
- from the RePEc website: www.RePEc.org
- from the CESifo website: <https://www.cesifo.org/en/wp>

The Measurement of Spatial Competition: Evidence from the Real Estate Market

Abstract

This study provides a test for measurement of spatial competition in residential real estate markets. Several alternative spatial competition measures are tested. We employ a Bertrand oligopoly model with differentiated products and adopt a Spatial Autoregressive model using a two stage least squares estimator. Our results show that commonly used count-based measures using the number of competitors in specific geographic radii are outperformed by price-based measures using prices of nearest competing neighbors. The main reason is that the latter measure accounts for heterogeneous neighborhood density of competitors. The measure captures the decaying pattern of spatial price competition over distance. The measure also stands out in capturing heterogeneous spatial price competition effects. We find that spatial price competition is more intense among high-value homes within the five nearest competing houses.

JEL-Codes: D400, R100, R300.

Keywords: price effects, real estate market, spatial competition, spatial econometrics, spatial markets.

Ralph Siebert
Department of Economics
Purdue University
403 Mitch Daniels Blvd.
USA – West Lafayette, IN 47907
rsiebert@purdue.edu

Xiaoyan Zhou
Department of Economics
Purdue University
403 Mitch Daniels Blvd.
USA – West Lafayette, IN 47907
zhou1057@purdue.edu

June 6, 2024

We would like to thank Yong Bao for their helpful feedback and comments.

1 Introduction

Competition is a powerful concept that is useful for determining prices and evaluating market outcomes. An established view on competition is that alternative goods offered on the market provide substitution possibilities for consumers, and this imposes downward pressure on prices (see [Lancaster \(1966\)](#), [Baumol \(1967\)](#), [Gorman \(1980\)](#), and [Boone \(2008b\)](#)).¹ A good understanding of competition is crucial for evaluating price effects of economic decisions.

This study concentrates on the measurement of competition in spatial markets where sellers compete with other sellers in the same local markets. Local markets are a widespread phenomenon that include accommodations, gasoline stations, hospitals, restaurants, and real estates (see [Pinkse et al. \(2002\)](#) and [Chen et al. \(2011\)](#)). We focus on residential real estate markets that are characterized by home sellers competing with other home sellers in the same local market (see [Glaeser et al. \(2005\)](#) and [Turnbull and Dombrow \(2006\)](#)). In residential real estate markets, there exists some uncertainty on the spatial dimension, the strength, and the decay of spatial competition. The aim of our study is to provide further insights into the measurement of spatial competition in the real estate market. We consider several alternative spatial competition measures such as count-based and price-based measures of sellers within specific geographic distances (radii) or specified as nearest competing neighbors. We find that commonly used count-based measures using the number of competitors in specific geographic radii are outperformed by price-based measures using prices of nearest competing neighbors.

Several theoretical studies focused on competition in spatial markets. One major finding is that firms only compete with their close neighbors (see [Hotelling \(1929\)](#), [Gabszewicz and Thisse \(1979\)](#), and [Salop \(1979\)](#)). The reason is that substitution opportunities for

¹Standard theoretical competition models, such as Cournot and Bertrand competition models, support this view.

consumers are limited in geographic space since geographic location of a good is an inherent feature. Since sellers compete for buyers that focus their search on substitute products within a local area, competition in spatial markets is limited by competing peers operating in the same geographic market (in close geographic proximity).

One challenging aspect of empirically evaluating spatial competition effects on prices is that competition itself is unobserved and needs to be proxied. One common approach for estimating spatial competition effects is to evaluate the influence that nearby competitors (usually formulated as counters) within specified geographic distances have on prices. Empirical studies measure spatial competition by the number of competitors within geographic distance to a seller such as a circle with an x -miles radius. This relates to the idea that competition generally intensifies with increase in the number of sellers (see [Arrow \(1962\)](#)). In spatial markets, close-by competitors have stronger impacts on nearby buyers than further distant competitors. Therefore, the spatial competition usually decays with geographic distance to a competitor. We refer to this as a *count-based competition measure based on geographic proximity*. While it seems intuitive that homes engage in price competition with their nearby competitors, using the geographic distance measure (based on radii) entails some caveats for real estate markets and might not be an appropriate concept to apply in this context. First, it only uses the number of competing sellers within regions but ignores any price information of competitors. Second, the number of competitors within a specific radius can vary drastically across neighborhoods/geographic locations. While some neighborhoods are denser and entail more competitors within a specific radius, other neighborhoods are more sparsely distributed. Hence, the use of geographic distances (such as radii of x miles) incorporates differential number of competitors and differential competitive strength across regions.

One distinguished feature of the real estate market is that spatial dependence is originated from adjacency effects. This adjacency effects are manifested by the “comparable-

sales approach”, that is, sellers and buyers assess own property valuations and list prices using neighborhood homes as references see also [Can \(1990\)](#)). A certain number of nearest comparable homes (often 3-5) serve as a reference basis for pricing. This approach is widely used by realtors, assessors, appraisers, sellers, and buyers when assessing house values. The nearest neighbor concept is also supported by the fact that most homes’ geographic information is made public on the internet. Therefore, agents are well informed about local home listings, which enforces competition. The nearest neighbor concept has the advantage (compared with geographic proximity or distance measures) that it adjusts to starkly varying property lot sizes across neighborhoods and market segments. For example, low-value homes usually have smaller lots than high-value homes. Therefore, neighborhoods characterized by low-value homes usually face more homes within a pre-specified geographic distance (i.e., one mile) than high-value homes. The geographic distance measure does not capture this lot size variation. Consequently, estimating an average competition effect based on geographic proximities would overestimate (underestimate) competitive price effects in neighborhoods with low-value (high-value) homes. Therefore, geographic distance measures might be prone to biases when neighborhoods or market segments strongly vary in lot sizes or neighborhood densities of competing peers.

In general, the reference pricing or nearest neighbor method supports the view that home sellers compete in prices and strategically interact depending on geographic proximity (see [Brueckner \(2003\)](#) and [Iwata et al. \(2019\)](#)). This suggests that prices of closest competing neighbors could be an appropriate competition measure. Hence, the theoretical foundation for strategic price interactions between home sellers is grounded by localized demand. A price reduction of a nearby competing home seller increases the likelihood that a potential buyer will purchase this house. In order to regain this customer a competing seller needs to respond to the price reduction and reduce its own price accordingly. Sellers compete for local buyers while considering prices of nearby competitors.

Using strategic price reactions as measurement for competition is not new and goes back to measurements of conduct and conjectural variations in which the slopes of price reaction functions are measured (see [Bowley \(1924\)](#), [Bresnahan \(1981\)](#), [Genesove and Mullin \(1998\)](#), and [Boone \(2008b\)](#), among others).² If products are substitutes, price reaction functions have a positive slope, that is, a price reduction by a competitor will be responded by an own price reduction. Hence, sellers' price responsiveness (as measured by the slopes of firms' best-reply functions) is used as competition measure, where a more responsive price reaction (a steeper slope of these reaction functions) represents more intense competition.³ These price reaction functions form the basis of the price-based competition measure, which is considered as an alternative to the count-based measures described earlier.⁴

Our study focuses on the housing market, which is a natural setting for assessing competition and price effects in spatial markets. A house represents a differentiated good with well-defined product attributes (house size, value, etc.), and geographic location is an intrinsic characteristic. These well-defined housing attributes enable us to identify competing peers and to establish proximity measures to evaluate spatial competition and prices.⁵ We empirically test for spatial competition and employ a Bertrand oligopoly model with differentiated products that forms the theoretical basis, see also [Pinkse et al. \(2002\)](#). We experiment with alternative spatial measures for evaluating the strength of spatial competition, including count-based and price-based methods as well as geographic radii and nearest neighbor concepts. Based on home transaction information in Orange County

²The strategic price reactions as a measurement for spatial competition has been used in spatial markets (see [Pinkse et al. \(2002\)](#) and [Pinkse and Slade \(2010\)](#)).

³Note that this measure is also related to own and cross-price elasticities of demand, the established measures of substitutability sellers.

⁴An alternative way to measure competition is the use of price cost margins. However, as [Boone \(2008a\)](#) remarks, theoretical studies show inconsistencies where more intense competition can lead to higher price cost margins rather than lower price cost margins, see [Rosenthal \(1980\)](#), [Stiglitz \(1989\)](#), [Bulow and Klemperer \(2002\)](#), and [Amir \(2002\)](#).

⁵We define "competing peers" as a current set of housing units that are listed on the market at the same time. Note that we do not evaluate price dynamics caused by changing sets and prices of competitors over time. While this type of price dynamics is an interesting research focus, it is beyond the scope of this paper.

(California), we estimate a spatial autoregressive model using a two stage least squares estimation method.

We find that price-based competition measures (based on price reaction functions) using the closest neighbor approach performs best for competition measurement in spatial markets. The main reason is that it uses price information and accounts for heterogeneous neighborhood and competition density of local markets. This finding properly reflects inherent institutional characteristics of the real estate market, such as the comparable sales approach being limited to a few nearest neighbors. Second, the measure shows intensive competitive effects that are strongly declining in the number of closet competitors. For example, we find that price competition effects of the nearest five neighbors is about 10 times larger than the ones that relate to further distant neighbors. The strong spatial decay accurately reflects the nature and understanding of spatial price competition among houses, since substitution opportunities diminish with geographic distance. Finally, the measure captures differential price competition intensities across home values. That is, the measure shows more (less) intense spatial price competition among high (low) value homes. This especially applies to nearby competing homes. Furthermore, the decay of price competition is slower among high-value homes. For example, while for high-value houses competitive price effects reach out toward the 20 nearest competitors, for low-value houses these competition effects affect only the 5 nearest neighboring homes.

2 Related Literature

A common approach in real estate economics is the estimation of price functions, also referred to as hedonic price functions (see [Rosen \(1974\)](#)). A hedonic price function establishes a functional relationship between the house price and various associated house attributes. The estimated coefficients reflect consumers' willingness to pay for housing attributes (also

called hedonic prices, or implicit (marginal) prices of house attributes).⁶ Can (1992) and Can and Megbolugbe (1997) remark that not accounting for spatial dependence can result in omitted variable bias, as errors are spatially dependent.

Studies address this concern by adding spatial dependence in house prices to their models (usually in the form of locational spillovers) to account for the influence of past transaction prices of neighboring homes on current home prices within the same neighborhood (see Can (1990), Can (1992), Can and Megbolugbe (1997), and Glaeser et al. (2005)). Scholars often adopt a spatial econometric approach that measures locational spillovers based on weighted average prices of prior sales located within certain distances (see Can (1992) and Can and Megbolugbe (1997)). For example, Can (1992) finds that a \$1,000 increase in the weighted average of adjacent properties' sale prices increases the sale price of a home by around \$400. In contrast to these studies, we are rather interested in the measurement of spatial competition effects—that is, the influence of other contemporaneously listed prices of “competing peers” on the price of a home.

Several empirical studies focus on the evaluation of spatial competition effects while incorporating information on contemporaneous prices of competing peers into these spatial econometric models (see Pinkse and Slade (2010) and Pinkse et al. (2006)). The rationale of including this type of measures stems from standard theoretical models of imperfect price competition, such as Bertrand competition, that describe price-setting behavior as strategic responses to competing peers' contemporaneous prices, i.e., the price reaction functions (see Dixit (1979) as well as Hotelling (1929) and Salop (1979) for specialized locational models). This measurement type gained popularity in spatial econometrics and is applied in modified forms serving different purposes.⁷ We adjust the measures such that they suit the principle of spatial competition while defining competing peers based on geographic proximity and

⁶The hedonic price function exhibits a market-clearing function that results from the interaction between buyers' bid functions and sellers' supply functions (see Rosen (1974), pp. 50-51).

⁷These studies usually focus on the measurement of price spillovers and evaluate whether contemporaneous home sale prices are influenced by the prices of nearby sold houses.

nearest neighbors; we refer to them as *price-based competition measures*.

The implementation of *price-based competition measures* into an econometric framework exposes a challenge since house prices are jointly determined and thus endogenous, also referred to as “spatial endogeneity” (see e.g., [Anselin \(1988\)](#)). The use of standard econometric approaches, such as OLS, results in potentially biased estimates. One alternative estimation method is the traditional instrumental variable approach where researchers instrument for the potentially endogenous regressors (contemporaneous prices of competing peers). Appropriate instruments, however, are difficult to find—especially in spatial models where geographic markets and neighborhoods differ strongly. In this case, the popular Hausman-type of instruments (that use prices in neighboring markets as instruments) are less appropriate since home prices can be correlated with home prices in adjacent neighborhoods.

To resolve this “spatial endogeneity” problem, we adopt a spatial econometric framework that controls for the spatial correlation among house prices (see [Anselin \(1988\)](#)). More specifically, we use a high-order spatial autoregressive model that explicitly addresses spatial dependence of prices by applying a transformation process (see also [Can \(1992\)](#) and [Can and Megbolugbe \(1997\)](#)).⁸ Moreover, the SAR model allows us to construct alternative valid instrumental variables that are based on spatial weight matrices that characterize the strength of connectedness between pairs, and based on exogenous regressors (see e.g., [Kelejian and Prucha \(1998\)](#) and [Kelejian and Prucha \(2001\)](#)). It is important to note that this choice of instrumental variables is feasible only in spatial econometric models and does not apply to non-spatial approaches. The instrumental variable approach of estimating a SAR model is introduced in [Anselin \(1988\)](#). In addition, [Kelejian and Prucha \(1998\)](#) and [Kelejian and Prucha \(2010\)](#) illustrate the generalized spatial two-stage least squares approach to estimating a spatial autoregressive model with autoregressive disturbance,

⁸Further details are provided later.

which is further extended by [Badinger and Egger \(2011\)](#) to accommodate multiple weight matrices in the setting of a high-order spatial model.

3 Data Description and Competition Measures

We established a comprehensive database on the residential real estate market sourced from the multiple listing service database and the Freddie Mac SBL database. The database holds information on 16,074 residential houses in Orange County, California, that were sold in 2019. It contains house-specific information on prices, list and sale dates, geographic locations, and further house attributes, including the size, age, number of bedrooms, number of bathrooms, lot size, and so on.⁹

[Table 1](#) shows summary statistics of our count-based competition measures. Real house prices amount to \$908,517 on average, with a large standard deviation of \$448,847.¹⁰

[Figure 1](#) presents a map of average home prices across census tracts. The figure shows large regional differences in average prices. For example, neighborhoods located close to the seashore or in the mountainous area tend to be more expensive on average. One would suspect that housing units are significantly larger and more sparsely distributed in more expensive neighborhoods compared to those located in cheaper neighborhoods.

[Figure 2](#) shows the average number of competing houses listed at the same time for each census tract. The figure illustrates large listing variations across neighborhoods. The average number of competitors seems to be relatively larger in the census tracts close to the sea, which overlap with higher-priced neighborhoods (as shown in [Figure 1](#)).

We now turn to the definitions of the *count-based competition measures*, which use the

⁹Note that since we intend to measure the degree of competition among houses, we use last listed prices of other houses (listed at the same time). The last list prices represent the most appropriate measure since final transaction prices of other contemporaneously listed houses would be unknown at the time of listing. Throughout the remainder of the study, we denote final list prices simply as prices.

¹⁰We adjust the nominal house prices using the monthly consumer price index data from the Bureau of Labor Statistics, and we measure all the house prices used for estimation in January 2021 dollars.

number of competitors (competing peers) for the measurement of competitive price effects.

We consider the following three *count-based competition measures*:

(1) *Count-based competition measure using geographic proximity*: This measure counts the number of nearby competitors (competing peers) that operate within specified geographic distances from the point of interest (see [Heggestad and Rhoades \(1978\)](#), [Dranove et al. \(1992\)](#), [Pinkse et al. \(2002\)](#), [Slade \(2005\)](#), [Davis \(2006\)](#), [Gaynor et al. \(2015\)](#), and [Cooper et al. \(2019\)](#)). In alignment with previous studies, we consider the number of houses listed at the same time (“competing peers”) in specific distance rings (< 3 miles and 3-5 miles) to evaluate their effects on the price of a house (see e.g., [Turnbull and Dombrow \(2006\)](#)). The justification of using this concept for describing the nature of spatial price competition usually originates from two arguments: (1) A higher count of competing peers within a specific radius provides more substitution possibilities to consumers and downward pressure on prices; and (2) Competing peers located further away have lower competitive effects on prices due to regional preferences and buyers’ diminished substitution opportunities. Diminished substitution possibilities over distance reduce competitive price effects. [Table 1](#) shows that, on average, 150 (211) houses compete in a 0-3 (3-5) miles radius. The large standard deviation of 97 (135) and maximum of 898 (1,315) indicate that there is a large degree of heterogeneity of competitors within 0-3 (3-5) miles—that is, the density of competitors varies strongly across regions. Overall, the data exhibit a large variation in the number of competitors existing within 3 miles and between 3 and 5 miles away from housing units.

(2) *Count-based competition measure using characteristics proximity*: This measure considers the similarity in other product attributes (beyond geographic distance). We consider the number of similarly sized competing peers (i.e., we consider those with size differences less than 500 square feet and 500 to 1,000 square feet). The reasoning is that a house facing a large number of similarly sized competitors provides more substitution opportunities for

buyers, which imposes downward price pressure. [Table 1](#) shows that, on average, 1,173 homes compete within a 500-square foot difference, and 845 homes compete with a 500 to 1,000 square foot difference.

(3) *Count-based competition measure using a combination of geographic and characteristics proximity*: This measure is a combination of the previous two measures and combines the number of houses of similar size within specified geographic distances. It considers the number of similarly sized listed houses within specific geographic distances. For example, it counts the number of houses within 3 miles, and 3 to 5 miles away from the house of interest that do not exceed a size difference of 1,000 square feet compared to the house of interest. [Table 1](#) shows that 100 (131) houses are listed within 3 miles (within 3 to 5 miles) and within 1,000 square feet.

As mentioned earlier, our study also considers two *price-based competition measures* that build on the standard price competition concept (such as Bertrand competition) and describe a provider’s best price response based on contemporaneous price information of competing peers.

4) *Price-based competition measure using geographic proximity*: This measure includes prices of contemporaneously listed homes within specified geographic distances (within 1 mile, 1 to 3 miles, and 3 to 5 miles) from the house of interest. The underlying rationale for competition is similar to before—that is, smaller geographic distance increases substitution possibilities for buyers, which reduces prices.

5) *Price-based competition measure using nearest neighbor proximity*: This measure includes prices of contemporaneously listed neighboring homes (considering the nearest 5, 20, 50, etc. neighbors). The benefit of using the “nearest neighbor” concept is that it avoids the necessity of pre-specifying geographic proximities or distance rings and provides more consideration for starkly varying geographic markets and neighborhood densities. This is advantageous since neighborhoods differ strongly in their density of competing listings. For

example, while denser urban neighborhoods have many houses within a specific distance, say 1 mile, more rural types of dispersed neighborhoods have fewer houses within 1 mile. Consequently, denser (disperse) neighborhoods contain higher (fewer) counts of competing peers. As can be seen in [Table 1](#), the densities of “competing” houses vary greatly across regions. Neighborhoods with small lot sizes and large neighborhood densities accumulate a higher number of competing peers in the geographic distance measure, of which most competitors do not have a competitive influence on the price of a house. Consequently, geographic proximity measures (distance rings of 1 mile, 1 to 3 miles, etc.) that are fixed across neighborhoods can result in large variations in the number of competing peers, many of which may not have a competitive impact on the house under consideration. Hence, there is a concern that measures based on fixed distance rings are inappropriate since they ignore that the density of houses for sale could vary drastically across neighborhoods. The “nearest neighbors” concept allows for more flexible distance rings.

4 Baseline Model Specification Using Count-Based Competition Measures

We begin our analysis by establishing a base case that builds on a hedonic price function (see [Rosen \(1974\)](#)) while concentrating on three commonly used *count-based competition measures*. We regress house prices on housing attributes and various fixed effects. The regression equation is specified as follows:

$$\log(\mathbf{P}) = \alpha \mathbf{\iota}_N + \mathbf{X}_h \boldsymbol{\beta}_h + \mathbf{X}_d \boldsymbol{\beta}_d + \mathbf{X}_c \boldsymbol{\beta}_c + \boldsymbol{\epsilon}, \quad (1)$$

where $\mathbf{P} = (P_1, \dots, P_N)'$ denotes the vector of prices for all houses sold in 2019, where houses are denoted by $1, \dots, N$. $\mathbf{\iota}_N$ denotes an $(N \times 1)$ vector of ones, \mathbf{X}_h includes observed values of important house attributes (we use logged house size, age, number of bedrooms,

number of bathrooms, and the logged lot area size), and \mathbf{X}_d consists of the census tract fixed effects to absorb neighborhood effects and monthly dummies to accommodate seasonality in the local housing market. \mathbf{X}_c is a matrix containing the three *count-based competition measures* based on: (1) geographic proximity, which includes the number of listed houses in 0-3 miles and 3-5 miles radii; (2) characteristics proximity, which involves the number of competing houses with a house size difference of less than 500 square feet and 500 to 1,000 square feet; and (3) a combination of geographic and characteristics proximity, which includes the number of competing houses with size differences of less than 1,000 square feet that are located within geographic distances of (0, 3), and [3, 5) miles.

The coefficients β_h , β_d , and β_c denote the vectors of coefficients associated with \mathbf{X}_h , \mathbf{X}_d , and \mathbf{X}_c , respectively. The key interest lies in β_c , measuring the price effects of competition.

Table 2 presents the estimation results of three specifications that contain the *count-based competition measures*. In all three specifications, the *count-based competition measures based on geographic proximity* are insignificant, with only two exceptions. In specifications (2) and (3), the number of competing peers located 3 to 5 miles away has a significantly positive impact on house prices. This result is unexpected, we would rather expect a negative coefficient estimate since nearby houses are substitutes. In general, the three *count-based competition measures* appear less appropriate for measuring spatial competition in housing markets.

The main reason why the above measures may not perform well is that the neighborhood density varies drastically across areas such that the number of competing peers in specified geographic distances fails to properly adjust to varying neighborhood density. We, therefore, adopt the nearest neighbor concept.

Another reason why this specification may not perform well is that the *count-based competition measures* do not include information on competing peers' prices. This could be relevant information to use since theoretical contributions (such as Bertrand competition

models) relate to competitors’ prices as a strategic variable when determining prices.

In the following, we focus on *price-based competition measures*, which include information on competitors’ prices as a regressor. The measure builds on standard models of price competition, such as differentiated oligopoly models (proposed by [Dixit \(1979\)](#)), and more specialized locational models, including [Hotelling \(1929\)](#) and [Salop \(1979\)](#). These models establish price reaction functions that describe price-setting behavior as a best response to competing peers’ prices. If goods are substitutes, price reaction functions are upward sloping—that is, a provider’s best response to price reductions by competing peers is to reduce its own price. The price response (captured by the estimated coefficients, as will be explained later) is larger if products are closer substitutes such that providers operate in a more competitive market.

One empirical challenge with including price-based competition measures as an additional regressor is that they are endogenous since competitors’ prices enter the measure and prices are jointly determined. This would result in potentially bias when using standard OLS estimation procedures (see e.g., [Can \(1992\)](#) and [Can and Megbolugbe \(1997\)](#)). We adopt an estimation strategy that accounts for this endogeneity concern as will be explained later.¹¹

5 Conceptual Framework

In this section, we follow [Mobley \(2003\)](#) and [Iwata et al. \(2019\)](#) and build on a Bertrand oligopoly model to illustrate the theoretical framework for applying the spatial econometric approach to modeling spatial price competition. To start with, we define the spatial market of house i as a certain neighborhood surrounding that house where price competition takes place (see e.g., [Iwata et al. \(2019\)](#)). To be more specific, houses located outside the spatially defined market are not considered substitutes for house i . Therefore, houses outside of the

¹¹Further details follow in [Section 6](#).

spatial market have no competition effects on house i 's price. Following [Iwata et al. \(2019\)](#), we assume a linear demand function. We normalize the demand for house i to be between 0 and 1 so that it can be interpreted as the probability that house i is purchased. Furthermore, we assume that the demand of house i depends on its own price, the weighted average price of competing houses in its spatial market, and house and neighborhood characteristics \mathbf{X} , which include \mathbf{X}_h , \mathbf{X}_d , and \mathbf{X}_c as introduced in the baseline model. To be more specific, we denote the demand function of house i as $d_i(P_i, \mathbf{w}_i \mathbf{P}, \mathbf{X}_i)$, where \mathbf{w}_i denotes the i -th row of the specified weight matrix \mathbf{W} in the spatial autoregressive model, which we will further illustrate in [Section 6](#). Hence, the demand function is given as below:

$$d_i(P_i, \mathbf{w}_i \mathbf{P}, \mathbf{X}_i) = \alpha P_i + \lambda \mathbf{w}_i \mathbf{P} + \mathbf{X}_i \boldsymbol{\eta}.$$

In this setting, the owner of house i chooses its price to maximize the expected profit, which can be put as

$$\begin{aligned} \Pi_i(P_i, \mathbf{w}_i \mathbf{P}, \mathbf{X}_i) &= (P_i - c_i) d_i(P_i, \mathbf{w}_i \mathbf{P}, \mathbf{X}_i) + (-c_i)(1 - d_i(P_i, \mathbf{w}_i \mathbf{P}, \mathbf{X}_i)) \\ &= P_i(\alpha P_i + \lambda \mathbf{w}_i \mathbf{P} + \mathbf{X}_i \boldsymbol{\eta}). \end{aligned}$$

Here, c_i could be the construction cost of house i or the former acquisition cost. In either case, c_i is considered a sunk cost when the homeowner decides on the listed price of house i . Based on the law of demand, we assume that $\alpha < 0$ and $\lambda > 0$, given that the competing houses in the spatial market are substitutes for house i . Using the first-order condition with regards to P_i , we can derive a linear best response function for house i 's price, which is given by

$$P_i(\mathbf{w}_i \mathbf{P}, \mathbf{X}_i) = -\frac{\lambda}{2\alpha} \mathbf{w}_i \mathbf{P} - \frac{1}{2\alpha} \mathbf{X}_i \boldsymbol{\eta}.$$

To simplify the notations, we further let $\theta = -\frac{\lambda}{2\alpha}$ and $\beta = -\frac{1}{2\alpha}\eta$, to establish the linear best response function:

$$P_i(\mathbf{w}_i\mathbf{P}, \mathbf{X}_i) = \theta\mathbf{w}_i\mathbf{P} + \mathbf{X}_i\beta, \quad (2)$$

which results in the spatial autoregressive model specification with the spatial dependence parameter $\theta > 0$. By connecting this model framework with the competition measures illustrated in [Section 3](#), we can see that the *count-based competition measures* appear as part of the neighborhood attributes in \mathbf{X}_i . In contrast, the *price-based competition measures* are represented by $\mathbf{w}_i\mathbf{P}$, and the magnitude of θ represents the strength of price responses serving as a measurement for competition. That is, the steeper the best response function of P_i with regards to the weighted average price of competing houses, the stronger is the price competition in the spatial market. Under this theoretical framework, the *price-based competition measures* characterize an opportunity to measure spatial competition as the interaction among neighboring houses' in a particular spatial market (see e.g., [Boone \(2008a\)](#)).¹²

Note, *price-based competition measures using geographic proximity* and *nearest-neighbor proximity* respectively reflect different ways of specifying the spatial market of a particular house. When we consider geographic proximity, we assume that the spatial market is defined by a specific distance ring surrounding the house under consideration, and that the houses outside of the distance ring do not exert any competitive price effects. In contrast, when we adopt nearest-neighbor proximity, we are assuming that the spatial market is composed of the nearest 5, 20, 50, etc. neighbors of the house under consideration. Therefore, when we estimate the θ parameter from data, we are in fact estimating the strength of price competition within the spatial market defined by the corresponding spatial weights.

The following section illustrates multiple types of spatial weight matrices that we use to

¹²Note that the hedonic housing price function ([Rosen \(1974\)](#)) that we adopted as the baseline model in [Section 4](#) is a special case of this framework when $\theta = \lambda = 0$, i.e. the prices of neighboring houses do not affect the demand for the house under consideration.

characterize different spatial markets.

6 Main Empirical Model: Price-based Competition Measures

To resolve the endogeneity issue that arises from the inclusion of competitors' prices, we follow the literature on spatial econometrics and adopt a high-order spatial autoregressive (SAR) model. This approach no longer treats the average prices of neighboring houses as independent explanatory variables but accommodates the dependence of neighboring houses through spatial weight matrices.

6.1 Spatial Autoregressive Model Specification

The high-order spatial autoregressive model is specified as follows:

$$\log(\mathbf{P}) = \sum_{q=1}^3 \theta_q \mathbf{W}_q^{(1)} \log(\mathbf{P}) + \mathbf{X}\boldsymbol{\beta}_1 + \boldsymbol{\varepsilon}_1, \quad (3a)$$

$$\log(\mathbf{P}) = \sum_{q=1}^3 \psi_q \mathbf{W}_q^{(2)} \log(\mathbf{P}) + \mathbf{X}\boldsymbol{\beta}_2 + \boldsymbol{\varepsilon}_2, \quad (3b)$$

In this model specification, \mathbf{W}_1 , \mathbf{W}_2 , and \mathbf{W}_3 refer to three ($N \times N$) spatial weight matrices that incorporate the two alternative *price-based competition measures* and measure the competitive price effects of nearby homes. This empirical model specification stems from the best response function (equation (2)), derived in a Bertrand oligopoly model. However, instead of specifying only one weight matrix as in [Section 5](#), here we include multiple weight matrices with the aim of capturing the potential decaying pattern in the price competition effects as we consider the competing houses located farther away.

The first specification is shown in equation (3a). It includes *price-based competition*

measures using geographic proximity, which are considered by the weight matrices $W_1^{(1)}$, $W_2^{(1)}$, and $W_3^{(1)}$. The three weight matrices carry price information on the competing peers located within 1 mile, 1 to 3 miles, and 3 to 5 miles distances, respectively.¹³ \mathbf{P} is again the vector of prices for all housing units. Therefore, $W_1^{(1)} \log(\mathbf{P})$ gives the vector of weighted average logged prices for neighboring competing houses located within 1 mile. The coefficients (θ_1 , θ_2 , and θ_3) represent the competitive price effects associated with $W_1^{(1)}$, $W_2^{(1)}$, and $W_3^{(1)}$ and measure the price competition effects that contemporaneously listed homes within specified geographic distances exert on other houses. For example, θ_1 measures the effect on prices originated by the weighted average of neighboring home prices within 1 mile as associated with $W_1^{(1)}$. Consequently, the above specification reflects the principle of best response functions, where prices are explained as best responses to competitors' prices. A higher estimated θ coefficient stands for higher competition and a more extensive price undercutting as a response to competing peers' prices. Note, we also control for all the *count-based competition measures* entering the matrix \mathbf{X} (see equation (1)). Again, apart from the competition measures, we also control for house attributes, census-tract fixed effects, and monthly fixed effects. To be more specific, $\mathbf{X} = (\boldsymbol{\iota}_N, \mathbf{X}_h, \mathbf{X}_d, \mathbf{X}_c)$. The associated coefficients β_1 measure the corresponding effects of \mathbf{X} on price. Note that we have included census-tract fixed effects to control for some unobserved neighborhood factors that may impact the prices of multiple nearby houses in similar ways so that the estimates of θ_1 , θ_2 , and θ_3 only capture the price competition effects.

A second specification is shown in equation (3b) and contains *price-based competition measures using nearest neighbor proximity*, which are considered by the weight matrices $W_1^{(2)}$, $W_2^{(2)}$, and $W_3^{(2)}$. The three weight matrices include price information on the 1-5, 6-20, and 21-50 nearest neighbors, respectively. The associated coefficients (ψ_1 , ψ_2 , and ψ_3) measure the competitive effects exerted by prices of nearest neighboring homes (1-5, 6-

¹³The row sums of all weight matrices are normalized to 1.

20, and 21-50 nearest neighbors, respectively). For instance, ψ_1 represents the competitive effects on prices originated by the weighted average of the five nearest neighboring home prices. The matrix \mathbf{X} in equation (3b) is the same as in equation (3a), and β_2 measures the corresponding effects of \mathbf{X} on price.

Regarding identification and potential endogeneity, first note that prices of all housing units are treated as potentially endogenous, and the spatial dependence among them are accommodated by the weight matrices, $\{\mathbf{W}_q^{(1)}\}_{q=1}^3$ and $\{\mathbf{W}_q^{(2)}\}_{q=1}^3$, multiplied by the price vector. To resolve “spatial endogeneity” concerns, we can control for the spatial correlation among house prices (Anselin (1988)) using the SAR model specification. Furthermore, we adopt the 2SLS approach to estimating the high-order SAR model, which is robust to spatial endogeneity and potential heteroskedasticity (see e.g., Kelejian and Prucha (2010) and Badinger and Egger (2011)). For the instrumental variables, following Badinger and Egger (2011), we consider the linearly independent terms of

$$(\mathbf{X}, W_1^{(1)}\mathbf{X}, W_2^{(1)}\mathbf{X}, W_3^{(1)}\mathbf{X}, (W_1^{(1)})^2\mathbf{X}, (W_2^{(1)})^2\mathbf{X}, (W_3^{(1)})^2\mathbf{X}, W_1^{(1)}W_2^{(1)}\mathbf{X}, W_2^{(1)}W_3^{(1)}\mathbf{X})$$

and

$$(\mathbf{X}, W_1^{(2)}\mathbf{X}, W_2^{(2)}\mathbf{X}, W_3^{(2)}\mathbf{X}, (W_1^{(2)})^2\mathbf{X}, (W_2^{(2)})^2\mathbf{X}, (W_3^{(2)})^2\mathbf{X}, W_1^{(2)}W_2^{(2)}\mathbf{X}, W_2^{(2)}W_3^{(2)}\mathbf{X})$$

for equations (3a) and (3b), respectively. To see the validity of the proposed instrumental variables, let \mathbf{W}_1 and \mathbf{W}_2 denote two arbitrary candidate weight matrices in the high-order SAR model. First note that $(\mathbf{W}_1)^j\mathbf{X}$, $(\mathbf{W}_2)^j\mathbf{X}$, and $\mathbf{W}_1\mathbf{W}_2\mathbf{X}$ are correlated with $\mathbf{W}_1 \log(\mathbf{P})$ and $\mathbf{W}_2 \log(\mathbf{P})$, for $j = 0, 1, 2$. Also, as long as \mathbf{X} is exogenous, $(\mathbf{W}_1)^j\mathbf{X}$, $(\mathbf{W}_2)^j\mathbf{X}$, and $\mathbf{W}_1\mathbf{W}_2\mathbf{X}$ are also exogenous, namely uncorrelated with the error term (ϵ_1 and ϵ_2 respectively in equations (3a) and (3b)), conditional on \mathbf{X} .¹⁴

¹⁴This selection of instruments is reasonable in our residential house market setting. The intuition is

7 The Main Estimation Results

Specification (1), as shown in equation (3a), relates to the *price-based competition measure using geographic proximity*, with geographic distances falling into the three distance rings, (0, 1), [1, 3), and [3, 5) miles. We add all three *count-based competition measures* from before and also allow for heterogeneous or differential competitive price effects across various groups of houses, including small and large houses, houses with no more than and more than two bedrooms, and low-value and high-value houses.¹⁵ One reason to accommodate heterogeneity is that consumers look for specific types of houses such that substitution opportunities and price competition effects are limited to specific house types. Those substitution patterns could differ across home market segments due to differential willingness to pay and substitution opportunities. This specification also incorporates the *price-based competition measure using geographic proximity*.

The estimation results for specification (1), equation (3a), are shown in Table 3. For instance, the results from column 1 (column 2) show that for small (large) houses, a 1 percent price increase for houses within one mile results in an, on average, 0.002 (0.002) percent price increase for the housing unit under consideration. All coefficient estimates for the *price-based competition measure using geographic proximity* are positive across all geographic distances and for all market segments (that is, for smaller and larger houses as well as for low-value and high-value homes). Most coefficients are not significantly different from zero, or rather small in magnitude, such that they do not support meaningful evidence for spatial competition. The estimation results do not show diminishing coefficient estimates over distance and, therefore, do not provide supportive evidence for a geographic decay of price competition effects. This is somewhat surprising since homes in closer proximity are

that a home's own characteristics and weighted neighboring prices serve as appropriate instruments for own price, while neighboring characteristics do not have a direct effect on own price.

¹⁵The two groups of small and large houses are divided by the median square footage of the full sample. Similarly, the groups of low-value and high-value houses are divided by the median price.

supposed to exert larger competitive impacts due to larger substitution opportunities, and these measures would not capture this. Moreover, it is noteworthy that for all market segments except for the low-value houses, at least half of the coefficient estimates on the *count-based competition measures* are insignificant. In particular, coefficient estimates on all the *count-based competition measures* are insignificant for the small houses. Among those with significant estimates, a number of them show a counterintuitive positive impact on house prices. This result provides further evidence that the *count-based competition measures* are less appropriate in explaining price competition effects.

Specification (2), equation (3b), includes the *price-based competition measures using nearest neighbor proximity*. The corresponding estimation results are shown in Table 4. For example, the results from column 1 (column 2) show that for small (large) houses, a 1 percent price increase for the five nearest competing peers is expected to lead to a 0.145 (0.159) percent price increase for the housing unit under consideration. Turning to the nearest neighbors ranked 6-20, the coefficient estimate is significantly positive. The magnitude of competition effects has become smaller, which is estimated to be 0.090 and 0.044 for small and large houses, respectively. For the nearest neighbors ranked 21-50, the estimated price effect has an even smaller effect that is statistically insignificant. Turning to the *count-based competition measures* at the lower panel of the table, it should be recognized that many associated coefficients remain insignificant and that they still carry a number of significantly positive coefficient estimates that are counterintuitive. This result further confirms the fact that *count-based competition measures* include limited additional important information that is helpful in explaining price effects in spatial competition.

It should be noted that the coefficient estimates on the average prices of competitors are more reasonable when the *price-based competition measure using nearest neighbor proximity* (specification (2)) is adopted relative to using the *price-based competition measure using geographic proximity* (specification (1)) since they are more significant and econom-

ically more meaningful. Importantly, they show a decaying pattern in magnitude as we consider neighbors located farther away. That is, for small (large) houses, the price effects decline from 0.145 (0.159) for the five nearest neighbors to 0.090 (0.044) for the nearest neighbors ranked 6-20, and further decrease to 0.029 (0.013) for those ranked 21-50. The decaying price effect is a result that confirms our understanding of spatial competition since willingness and possibilities to substitute diminish with distance from a house under consideration.

Furthermore, the results under specification (2) (as shown in columns 3 and 4 of [Table 4](#)) indicate that for houses with no more than (more than) two bedrooms, the magnitude of price effects from the five nearest competing houses is 0.166 (0.195), and it again declines as we consider the neighbors that are located farther away. The pattern of results for these two subgroups is similar to that of small and large houses. Hence, spatial price competition effects are relatively homogeneous across houses with different sizes and across houses with different numbers of bedrooms.

In comparing the coefficient estimates for low-value and high-value homes (see columns 5 and 6 in [Table 4](#), respectively), we find that price competition effects differ starkly across houses with different values. The estimated competition effect from the five nearest competing houses is much larger in magnitude for the high-value houses (0.210) compared to the low-value houses (0.146). This result indicates that price competition among the five nearest listed housing units is more intense among more expensive houses. At first glance, this result seems surprising and contradictory to the fact that listed houses tend to be more sparsely distributed in high market segments. However, although there are more listed houses within a certain geographic distance for low-value houses, the more distant competing peers may not exert a competitive effect anymore. If we adopt *count-based and price-based competition measures using geographic proximity*, they are still included regardless of their limited price competition effects. This may result in a distorted competitive

price effect, while the *price-based competition measure using nearest neighbor proximity* prevents this distortion effect. Therefore, the prices of the five nearest competing houses exert higher price competitive effects among high-value houses compared to low-value homes.

Furthermore, the price competition effects decay relatively slower among high-value houses compared to low-value houses. To be more specific, the 20 nearest neighboring houses have significant competition effects for high-value houses. In contrast, for low-value houses, only the 5 nearest competitors have significant price effects on the house under consideration. This finding is intuitive because high-value home buyers may have relatively more cars for daily transportation, and therefore they have less restrictions on the geographic location of future home, and tend to consider a larger set of competing choices.

In addition, [Table 5](#) presents the p-values for some relevant statistical tests. First, before conducting estimation of the high-order SAR model, we test for the presence of spatial correlation in $\log(\mathbf{P})$ associated with each weight matrix based on the Lagrangian multiplier (LM) test statistic of spatial correlation in the dependent variable of a linear regression (see [Anselin \(1988\)](#)).¹⁶ A small p-value shows the existence of spatial correlation in $\log(\mathbf{P})$ associated with the corresponding weight matrix. The table shows that for each of the $W_1^{(1)}$, $W_2^{(1)}$, and $W_3^{(1)}$ under specification (1), equation (3a), nonzero spatial correlation in house prices exists for only two of the six market segments, using the significance level $\alpha = 0.05$. In comparison, under specification (2), equation (3b), we find rather strong evidence of nonzero spatial correlation based on $W_1^{(2)}$ for all the six market segments, which again shows that average prices from the five nearest competitors make significant contributions to the spatial price competition, regardless of the market segments. Also, for each of $W_2^{(2)}$ and $W_3^{(2)}$, we can reject the null hypothesis of zero spatial correlation at $\alpha = 0.05$ for four of the six market segments. In general, these results again show that

¹⁶We adopt the publicly available MATLAB code for the LM test written by James P. LeSage and Shifeng Wang.

the *price-based competition measure using nearest neighbor proximity* (specification (2)) are more appropriate in measuring the spatial price competition among houses, compared to using the *price-based competition measure using geographic proximity* (specification (1)).

In Table 5, we also report the p-values of testing the decaying pattern in price competition effects. Under specification (2), we can reject the null hypothesis that $\psi_1 \leq \psi_2$ in favor of $\psi_1 > \psi_2$ for all the six market segments under $\alpha = 0.05$. This serves as formal evidence that the price effect from the five nearest competing houses is stronger than the one related to the competitors ranked in 6-20. Moreover, we also conducted the post-estimation tests of presence of spatial correlation in the errors based on the estimated residual $\hat{\epsilon}_1$ and $\hat{\epsilon}_2$, where $\hat{\epsilon}_1 = \log(\mathbf{P}) - \sum_{q=1}^3 \hat{\theta}_q \mathbf{W}_q^{(1)} \log(\mathbf{P}) - \mathbf{X} \hat{\beta}_1$ and $\hat{\epsilon}_2 = \log(\mathbf{P}) - \sum_{q=1}^3 \hat{\psi}_q \mathbf{W}_q^{(2)} \log(\mathbf{P}) - \mathbf{X} \hat{\beta}_2$. These tests are based on the testing procedure suggested by Kelejian and Prucha (2001), and the corresponding p-values are all large and close to 1. This indicates that there is no leftover spatial correlation in the errors and that the contemporaneous prices of nearest competitors can explain the competition effects and variations in prices reasonably well.

Heterogeneous Price Effects Across Homes in Different Neighborhoods

Building on the previous finding (Table 4, columns 5 and 6) that price competition effects are heterogeneous across low-value and high-value houses and the fact that neighborhoods differ starkly in value (see Figure 1), we visualize how price competition effects vary across different neighborhoods. We intend to further investigate heterogeneous competitive price effects across disaggregated geographic neighborhoods.

Based on the *price-based competition measure using nearest neighbor proximity*, we separately estimate our model for different neighborhoods classified by census tracts. We use the census tract division code as the group classifier, and we end up with 17 different groups or neighborhoods. We present the estimated coefficients on $\mathbf{W}_1^{(2)} \log(\mathbf{P})$, $\mathbf{W}_2^{(2)} \log(\mathbf{P})$, and $\mathbf{W}_3^{(2)} \log(\mathbf{P})$ by census tract in Figure 3. In this figure, the maps from left to right present

the estimated competition effects from the nearest competing houses ranked 1-5, 6-20, and 21-50, respectively. The areas that are colored blue have significantly positive coefficient estimates. Darker blue areas have relatively larger magnitudes of competition effect estimates. For areas in light gray, the corresponding estimates are not significant.

As shown in [Figure 3](#), the estimated competition effects from the five nearest competing houses tend to be stronger in neighborhoods near the seashore, where the average house prices are relatively higher, as can be seen in [Figure 1](#). This is in line with the results from [Table 4](#), column 6, which shows that high-value homes face more competitive price effects. Furthermore, when we consider the nearest competitors ranked 6-20, the price competition effects are significant only for a small number of census tracts that are relatively close to the sea. It shows that the price competition effects decay relatively slower in more expensive neighborhoods, which is again consistent with the results from [Table 4](#), column 6. Also, when we move on to the nearest competitors ranked 21-50, the price competition effects become insignificant for all census tracts.

In addition, as a robustness check, we conduct estimations by census tract under another specification where the three weight matrices characterize the nearest competing houses ranked in positions 1-10, 11-20, and 21-30 so that we have equal numbers of competitors that fall into these three distance rings. We find that the distribution of estimated price effects from the 10 nearest competing houses under this specification is relatively similar to that from the five nearest competitors in [Figure 3](#). Consistent with our earlier results, the estimated price effects from the 10 nearest competitors also tend to be larger in magnitude for more expensive neighborhoods.

8 Conclusion

This study tests the performance of alternative measures for price competition effects in spatial markets. Our estimation results show that the *price-based competition measure using nearest neighbor proximity* outperforms other *price-based* and *count-based competition measures*. The *price-based competition measure using nearest neighbor proximity* returns reasonable estimation results that are consistent with our understanding of spatial competition. The results clearly illustrate a decaying pattern of spatial price competition. This result—that the spatial price competition pattern in residential housing markets is more closely related to the relative distance (nearest neighbors ranked in particular positions) compared to the absolute distance (neighbors located in fixed distance rings)—is well aligned with institutional features such as the “comparable sales” approach. Furthermore, compared to using fixed geographic distance rings, adopting the nearest neighbor approach may better accommodate the substantial heterogeneity in the density of houses on sales across neighborhoods. We also find that spatial price competition effects are relatively homogeneous across houses of different sizes and across houses with different numbers of bedrooms but heterogeneous across houses with different prices. That is, price competition is stronger among high-value homes, especially within the five nearest competitors.

For future research, it would be interesting to see whether *price-based competition measures* perform similarly well in other spatial markets.

References

- Amir, Rabah (2002) “Market structure, scale economies and industry performance.”
- Anselin, Luc (1988) *Spatial Econometrics: Methods and Models*: Dordrecht: Kluwer Academic Publishers.
- Arrow, Kenneth Joseph (1962) “Economic welfare and the allocation of resources for invention,” in *Nelson, R. (Ed.), The Rate and Direction of Inventive Activity: Economic and Social Factors*: Princeton University Press.

- Badinger, Harald and Peter Egger (2011) "Estimation of higher-order spatial autoregressive cross-section models with heteroscedastic disturbances," *Papers in Regional Science*, 90 (1), 213–235, [10.1111/j.1435-5957.2010.00323.x](#).
- Baumol, William J. (1967) "Calculation of Optimal Product and Retailer Characteristics: The Abstract Product Approach," *Journal of Political Economy*, 75 (5), 674–685, [10.1086/259342](#).
- Boone, Jan (2008a) "Competition: Theoretical parameterizations and empirical measures," *Journal of Institutional and Theoretical Economics (JITE)*, 587–611, [10.1628/093245608786534640](#).
- (2008b) "A New Way to Measure Competition," *The Economic Journal*, 118, 1245–1261, [10.1111/j.1468-0297.2008.02168.x](#).
- Bowley, Arthur L (1924) *The mathematical groundwork of economics: an introductory treatise*: Clarendon Press.
- Bresnahan, Timothy F (1981) "Duopoly models with consistent conjectures," *American Economic Review*, 71 (5), 934–945.
- Brueckner, Jan K (2003) "Strategic interaction among governments: An overview of empirical studies," *International regional science review*, 26 (2), 175–188, [10.1177/0160017602250974](#).
- Bulow, Jeremy and Paul Klemperer (2002) "Prices and the Winner's Curse," *RAND Journal of Economics*, 1–21, [10.2307/2696372](#).
- Can, Ayse (1990) "The Measurement of Neighborhood Dynamics in Urban House Prices," *Economic Geography*, 66 (3), 254–272, [10.2307/143400](#).
- (1992) "Specification and estimation of hedonic housing price models," *Regional Science and Urban Economics*, 22, 453–474, [10.1016/0166-0462\(92\)90039-4](#).
- Can, Ayse and Isaac Megbolugbe (1997) "Spatial Dependence and House Price Index Construction," *Journal of Real Estate Finance and Economics*, 14 (3), 203–222, [10.1023/A:1007744706720](#).
- Chen, Yong, John M. Clapp, and Dogan Tirtiroglu (2011) "Hedonic estimation of housing demand elasticity with a markup over marginal costs," *Journal of Housing Economics* (4), 233–248, [10.1016/j.jhe.2011.07.001](#).
- Cooper, Zack, Stuart V Craig, Martin Gaynor, and John Van Reenen (2019) "The Price Ain't Right? Hospital Prices and Health Spending on the Privately Insured," *The Quarterly Journal of Economics*, 134 (1), 51–107, [10.1093/qje/qjy020](#).
- Davis, Peter (2006) "Spatial competition in retail markets: movie theaters," *RAND Journal of Economics*, 37 (4), 964–982, [10.1111/j.1756-2171.2006.tb00066.x](#).
- Dixit, Avinash (1979) "A model of duopoly suggesting a theory of entry barriers," *The Bell Journal of Economics*, 20–32, [10.2307/3003317](#).

- Dranove, David, Mark Shanley, and Carol Simon (1992) "Is Hospital Competition Wasteful?" *RAND Journal of Economics*, 23 (2), 247–262, [10.2307/2555987](#).
- Gabszewicz, J Jaskold and J.-F. Thisse (1979) "Price competition, quality and income disparities," *Journal of Economic Theory* (3), 340–359, [10.1016/0022-0531\(79\)90041-3](#).
- Gaynor, Martin, Kate Ho, and Robert J. Town (2015) "The Industrial Organization of Health-Care Markets," *Journal of Economic Literature*, 53 (2), 235–284, [10.1257/jel.53.2.235](#).
- Genesove, David and Wallace P. Mullin (1998) "Testing static oligopoly models: conduct and cost in the sugar industry, 1890-1914," *RAND Journal of Economics*, 29 (2), 355–377, [10.2307/2555893](#).
- Glaeser, Edward L., Joseph Gyourko, and Raven Saks (2005) "Why is Manhattan so expensive? Regulation and the rise in housing prices," *Journal of Law and Economics*, 48 (2), 331–368, [10.1086/429979](#).
- Gorman, W. M. (1980) "A Possible Procedure for Analysing Quality Differentials in the Egg Market," *Review of Economic Studies*, 47 (5), 843–856, [10.2307/2296916](#).
- Heggstad, Arnold A. and Stephen A. Rhoades (1978) "Multi-Market Interdependence and Local Market Competition in Banking," *The Review of Economics and Statistics*, 60 (4), 523–532, [10.2307/1924244](#).
- Hotelling, Harold (1929) "Stability in competition," *The Economic Journal*, 39 (153), 41–57, [10.2307/2224214](#).
- Iwata, Shinichiro, Kazuto Sumita, and Mieko Fujisawa (2019) "Price competition in the spatial real estate market: allies or rivals?" *Spatial Economic Analysis*, 14 (2), 174–195, [10.1080/17421772.2019.1532596](#).
- Kelejian, Harry H and Ingmar R Prucha (1998) "A generalized spatial two-stage least squares procedure for estimating a spatial autoregressive model with autoregressive disturbances," *Journal of Real Estate Finance and Economics*, 17, 99–121, [10.1023/A:1007707430416](#).
- (2001) "On the asymptotic distribution of the Moran I test statistic with applications," *Journal of econometrics*, 104 (2), 219–257, [10.1016/S0304-4076\(01\)00064-1](#).
- (2010) "Specification and estimation of spatial autoregressive models with autoregressive and heteroskedastic disturbances," *Journal of Econometrics*, 157 (1), 53–67, [10.1016/j.jeconom.2009.10.025](#).
- Lancaster, Kelvin J. (1966) "A New Approach to Consumer Theory," *Journal of Political Economy*, 74 (2), 132–157, [10.1086/259131](#).
- Mobley, Lee R (2003) "Estimating hospital market pricing: an equilibrium approach using spatial econometrics," *Regional Science and Urban Economics*, 33 (4), 489–516, [10.1016/S0166-0462\(02\)00059-5](#).

- Pinkse, Joris and Margaret E. Slade (2010) “The Future of Spatial Econometrics,” *Journal of Regional Economics*, 50 (1), 103–117, [10.1111/j.1467-9787.2009.00645.x](#).
- Pinkse, Joris, Margaret E. Slade, and Craig Brett (2002) “Spatial Price Competition: A Semiparametric Approach,” *Econometrica*, 70 (3), 1111–1153, [10.1111/1468-0262.00320](#).
- Pinkse, Joris, Margaret Slade, and Lihong Shen (2006) “Dynamic Spatial Discrete Choice Using One-step GMM: An Application to Mine Operating Decisions,” *Spatial Economic Analysis*, 1 (1), 53–99, [10.1080/17421770600661741](#).
- Rosen, Sherwin (1974) “Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition,” *Journal of Political Economy*, 82 (1), 34–55, [10.1086/260169](#).
- Rosenthal, Robert W (1980) “A model in which an increase in the number of sellers leads to a higher price,” *Econometrica: Journal of the Econometric Society*, 1575–1579, [10.2307/1912828](#).
- Salop, Steven C (1979) “Monopolistic competition with outside goods,” *The Bell Journal of Economics*, 141–156, [10.2307/3003323](#).
- Slade, Margaret E. (2005) “The Role of Economic Space in Decision Making,” *Annals of Economics and Statistics* (77), 1–20, [10.2307/20079111](#).
- Stiglitz, Joseph E (1989) “Imperfect information in the product market,” *Handbook of Industrial Organization*, 1, 769–847, [10.1016/S1573-448X\(89\)01016-2](#).
- Turnbull, Geoffrey K. and Jonathan Dombrow (2006) “Spatial Competition and Shopping Externalities: Evidence from the Housing Market,” *Journal of Real Estate Finance and Economics*, 32, 391–408, [10.1007/s11146-006-6959-4](#).

Table 1: Descriptive statistics for main variables

	Mean	Std	Max	Min
House price (in 2021 January dollars)	908,517	448,847	3,124,147	81,772
House size	1,997	841	5,945	500
Number of bathrooms	2.68	0.90	9.00	1.00
Number of bedrooms	3.47	0.92	9.00	0.00
Lot area size	6,540	4,878	49,179	0
Age	44	18	141	0
<i>Count-based competition measure using geographic proximity</i>				
< 3 mile	150	97	898	0
[3, 5) miles	211	135	1,315	0
<i>Count-based competition measure using characteristics proximity</i>				
< 500 sq ft	1,173	825	8,133	1
[500, 1,000) sq ft	845	564	5,822	1
<i>Count-based competition measure using a combination of geographic and characteristics proximity</i>				
< 3 mile; < 1,000 sq ft	100	72	713	0
[3, 5) miles; < 1,000 sq ft	138	100	1,030	0

Number of observations: 16,074

Table 2: OLS estimates of the effects of competitions on house prices

$\log(\mathbf{P})$	(1)	(2)	(3)
<i>Count-based competition measure using geographic proximity</i>			
< 3 miles	-0.039 (0.038)	0.056 (0.041)	0.001 (0.068)
[3, 5) miles	0.010 (0.028)	0.089** (0.029)	0.116* (0.048)
<i>Count-based competition measure using characteristics proximity</i>			
< 500 sq ft		-0.001 (0.004)	-0.003 (0.005)
[500, 1000) sq ft		-0.040** (0.005)	-0.041** (0.005)
<i>Count-based competition measure using a combination of geographic and characteristics proximity</i>			
< 3 miles; < 1,000 sq ft			0.104 (0.085)
[3, 5) miles; < 1,000 sq ft			-0.032 (0.067)
N	16,074	16,074	16,074
Adjusted R squared	0.883	0.884	0.884

* $p < 0.05$, ** $p < 0.01$. Robust standard errors in parentheses. Control variables include the size, age, number of bedrooms, number of bathrooms, lot area size, census tract fixed effects, and monthly fixed effects.

Table 3: Estimated correlation in prices among housing units, Specification (1)

	Small (1)	Large (2)	≤ 2 bedrooms (3)	> 2 bedrooms (4)	Low-value (5)	High-value (6)
<i>Price-based competition measure using geographic proximity</i>						
$\mathbf{W}_1^{(1)} \log(\mathbf{P})$	0.002 (0.001)	0.002 (0.001)	0.001 (0.001)	0.006** (0.001)	0.003** (0.001)	0.002* (0.001)
$\mathbf{W}_2^{(1)} \log(\mathbf{P})$	0.016 (0.011)	0.012 (0.013)	0.002 (0.002)	0.023 (0.015)	0.003 (0.008)	0.015* (0.006)
$\mathbf{W}_3^{(1)} \log(\mathbf{P})$	0.178** (0.049)	0.007 (0.004)	0.002 (0.004)	0.013** (0.005)	0.079 (0.051)	0.004 (0.006)
<i>Count-based competition measure using geographic proximity</i>						
< 3 miles	-0.254 (0.140)	-0.020 (0.073)	-0.485* (0.242)	0.094 (0.066)	-0.262* (0.107)	0.015 (0.076)
$[3, 5]$ miles	-0.106 (0.111)	-0.010 (0.050)	-0.263 (0.180)	0.119* (0.047)	-0.205* (0.086)	0.115* (0.053)
<i>Count-based competition measure using characteristics proximity</i>						
< 500 sq ft	0.009 (0.008)	0.072** (0.011)	-0.020 (0.011)	-0.011 (0.006)	0.028** (0.005)	0.034** (0.009)
$[500, 1000]$ sq ft	-0.006 (0.012)	-0.077** (0.009)	0.107** (0.019)	-0.046** (0.005)	-0.045** (0.006)	-0.053** (0.009)
<i>Count-based competition measure using a combination of geographic and characteristics proximity</i>						
< 3 miles; $< 1,000$ sq ft	0.281 (0.158)	-0.017 (0.106)	0.621* (0.292)	0.033 (0.083)	0.279* (0.119)	-0.043 (0.113)
$[3, 5]$ miles; $< 1,000$ sq ft	0.115 (0.140)	0.056 (0.072)	-0.055 (0.234)	0.016 (0.065)	0.276** (0.100)	-0.145 (0.089)
N	8,038	8,036	2,109	13,965	8,037	8,037

* $p < 0.05$, ** $p < 0.01$. Standard errors are presented in parentheses. Control variables include the size, age, number of bedrooms, number of bathrooms, lot area size, census-tract fixed effects, and monthly fixed effects.

Table 4: Estimated correlation in prices among housing units, Specification (2)

	Small (1)	Large (2)	≤ 2 bedrooms (3)	> 2 bedrooms (4)	Low-value (5)	High-value (6)
<i>Price-based competition measure using nearest neighbor proximity</i>						
$\mathbf{W}_1^{(2)} \log(\mathbf{P})$	0.145** (0.021)	0.159** (0.015)	0.166** (0.045)	0.195** (0.011)	0.146** (0.021)	0.210** (0.016)
$\mathbf{W}_2^{(2)} \log(\mathbf{P})$	0.090** (0.023)	0.044* (0.019)	0.030 (0.038)	0.047** (0.013)	0.027 (0.022)	0.053** (0.020)
$\mathbf{W}_3^{(2)} \log(\mathbf{P})$	0.029 (0.025)	0.013 (0.009)	0.015 (0.009)	0.018 (0.011)	-0.006 (0.028)	0.015 (0.008)
<i>Count-based competition measure using geographic proximity</i>						
< 3 miles	-0.297* (0.139)	-0.030 (0.074)	-0.479* (0.243)	0.076 (0.066)	-0.245* (0.106)	0.016 (0.077)
$[3, 5]$ miles	-0.034 (0.110)	-0.022 (0.049)	-0.207 (0.175)	0.107* (0.046)	-0.196* (0.083)	0.095 (0.053)
<i>Count-based competition measure using characteristics proximity</i>						
< 500 sq ft	0.003 (0.008)	0.072** (0.011)	-0.026* (0.011)	-0.008 (0.006)	0.025** (0.004)	0.036** (0.008)
$[500, 1000]$ sq ft	-0.009 (0.012)	-0.077** (0.009)	0.094** (0.019)	-0.049** (0.005)	-0.046** (0.006)	-0.056** (0.008)
<i>Count-based competition measure using a combination of geographic and characteristics proximity</i>						
< 3 miles; $< 1,000$ sq ft	0.361* (0.156)	0.001 (0.105)	0.653* (0.295)	0.081 (0.082)	0.294* (0.118)	-0.027 (0.113)
$[3, 5]$ miles; $< 1,000$ sq ft	0.067 (0.140)	0.094 (0.072)	-0.025 (0.229)	0.034 (0.063)	0.267** (0.096)	-0.080 (0.087)
N	8,038	8,036	2,109	13,965	8,037	8,037

* $p < 0.05$, ** $p < 0.01$. Standard errors are presented in parentheses. Control variables include the size, age, number of bedrooms, number of bathrooms, lot area size, census-tract fixed effects, and monthly fixed effects.

Table 5: P values of relevant statistical tests

Specification (1)	Small (1)	Large (2)	≤ 2 bedrooms (3)	> 2 bedrooms (4)	Low-value (5)	High-value (6)
Tests of presence of spatial correlation in $\log(\mathbf{P})$ associated with						
$\mathbf{W}_1^{(1)}$	0.059	0.126	0.105	0.000	0.004	0.075
$\mathbf{W}_2^{(1)}$	0.004	0.187	0.289	0.002	0.395	0.076
$\mathbf{W}_3^{(1)}$	0.000	0.223	0.608	0.046	0.233	0.185
Tests of decaying pattern in price competition effects						
$H_0:\theta_1 \leq \theta_2; H_a:\theta_1 > \theta_2$	0.888	0.797	0.671	0.877	0.523	0.975
$H_0:\theta_2 \leq \theta_3; H_a:\theta_2 > \theta_3$	0.999	0.344	0.475	0.259	0.933	0.132
Specification (2)	Small (1)	Large (2)	≤ 2 bedrooms (3)	> 2 bedrooms (4)	Low-value (5)	High-value (6)
Tests of presence of spatial correlation in $\log(\mathbf{P})$ associated with						
$\mathbf{W}_1^{(2)}$	0.000	0.000	0.000	0.000	0.000	0.000
$\mathbf{W}_2^{(2)}$	0.000	0.002	0.235	0.000	0.710	0.003
$\mathbf{W}_3^{(2)}$	0.086	0.012	0.036	0.000	0.261	0.009
Tests of decaying pattern in price competition effects						
$H_0:\psi_1 \leq \psi_2; H_a:\psi_1 > \psi_2$	0.034	0.000	0.007	0.000	0.000	0.000
$H_0:\psi_2 \leq \psi_3; H_a:\psi_2 > \psi_3$	0.036	0.075	0.359	0.054	0.182	0.046

H_0 and H_a respectively denote the null hypothesis and alternative hypothesis of the corresponding test. For the tests of presence of spatial correlation in $\log(\mathbf{P})$, H_0 is zero spatial correlation associated with the corresponding weight matrix, and H_a is nonzero spatial correlation associated with the corresponding weight matrix.

Figure 1: Average house prices by census tract

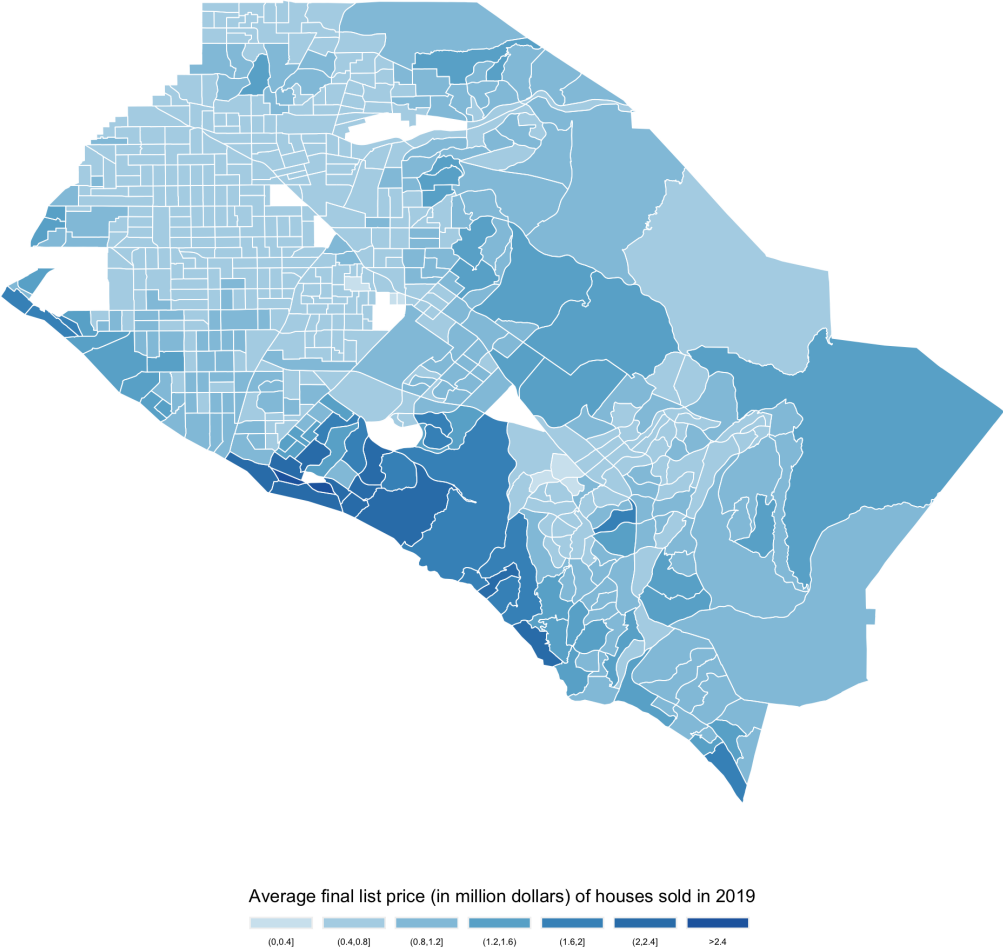


Figure 2: Average number of competing listed houses by census tract

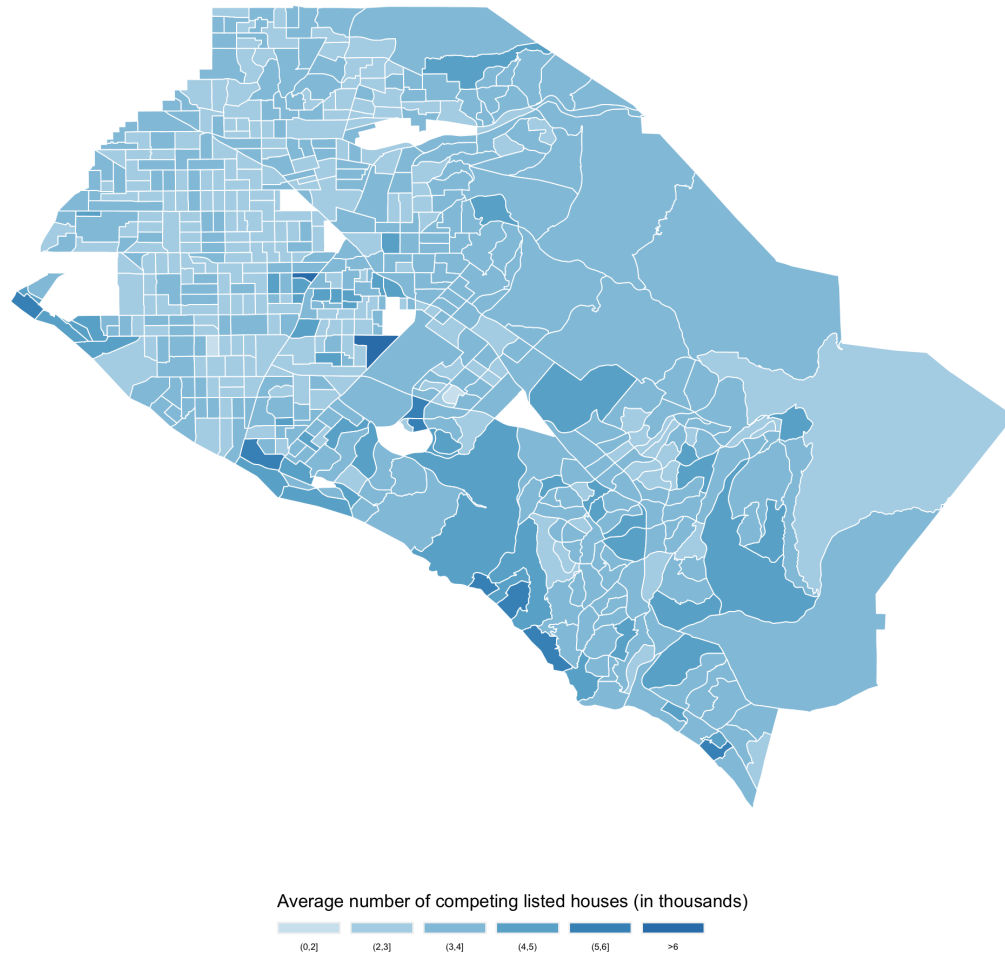
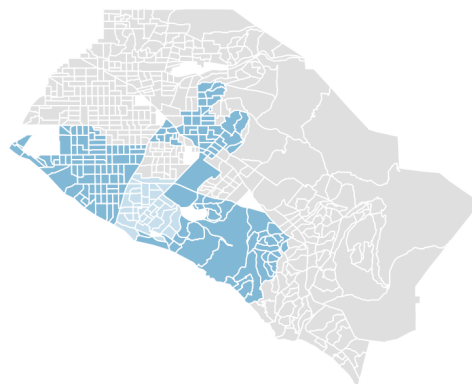
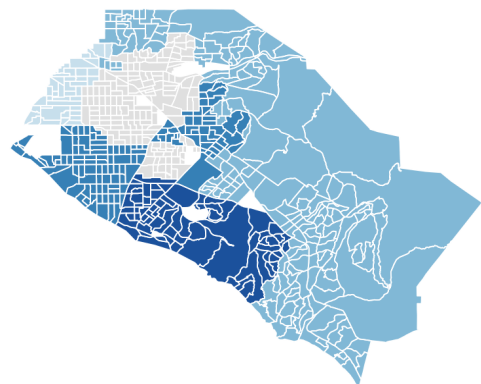


Figure 3: Estimated competition effects from nearest competitors by census tract

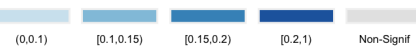
1-5

6-20

21-50



Estimated price competition effects



(0,0.1)

[0.1,0.15)

[0.15,0.2)

[0.2,1)

Non-Signif