Does Quality Matter in Local Consumption Amenities? An Empirical Investigation with Yelp ☆

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Abstract

The possibility that local consumption amenities provided by bars, restaurants, and other retail services improve neighborhood or city attractiveness has received increasing attention in the literature. Empirical research thus far has focused on the number of establishments in an area.

This paper proposes and tests a method for differentiating consumption amenities along a quality dimension, based on either consumer ratings or price estimates from Yelp.com. Appealing to the implicit market model of Rosen (1974), consumption amenity is capitalized in the value of nearby housing. The results demonstrate that both the quantity and quality aspects of consumption amenities matter, and that consumer ratings are more informative about unobservable restaurant amenity than price estimates. Furthermore, comparisons between the results for the pre- and post-Yelp periods show that such capitalization differentials are only observed when information on quality is readily available to and widely used by the public. The method used in this paper to measure the quality of consumption amenities could be applied to other private retail businesses or even local public goods.

Keywords: Real estate market, Hedonic analysis, Local amenity capitalization, Consumption amenities, Information value

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1. Introduction

Cities that are rich in consumption amenities, such as restaurants and live performance venues, have experienced faster growth in the last four decades (Glaeser et al., 2001). The importance of consumption amenities to population growth has been well documented in the literature, where most of the empirical comparisons are inter-regional.[1] The recognition of the importance of consumption amenities is not limited to academic discussions. Inspired by New Urbanism, an urban design movement that promotes walkable neighborhoods with mixed housing types, billions of dollars have been invested into planning policies that promote development of such neighborhoods.

A substantial literature is devoted to measure the value of local amenities, everything from access to parks and open space to sex offenders in the neighborhood.[2] Curiously, there is generally little concern about the quality as opposed to quantity of local amenities in the literature,[3] with the one exception of the standard usage of school test results as proxies for quality in the literature on the implicit value of local schools.[4] There are two potential explanations for the existence of such a divide. The first one is that what matters most about local amenities is their availability, rather than quality. While this might be true for some amenities that are fairly homogeneous in terms of quality (e.g. the study of local house price effects of Wal-Mart by Pope and Pope (2014)), it is hard to make the same argument for most consumption and service goods. The second and more likely explanation for the existence of such a divide is that, other than school test results, consistent measures of quality for local amenities are hard to obtain. Therefore, attention has been focused on accessibility to rather than quality of local amenities.

In this paper, I develop an approach, using information collected from Yelp.com, to measure the effects of both quantity and quality of local consumption amenities, specifically from restaurants, on compensating differentials in the values of surrounding properties. Simply put, the two main research questions are: (1) is access to restaurants capitalized into nearby home values; (2) does information on restaurant amenity from Yelp matter in the valuation process.

The empirical investigation uses detailed housing transaction data for Washington, D.C. and

[1] For theoretical model, see Rappaport (2008); for empirical work, see Carlino and Saiz (2008).

[2] See, for example, Nelson (1978), Carlino and Coulson (2004) , Figlio and Lucas (2004) , and Linden and Rockoff (2008).

[3] Notable exceptions include Sirpal (1994) and Des Rosiers et al. (1996) who examine the externalities associated with shopping centers and explore different capitalization effects in the size of the shopping centers.

[4] See, for example, Black (1999) , Figlio and Lucas (2004) , and Clapp et al. (2008).

micro-geographic data on local businesses collected from Yelp.com. With precise information on the physical addresses for both the properties and the restaurants, I am able to explore variations in the capitalization of consumption amenities at spatial scales as fine as a census block.

I focus on the District of Columbia in this study for three reasons. First, the value of consumption amenities is best examined in an urban context where walking is an important mode of access, which makes D.C. an appropriate area for study. Second, D.C. ranks at the top in terms of U.S. per capita Personal Consumption Expenditure (PCE) at \$59,423, in contrast to a national average of \$35,498 for year 2012.[5] The third reason that makes D.C. a good fit for this study involving restaurant data collected from Yelp.com is that D.C. is considered, by the review site itself, one of the 14 Yelpest cities in North America.[6]

The empirical analysis of consumption amenity from neighborhood restaurants is implemented in two steps. In the first step, I estimate the implicit value of accessibility to neighborhood restaurants. Results show that restaurant access is positively capitalized into nearby home values. In the second step, I explore heterogeneity in the capitalization along the quality dimension and compare results using different amenity measures. Specifically, price estimates from Yelp represent *expected* amenity, while consumer ratings are used in constructing measures for *perceived* amenity. Results show that consumer ratings are more informative about household valuation of consumption amenities.

The paper fits squarely in the implicit markets literature that followed the theoretical insight of Rosen (1974). It contributes to a variety of current debates on the measurement and role of urban amenities. First, the "consumer city" literature considers consumption amenity as first of four particularly critical urban amenities (Glaeser et al., 2001). The quantity and quality of local amenities associated with private goods, such as restaurants, grocery stores, theaters, and other retail services, have important quality of life implications (Meltzer and Schuetz, 2011). I measure the consumption value derived from an important non-tradable service sector, the restaurant industry, and show that proximity to higher quality consumption amenities is valued by city dwellers.

Second, there are implications for a rich urban economics literature that studies the significance

[5]Estimates of household personal consumption expenditure are taken from a press release from the Bureau of Economic Analysis titled Personal Consumption Expenditure by State, 1997-2012 (Prototype Estimates), available at http://www.bea.gov/newsreleases/regional/pce/pce_newsrelease.htm.

[6]In July of 2013, Yelp started a new project called The Yelp Wordmap and the project is created using review information for the 14 Yelpest cities, according to its blog release for the project. http://officialblog.yelp.com/2013/07/the-yelp-wordmap-local-knowledge-revealed.html.

of consumption amenities for the growth of cities. This strand of literature has focused on examining the relation between the inter-city differences in consumption amenities and the differences in population growth and density. In a recent empirical work, Couture (2014) estimates the value of a consumption amenity, using data on individual travel decisions at different locations across the U.S.. I examine the relationship between variations in consumption amenities and property values at an intra-city level, and present empirical evidence for the importance of consumption amenities to neighborhood development.

Third, the paper is connected to a modest literature on the local value of information. Avery et al. (1999) model the market for social value of evaluation in a game theory framework. Other studies have quantified the effect of consumer reviews on business revenues, as they reduce the information asymmetry between buyers and sellers. Luca (2011) examines the causal effect of Yelp ratings on restaurant revenues in Seattle using a regression discontinuity framework, and finds that a one-star increase in Yelp rating leads to a 5 to 9 percent increase in revenue. By comparing results for the pre- and post-Yelp period, I show that provision of information on restaurant amenity over Yelp has an added effect on the capitalization of consumption amenities.

The paper proceeds as follows. In Section 2, a simple conceptual framework is introduced to motivate my empirical work. Section 3 describes the datasets used in the analysis and the construction of measures for local consumption amenities. Empirical models and estimation results are presented in Sections 4 and 5, respectively. Robustness checks are conducted and reported in Section 6.

2. Conceptual Framework

A stylized model with local consumption amenities, characterized by neighborhood restaurants of different amenity levels, is outlined in this section. It illustrates how information on restaurant amenity may be incorporated into residents' expected utilities.

Housing units are characterized by a vector of n observable attributes, $z_1, ..., z_n$. Most of these attributes are physical characteristics of the housing unit that can be influenced by producers. However, some pertain to the neighborhood and, for notational convenience, the n^{th} attribute is consumption amenity from nearby restaurants.[7]

[7] Consumption amenities from distant restaurants are shared by all housing in the city and is treated as constant

Utility is a function of housing characteristics, z, and a composite commodity, x, whose price is set to unity. Each household maximizes utility subject to the available budget and existing set of prices, represented in equation 2.1, where y is income:

$$\max_{z,x} U(x, z(z_1, ..., z_n)) \text{ subject to } y = p(z) + x. \tag{2.1}$$

The hedonic price function, $p(z) = p(z_1, , z_n)$, reflects consumers' valuation of the attributes, as well as the supply costs of producers. The first order condition concerning the local consumption amenity, z_n, is given in equation 2.2:

$$\frac{\partial p(z)}{\partial z_n} = \frac{U_{z_n}}{U_x}. \tag{2.2}$$

Complications arise when the housing attribute regarding local consumption amenity, z_n, is observed imperfectly. Assume that z_n is a function of the number of good $(H - type)$ and inferior $(L - type)$ restaurants, as in equation 2.3:

$$z_{n_i} = h(N_i^H) + l(N_i^L), \tag{2.3}$$

where N_i^H and N_i^L are the numbers of good and inferior restaurants in neighborhood i respectively. Consumption amenity from restaurants could include quality and variety of food, atmosphere associated with the dining experience, or saving on time to cook. Disamenities arise because restaurants could have undesirable aspects such as noise or crowding, and disagreeable patrons besides having low quality food and service. Assume that good $(H - type)$ restaurants generate more amenity than disamenty, while the reverse may be true for inferior $(L - type)$ restaurants. In other words, h_{N^H} is strictly positive and h_{N^L} is lower than h_{N^H}, and could even be negative. Therefore, the outcome utility level depends not only on the number of restaurants, but their amenity levels.

The term *restaurant amenity* has several dimensions. At its simplest level, it refers to the dining experience itself, i.e. quality of the food and service. At another level it may reflect convenience or atmosphere rather than the culinary achievement of the chef. Given the high cost of "fine dining", it may be that access to restaurants that provide ordinary fare in a cheerful atmosphere for frequent consumption generate more restaurant amenity than those that feature dining in a more formal

across housing units in the model and in my empirical test.

setting. Fortunately, Yelp.com allows one to observe both the cost and the subjective rating of each restaurant so that these elements of restaurant amenity can be evaluated independently.

In the absence of information on restaurant amenity, consumers know the number of restaurants proximate to a unit, N_i, but estimate expected utility based on area averages. To assist the analysis, let $\bar{\sigma_H} = \bar{N_H}/N_i$ denote the average proportion of good restaurants in the area, now rewrite expected z_n for property i with N_i restaurants in the vicinity as in equation 2.4:

$$\hat{z_{n_i}} = h(\bar{\sigma_H} * N_i) + l((1 - \bar{\sigma_H}) * N_i). \tag{2.4}$$

This means that, in the absence of information on restaurant amenity, estimates of z_n may be written as a function of the number of restaurants in a neighborhood. In that case, equation 2.4 collapses to:

$$\hat{z_{n_i}} = r(N_i). \tag{2.5}$$

With significant improvement in the availability of information on neighborhood restaurant amenity brought by Yelp, households are able to obtain information on the amenity of nearby restaurants (i.e. N_i^H and N_i^L , or σ_{H_i}) at low cost (e.g. by looking up restaurants' Yelp ratings online). They can observe the ratings of each restaurant on the web site and update their perceptions of neighborhood restaurant amenity accordingly. They can make similar adjustments to their estimates of z_n according to equation 2.3.

Under the assumption that Yelp ratings reflect the truth about restaurant amenity, the "measurement error" in households' estimates of restaurant amenity in the imperfect information situation is resolved by Yelp.[8] Estimates of restaurant amenity in neighborhood i would rise or fall towards their true value σ_{H_i}. The adjustment from the less-informed case to the well-informed case is the difference between the two expected utilities using z_n as defined in equations 2.5 and 2.3. For houses that have more good restaurants nearby (i.e. $\sigma_{H_i} > \bar{\sigma_H}$), we would expect to see house prices rise, as households adjust their expected utility and willingness-to-pay according to available information on restaurant amenity. In contrast, property values of houses that have fewer

[8]One concern is that business owners know the importance of Yelp ratings, therefore would try to game the system by providing fake reviews. In that case, Yelp ratings would overstate the amenity of restaurants and local businesses alike. This resulting error in the independent variable, restaurant amenity based on their Yelp ratings, would produce attenuation bias in the estimated coefficient and work against my hypothesis that Yelp ratings and the subsequent amenity measures reflect actual restaurant amenity.

good restaurants in the neighborhood (i.e. $\sigma_{H_i} < \bar{\sigma_H}$) are expected to fall with the publication of information on restaurant amenity.

3. Data and Measures

3.1. Restaurant and Housing Data

The analysis is based on two datasets, one with information on residential properties, and the other covering restaurants in D.C.. Housing data come from the D.C. Office of Tax and Revenue (OTR)'s Computer Assisted Mass Appraisal (CAMA) Database, and restaurant data are collected from Yelp.com.

Operating as an online local guide and business review site, Yelp publishes user reviews for local businesses all over the world. I have collected information from Yelp.com, including restaurant names, addresses, Yelp ratings, review counts, and dollar signs (measuring the expected expenditure for a typical meal). Addresses are used to match these restaurants with the properties in the housing sample. The sample includes 2,750 restaurants in the metro D.C. area.[9] Yelp publishes a zero-to-five-star rating (with half-star increments) averaged across all reviews for a restaurant. This is the Yelp measure of restaurant amenity. Year of establishment is also available for most restaurants.[10] The year of establishment information along with the date of each property sale are used to insure that *only* restaurants that *existed* at the time of the transaction are used in constructing the local consumption amenity measures for that property.[11] Table 1 reports descriptive statistics for the restaurant sample, along with the correlation matrix for all restaurant variables.

The assessor dataset contains information on both physical and locational characteristics for most residential property sales in the District from 1980s to the end of 2013. The estimation sample is restricted to units with sale price within the range between the 1^{st} and 99^{th} percentile of the

[9] I restrict the sample to restaurants that are within one mile from at least one unit in the housing transaction dataset. This includes some restaurants in nearby Virginia and Maryland.". For the District of Columbia alone, the National Restaurant Association estimates the total number of "eating and drinking places" at 2,106 as of 2013, suggesting that my sample, and the Yelp listing in general, is comprehensive. Restaurants in my sample are results from searching "'restaurants' near 'Washington, DC'" through all the main restaurant types listed on Yelp.com, based on the web site's default best match sorting criterion. Food trucks and food stands are excluded from the sample, due to their temporary locations.

[10] In some cases, year of establishment was missing. In these cases year of first review was used to estimate age of the restaurant.

[11] Note that in a general restaurant search on Yelp.com, restaurants that are closed are usually not included in the search results. They are only reported when searching with a specific business name.

distribution. Geographical Information System (GIS) techniques are used to locate the properties and match them with neighborhood characteristics. There are 131 well-defined neighborhoods in the District of Columbia, each distinguished by their history, culture, and demographics.[12] To further control for differences in development and planning policies at the sub-neighborhood level, I identify the different zoning areas that each property belongs to and include zoning code fixed effects. Other locational characteristics include distance from each property to its nearest metro station, and to the city center (represented by the Federal Triangle metro station). Structural characteristics include property type;[13] land area of the house; grade and condition of the unit;[14] number of rooms, bedrooms, bathrooms, half-bathrooms, and fireplaces in the unit and so on. Table 2 presents a complete list of the structural characteristics that are included in the regressions.

Google Trends searches with combinations of terms "Yelp" and "DC" are used to identify the time when Yelp.com became a popular online search portal for the D.C. area. The Google Trends results show that the search volume for "Yelp DC" took a large jump from December of 2008 to January of 2009. In light of this result, the period before January 1st, 2009 is defined as pre-Yelp. The pre-Yelp sample includes all transactions between 2004 and 2008, and the post-Yelp sample is for 2009 to 2013. The sample includes in total 28,307 transactions in 119 distinct neighborhoods, and is restricted to properties with at least one restaurant present within a one-mile radius. Summary statistics for both the pre-Yelp period (14,298) and the post-Yelp period (14,009) are reported in Table 2.

3.2. Measures of Local Consumption Amenity using Neighborhood Restaurants

In order to measure the consumption value of nearby restaurants, I identify restaurants within a one-mile radius from each property, and record the Euclidian distances to the house.[15] The one-mile radius should be thought of as the radius of influence when valuing consumption amenities that are local, rather than the maximum of travel distance to a restaurant.[16] Applying a square

[12] Neighborhood definitions are obtained from the D.C. government website, available at `http://opendata.dc.gov/datasets/071aa9b40a1a4b38a938f8f5058068a8_18?filterByExtent=true&uiTab=table`.

[13] Property sales with property types other than single-family house and flat are excluded from the estimation, which amounts to less than 100 observations, including commercial properties, multi-family house, and garage.

[14] Grade is measured on a 12-point scale ranging from "Low Quality" to "Exceptional." Condition is measured on a 5-point scale ranging from "Poor" to "Very Good." Regressions of sale price on both the grade and condition measures confirm the lexicographic nature of the ranking system.

[15] This is achieved using the Stata package `geonear` written by Picard (2010).

[16] It is important to note that there is an unavoidable degree of arbitrariness in setting the radius of study. In Section 6 Robustness Check, I test the sensitivity of the estimation results to the choice of radius using a radius of

market model, which is commonly assumed when studying cities because of the rectangular grid structure of streets, the actual travel distance should be $\sqrt{2}$ times the radius (Arnott and Rowse, 2009). Thus, a radius of one-mile corresponds to a maximum travel distance of approximately 1.44 miles. Based on the estimates provided by Google Maps, this distance is approximately 26 minutes by foot or 6 minutes by car. In constructing these measures for a property, *only* restaurants that were established in the years *before* the sale year of that property are included. Based on my restaurant sample collected from Yelp, the turnover of restaurants in D.C. is about 23 restaurants per year out of a total of 2,750.[17]

3.2.1. Measure of Restaurant Accessibility (N_i)

R_i denotes the total number of restaurants within the radius of one-mile from property i. A successful match between a property i and a nearby restaurant j within the radius is indicated by $d_{i,j} = 1$, while unsuccessful matches are recorded as zeros. The effects of local consumption amenities associated with surrounding restaurants are assumed to be decreasing in distance. Following the conventional construction of accessibility indexes in the literature,[18] the accessibility measure N_i is constructed as the distance-weighted number of restaurants, where each successful match between a property i and a nearby restaurant j is weighted inversely to the θ^{th} power of its Euclidian distance:[19]

$$N_i = \sum_{j=1}^{R_i} \frac{d_{i,j}}{dist_{i.j}^{\theta}}. \tag{3.1}$$

In the baseline case, θ is equal to $1/2$.[20] Given that the study radius is one-mile, distances are measured in feet.[21] N_i is the distance-weighted number of neighborhood restaurants for house i, without distinguishing the amenity level of each restaurant.

0.5-mile (see Table 6).

[17]In the sample, out of the 2,268 restaurants that opened before 2012, 45 closed between November 2013 and January 2014. Overall there is substantial among existing restaurants in D.C..s

[18]See Bhat et al. (2000) for a literature review.

[19]Same results hold under a normal kernel weighting-scheme, with weights equal to $1/2 * exp(dist)^{-2}$.

[20]Results are robust to other θ values such as $1/3$, $1/4$, $1/5$, and 0.

[21]Results are robust to using other distance units such as yard and mile.

3.2.2. Measures of Perceived Restaurant Amenity using Yelp Ratings (H_i and L_i)

The Yelp rating is the average of all ratings by reviewers based on their level of satisfaction with the dining experience. It conveys information on *perceived* restaurant amenity, which facilitates the distinction between good and inferior restaurants for new customers. Given that the average Yelp rating for the restaurant sample is just below 3.5 stars (out of a maximum of 5 stars), those with a rating of 3.5 stars or more are placed in the higher-rating group, indicated by $h_j = 1$, and those with a rating of 3 stars or fewer in the lower-rating group, indicated by $l_j = 1$. Measures for restaurants with higher versus lower ratings are constructed as follows:

$$H_i = \sum_{j=1}^{R_i} \frac{d_{i,j} * h_j}{dist_{i.j}^{\theta}}. \tag{3.2}$$

$$L_i = \sum_{j=1}^{R_i} \frac{d_{i,j} * l_j}{dist_{i.j}^{\theta}}. \tag{3.3}$$

These two measures of *perceived* amenity constitute a decomposition of the N_i measure, i.e. the sum of H_i and L_i equals N_i for each property.

3.2.3. Measures of Expected Restaurant Amenity using Yelp Ratings (E_i and C_i)

Besides Yelp ratings, information on the price range for an average meal is also available in the restaurant data.[22] Berry and Waldfogel (2010) argue that, in the restaurant industry, quality is mainly produced through variable cost, rather than fixed cost. The implication is that an increase in the meal price should be, if not perfectly, proportionally compensated by an increase in the quality of the food and service. In that sense, information on expenditure level could correspond to *expected* restaurant amenity. With the average expenditure level indicator for the restaurant sample being slightly lower than $$ (out of a maximum of $$$$), I classify those with $$$ or $$$$ in the higher-cost group, indicated by $e_j = 1$, and those with $ or $$ in the lower-cost group, indicated by $c_j = 1$. Measures for the distance-weighted number of restaurants with higher versus lower cost

[22] According to Yelp.com: "Price range is the approximate cost per person for a meal including one drink, tax and tip. $= under $10; $$= $11-$30; $$$= $31-$60; $$$$= above $61."

are constructed similarly as above:

$$E_i = \sum_{j=1}^{R_i} \frac{d_{i,j} * e_j}{dist^{\theta}_{i.j}}. \tag{3.4}$$

$$C_i = \sum_{j=1}^{R_i} \frac{d_{i,j} * c_j}{dist^{\theta}_{i.j}}. \tag{3.5}$$

These two measures of *expected* amenity constitute another decomposition of the N_i measure, i.e. the sum of E_i and C_i equals N_i for each property. Table 3 reports summary statistics for these five measures.

4. Empirical Strategy

A major obstacle in measuring the implicit prices of local amenities is that variation in the local amenity may be correlated with neighborhood unobservables.[23] For this study specifically, the covariance of restaurant location and both observable and unobservable neighborhood characteristics makes it difficult to measure the value of local restaurants by comparing areas with restaurants with areas without them. Therefore, I exclude houses with no restaurants nearby from the estimation, and focus on variations in house prices among those have at least one restaurant nearby.[24]

Figures 1 and 2 map the spatial distribution of restaurants by neighborhood and the average residential property value by neighborhood for D.C., respectively, and show rather different spatial patterns. Restaurants tend to cluster in the central business/employment district, with Golden Triangle ranking at the top with 101 restaurants, followed by Dupont Circle (90), Downtown (70), and Georgetown (69).

In addition, I include neighborhood-year fixed effects in all regressions to control for any unobserved trend that affects house prices at the neighborhood level. With these neighborhood-year fixed effects, I am able to compare the value of home sales within very small areas in which the housing stock is more homogenous than in the usual aggregate comparisons, and exploit modest variations in both the quantity and amenity of neighborhood restaurants for houses that are sold in the same year. This notion is illustrated by Figure 3, which shows the locations of two houses in

[23] See Bartik (1987) and Epple (1987) for theoretical discussions.
[24] About 0.5% of the sample is dropped under this restriction.

the same neighborhood, and two circles that outline all restaurants located within 1 mile of each house.

4.1. Capitalization of Local Consumption Amenities

The empirical analysis is implemented in two steps. First, I test the hypothesis that local consumption amenities, characterized by neighborhood restaurants of *any* amenity, are capitalized into nearby home values. Second, I add information on restaurant amenity to the regressions, and compare the capitalization effects in these different cases to see (i) whether information on restaurant amenity matters, and (ii) what type of information about restaurant amenity matters most.

The major goal of this study is to determine whether measures of the quality aspect of local amenities are capitalized into local real estate values. Having information on quality publicly available to home buyers is a crucial element of the research design. If differences in restaurant amenity, measured by Yelp ratings, were capitalized into property values before these ratings were made public, this might imply either that the information in the Yelp ratings was well known or that the empirical model is misspecified. For example, Yelp ratings could reflect general attitudes toward the neighborhood rather than amenity of specific restaurants. Alternatively, there could be problems of simultaneous equations bias if higher property values were causing better Yelp ratings.

However, if Yelp rating effects only appear after the Yelp site is widely used, this before versus after difference eliminates issues of omitted variables (unless they changed just as Yelp use spread) and reverse causality from housing value to restaurant ratings. This research design in which publication of information is the basis for amenity capitalization was used by Figlio and Lucas (2004). They find that making school quality information public has a substantial effect on local property values, even though quality differences among local schools presumably existed before test scores and ratings were published.

4.1.1. Step I - Consumption Value of Restaurant Accessibility

In the first step, I examine whether accessibility to neighborhood restaurants, regardless of their levels of amenity, is capitalized into nearby home values. In order to examine separately the capitalization effects of local restaurants for the pre- and post-Yelp periods, I estimate equation 4.1:

$$lnValue_{ijyzs} = \mu + \alpha_{jy} + \delta_s + \lambda_z + \beta X_i + (1 - Y_y) * \gamma_1 N_i + Y_y * \gamma_2 N_i + \epsilon_{ijysz}, \qquad (4.1)$$

where $lnValue_{ijys}$ is the logarithm of sale price for property i in zone s neighborhood j sold in year y season s, α_{jy} are neighborhood-year fixed effects, δ_s are sale season fixed effects, λ_z are zone code fixed effects, X_i is a vector of both locational and structural characteristics listed in Table 2, and Y_y is an indicator of being in the post-Yelp period.[25] Following Coulson (2008), polynomials (up to the third power) of the variable *age* are included in attempt to capture the nonlinearities in the age effects, such as depreciation effects, survival effects, and vintage effects. The regression coefficients γ_1 and γ_2 captures the capitalization effect of the quantity or accessibility measure of neighborhood restaurants for the pre- and post-Yelp periods, respectively.

4.1.2. Step II - Consumption Value of Restaurant Amenity: Perceived vs. Expected

In the second step, I focus on the potential heterogeneity in restaurant amenity and the resulting differences in household valuation of the consumption amenities. I explore the heterogeneity along two dimensions using two different restaurant amenity measures.

First, using restaurant amenity measures constructed with the Yelp ratings, I examine whether *perceived* amenity of nearby restaurants translates into surrounding property values. Equation 4.2 includes the H and L measures separately:

$$lnValue_{ijysz} = \mu + \alpha_{jy} + \delta_s + \lambda_z + \beta X_i + (1 - Y_y) * (\eta_1 H_i + \pi_1 L_i) + Y_y * (\eta_2 H_i + \pi_2 L_i) + \epsilon_{ijysz}. \quad (4.2)$$

As before, the regression coefficients η and π captures the capitalization effects of neighborhood restaurants with higher and lower *perceived* amenity levels separately, while the subscripts 1 and 2 represent the pre- and post-Yelp periods, respectively.

A graphical illustration of the comparison between equations 4.1 and 4.2 is depicted in Figure 3. Consider two otherwise identical houses located in the same neighborhood, with the same number of neighborhood restaurants located nearby. It is also clear from Figure 1 that these two houses have the same accessibility to neighborhood restaurants (i.e. $N_1 = N_2$). However, house 1 has four restaurants with lower ratings and one with higher rating within the radius. While three out of five restaurants near the house 2 have higher ratings, and only one has lower rating. In this comparison, the only difference between the two houses is the composition of neighborhood restaurants in terms

[25] I also allow the coefficients on all of the control variables to be different for the pre- and post-Yelp periods, by including the same interaction terms as that of the restaurant measure with all of the control variables.

of *perceived* amenity. Therefore, after controlling for all structural and locational characteristics, the remaining price differences are attributed to the difference in the *perceived* amenity of local consumption amenities as measured by H and L.

Second, I explore the possibility of heterogeneous capitalization effects in the *expected* amenity of restaurants, based on the expenditure index. This exercise is also designed to examine the possibility that the positive capitalization effect of high amenity restaurants is due to an association between locations of high cost restaurants and high value properties. Equation 4.3 with the expected amenity measures, E and C, is specified as follows:

$$lnValue_{ijysz} = \mu + \alpha_{jy} + \delta_s + \lambda_z + \beta X_i + (1 - Y_y) * (\kappa_1 E_i + \phi_1 C_i) + Y_y * (\kappa_2 E_i + \phi_2 C_i) + \epsilon_{ijysz}. \quad (4.3)$$

One concern about this analysis could be the possibility that high amenity restaurants might be more expensive and tend to locate in areas where property values are higher, in which case, the *perceived* amenity measures and the *expected* amenity measures would convey the same information about neighborhood restaurants, and the estimates of η and π in equation 4.2 would be identical to those of κ and ϕ in equation 4.3. As a first step in addressing such concern, I report the correlation matrix among all restaurant variables in Table 1. A restaurant's Yelp rating and its expenditure level have a correlation coefficient of 0.147. The modest magnitude of the correlation between a restaurant's Yelp rating and its expenditure level confirm that these two measures convey different information. This will become further apparent later in the paper. It is also understandable because Yelp ratings are based on consumers' satisfaction with the dining experience, and thus reflect the price-quality ratio or atmosphere of the restaurant rather than the absolute quality of the food. If anything, consumers are likely to have higher expectations for upscale restaurants and, therefore, be less lenient in their reviews.

4.2. Effects of Information on Capitalization of Local Consumption Amenity

Before Yelp, homebuyers, and consumers in general, had limited knowledge of the amenity of neighborhood restaurants. The H and L measures for the pre-Yelp period serve as rather imperfect measures of private information at the time when public information on restaurant amenity was not easily accessible. By making the restaurant ratings public, Yelp creates an information channel through which the quality aspect of local consumption amenities is further capitalized into nearby home values. Based on the theoretical discussion in Section 2, by providing information on local business quality, Yelp reduces the "measurement error" in people's estimates of neighborhood restaurant amenity and assists them in distinguishing between good versus inferior restaurants. As a result, homebuyers' estimates of neighborhood restaurant amenity rise or fall towards the true values, and their expected utility and willingness-to-pay for local consumption amenities adjust accordingly, as reflected in the differences in the estimated coefficients on H and L for pre- and post-Yelp samples.

However, given that all restaurant data are collected in the post-Yelp period, it is possible that the constructed measures may not reflect local consumption amenities for the pre-Yelp period. It is possible that restaurant amenity changed over time. Indeed, some restaurants might change their behavior in response to consumer ratings and comments on Yelp. For the pre-Yelp period, the possibility that restaurants changed their behavior in response to their earlier Yelp ratings is one reason to suspect that ratings from the post-Yelp period might not indicate pre-Yelp status of the restaurant amenity. However, such restaurants may have arrived at their fixed level of amenity in the post-Yelp period, the statistical analysis assumes that the changes were not made to raise local house prices.

5. Estimation Results

Regression results for equations 4.1 through 4.3 are presented in Table 4. Column 1 reports results for equation 4.1 which examines the capitalization effect of accessibility to local restaurants, measured by N. Column 2 presents results for equation 4.2 where N is decomposed into two separate measures, H and L, based on the *perceived* amenity of restaurants. Column 3 reports results for the capitalization of local consumption amenities using the *expected* restaurant amenity measures, E and C, according to equation 4.3. All regressions include the structural and locational characteristics controls listed in Table 2, neighborhood-year fixed effects, sale season fixed effects, and zone code fixed effects. The numbers of observations and neighborhood-year fixed effects in each regression are reported towards the bottom of all tables, along with the adjusted R-squared. Robust standard errors are reported.[26]

As discussed above, during the pre-Yelp period, there was imperfect information on restaurant

[26] Results are robust to allowing for correlations between the error terms for observations in the same neighborhood sold in the same year (see Table 7).

amenity, or at least such information was not available from Yelp. Therefore, in the pre-Yelp period, households are able to observe the number of nearby restaurants (N), but have imperfect information on restaurant amenity. In other words, households observe H and L, and even, E and C, with "measurement error". Capitalization effects of different aspects of restaurant amenity in the pre- versus post-Yelp periods are reported by the coefficients of the interaction terms between different restaurant amenity measures and the pre-Yelp and post-Yelp indicators.

Comparing the estimated coefficients of these three sets of the local consumption amenity measures, namely quantity (N), perceived amenity (H and L) and expected amenity (E and C), across equations 4.1, 4.2, and 4.3, the patterns suggest three broad generalizations.

(i) Quantity of nearby restaurants is positively reflected in nearby house values in both periods. From column 1 of Table 4, the results show that a one-standard-deviation increase in N in the pre-Yelp period, on average, is associated with a 6.26% increase in property value.

(ii) Differences in *perceived* restaurant amenity are only capitalized into nearby housing values during the post-Yelp period. The estimated coefficients of *pre-Yelp*H* and *pre-Yelp*L* are virtually identical, indicating no differential quality effect. As noted above, the post-Yelp measures for *perceived* amenity might not be as accurate presentations of the pre-Yelp perceptions of restaurant amenity. Nonetheless, in the post-Yelp period, presence of restaurants with higher Yelp ratings in the locality is positively capitalized into nearby house prices, while lower amenity establishments have a non-significant capitalization effect. According to the estimated coefficient of *post-Yelp*H* in column 2 of Table 4, a one-standard-deviation increase in H in the post-Yelp period is associated with a 9.48% increase in home value. These results indicate that Yelp ratings are not correlated with an omitted variable that influences housing values, as there is no such effect in this period before full Yelp treatment. In addition, the concern that housing value might be causing high amenity restaurants to locate in an area, i.e. the reverse causality problem that high house price neighborhoods generate higher Yelp ratings, is inconsistent with the finding that higher Yelp ratings are not related to house value in the period before Yelp was widely used by the public.

(iii) Estimation results using restaurant amenity measures constructed from expenditure indicators show a significant contrast, compared to those constructed using Yelp ratings. Specifically, the number of expensive restaurants shows no statistically significance relative to property values, whereas the number of lower cost restaurants is positive related to home values. Unlike perceptions of amenity on Yelp, information on cost are available from a variety of public sources. Accordingly, the availability and use of Yelp may have, at most, augmented or confirmed information available from other public sources. Moreover, the results with expected amenity measures should be viewed as evidence to ease the concern over the possibility that results are driven by concentration of high cost restaurants in high income neighborhoods.

The difference in the results for the pre- versus post-Yelp periods suggests that, in the pre-Yelp period, the capitalization effects of restaurants with higher versus lower Yelp ratings are not consistent with their levels of perceived amenity. The validity of this conclusion depends on the proximity or accuracy of the constructed measures to the true level of local consumption amenities at the time. If the constructed measures reflect the level of local consumption amenities in the pre-Yelp period, this result suggests that local consumption amenities were not properly capitalized into nearby property values due to lack of information on the amenity of local restaurants. In this case, the inconsistent results can be viewed as evidence for the hypothesis that before Yelp publishes restaurant amenity information online, people have imperfect information on restaurant amenity and are subject to "measurement error" in their estimations. This finding is consistent with the Figlio and Lucas (2004) result that publication of school grades based on student test scores has a substantial and immediate effect on surrounding property values. Another possibility is that the constructed measures were not reflective of the true level of local consumption amenities associated with neighborhood restaurants at the time. It is possible that private information on local restaurant amenity existed and was incorporated into households' expected utility and willingness-to-pay. If that is the case, the estimates indicate that the *perceived* amenity of local restaurants was not measured by post-Yelp ratings. Unfortunately, the available restaurant data limits empirically testing to distinguish between the two alternative explanations.

6. Robustness Checks

Because the amenity measures are sensitive to the number of restaurants in an area, the first robustness test restricts the sample of housing transactions to include only properties with at least 5 restaurants within a one-mile radius. Results reported in Table 5 are largely consistent with the bench mark results reported in Table 4. Accessibility to neighborhood restaurants (N) is positively capitalized into nearby home values. Houses that have more restaurants with higher levels of *perceived* amenity (H), rather than higher levels of *expected* amenity (E) is have higher sale prices, but the effect is only significant in the post-Yelp period when information on restaurant amenity are easily accessible.

It is difficult to select the "optimal" radius for studying the value of local consumption amenities. In order to ease the concern about the effect of variations in population density across D.C., I reconstruct all five measures for local consumption amenities (N, H, L, E, and C) using a radius of 0.5-mile, instead of one-mile, to test the sensitivity of the estimation results to the choice of radius. Results for estimating equations 4.1, 4.2, and 4.3 are reported in Table 6, and show the same pattern as those with the one-mile radius measures.[27] Robustness check test results using a smaller radius confirm that consumption amenities are valued at a very local level. The pre-Yelp results with *perceived* amenity measures at a 0.5-mile radius are consistent with those for the post-Yelp period.

7. Conclusions

In this paper, I examine the relation between variations in local consumption amenities and property values at the neighborhood level, and present empirical evidence for the importance of consumption amenities for local property valuation.

In the current literature, local amenities other than public schools, are generally characterized by quantity in a geographic area rather than quality. This divide in the literature is likely due to the difficulty in obtaining consistent measures of quality for local goods, other than test results and other student achievement measures available for public schools. Given the heterogeneity of local goods, particularly private goods, it is hard to imagine that local home buyers ignore the quality dimension of local consumption amenities.

Relying on data collected from Yelp.com on restaurants in the metro D.C. area, I construct different measures of local consumption amenities provided by neighborhood restaurants. With the constructed measures, I explore the link between local restaurant amenity and surrounding housing values, conditional on other locational and structural characteristics. The results confirm that both the quantity and quality aspects of consumption amenity matter. By including the local consumption amenities measures for restaurants with higher and lower amenity separately, I demonstrate the heterogeneity in the capitalization effects of neighborhood restaurants that vary in their level

[27]For a clearer comparison, the estimation sample is restricted to properties with at least one restaurants in a one-mile radius as in the bench mark case. Results are robust to using a more restricted sample such as properties with at least one restaurants in a 0.5-mile radius.

of amenity. When incorporating the information on restaurant amenity, I find that the presence of more restaurants with higher *perceived* amenity, rather than *expected* amenity, is associated with higher values of nearby properties. This result suggests that the "micro consumer neighborhoods" which are much valued by homebuyers, are characterized by clusters of well-reviewed restaurants, rather than clusters of expensive ones. From the perspective of neighborhood development, it appears that rather than simply increasing the numbers of restaurants or the number of expensive restaurants, the key to raising local consumption amenity values is to increase the number of restaurants with higher perceived amenity given their cost.

This paper demonstrates that information on consumption amenities, collected from sites such as Yelp.com, can be used as an implicit markets measure of the value of these amenities, and has an effect on sale prices of nearby properties. It also establishes that these effects on property valuation can be substantial. Using information collected from review sites like Yelp, it is possible to construct consistent measures of amenity for other private consumption goods and services. Studies of the implicit value of local public goods including neighborhood parks and libraries, etc. could also benefit from inclusion of consumer ratings or reviews. There are two cautionary lessons from this exercise. First, when measuring amenities from local businesses, it is important to realize that their expenditure levels might not represent their local amenity values. Second, for information on local amenities to be properly capitalized, it must be that such information are easily accessible and actively used by individuals in the areas under study.

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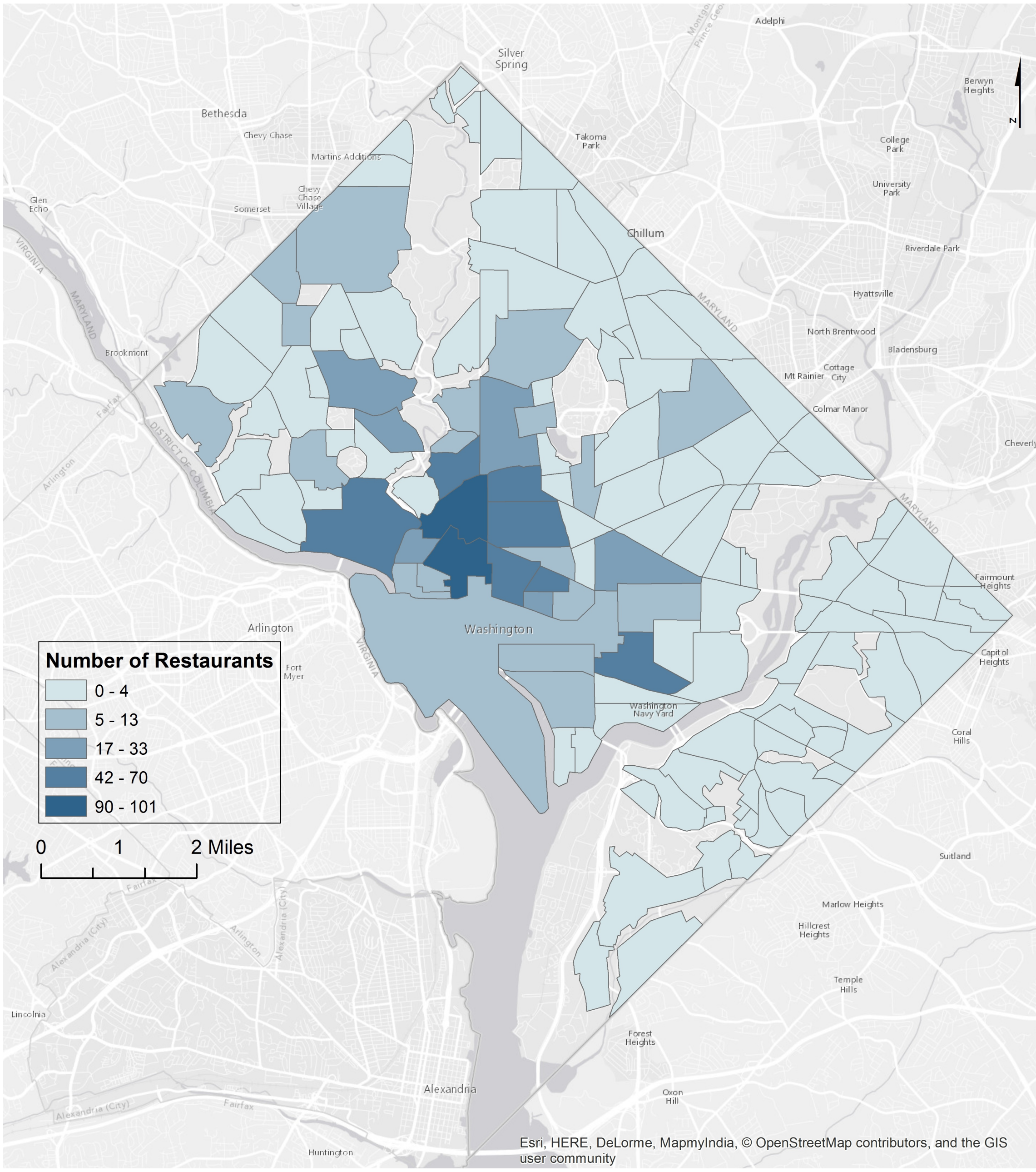
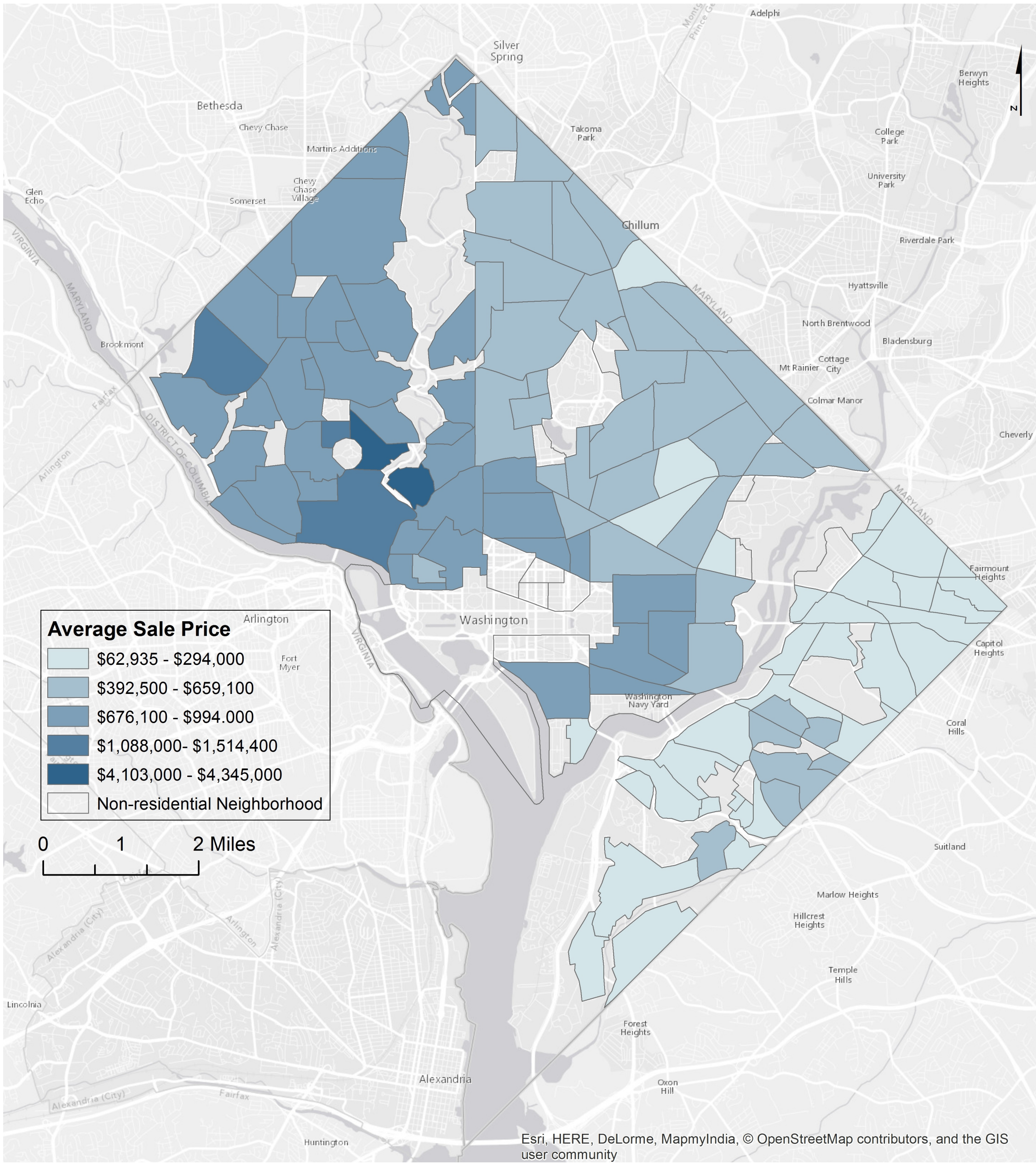
Figure 1: The Spatial Distribution of D.C. Restaurants by Neighborhood



Notes: The five classes shown are selected by the Jenks natural breaks classification method, which is a data clustering method that seeks to minimize variance within classes and maximize the variance between classes.

Figure 2: The Spatial Distribution of D.C. Residential Property Values by Neighborhood



Notes: The five classes shown are selected by the Jenks natural breaks classification method, which is a data clustering method that seeks to minimize variance within classes and maximize the variance between classes.

Figure 3: Illustration of Step I Analysis - Differences in Local Consumption amenities

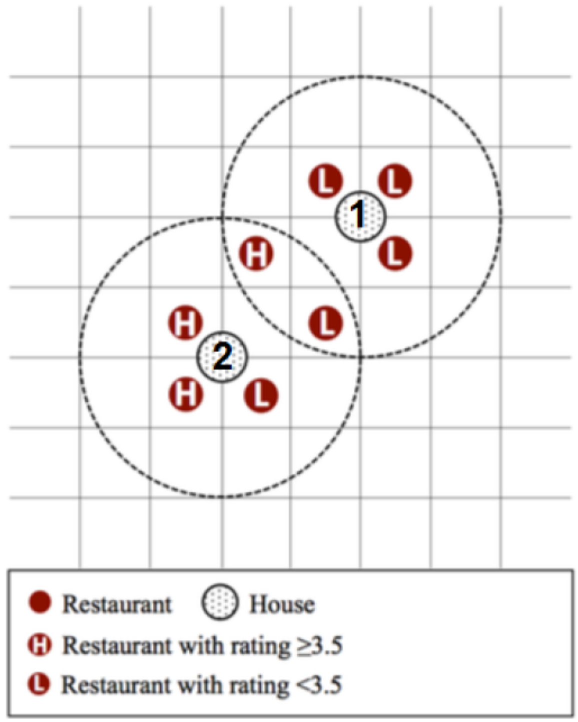


Table 1: Descriptive Statistics and Correlation Matrix for Restaurant Data

Variable	*Mean*	*Std Dev*	1	2	3	4
1. Yelp rating	3.319	0.717	1			
2. Expenditure level	1.712	0.709	0.147***	1		
3. Years of operation	5.942	7.653	0.013	0.141***	1	
4. Number of reviews	133.164	240.942	0.208***	0.272***	0.317***	1

Notes: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 2: Descriptive Statistics for Housing Data

	pre-Yelp				post-Yelp			
	Mean	*Std Dev*	*Min*	*Max*	*Mean*	*Std Dev*	*Min*	*Max*
lnValue	12.958	0.657	10.714	14.705	13.045	0.694	10.714	14.694
lnLandArea	7.772	0.648	5.684	12.140	7.728	0.671	5.591	10.535
Distance to nearest metro	0.694	0.404	0.029	2.190	0.6802	0.405	0.019	2.203
Distance to city center	3.518	1.342	0.803	7.019	3.377	1.355	0.802	7.056
Flat type indicator	0.158	0.365	0	1	0.142	0.349	0	1
Age of unit	80.201	29.897	1	249	82.187	29.832	0	238
Grade of unit	4.176	1.267	1	12	4.285	1.303	2	11
Condition of unit	3.594	0.675	1	6	3.804	0.711	1	6
# of bathrooms	2.061	1.000	0	10	2.291	0.978	0	11
# of half-bathrooms	0.613	0.608	0	4	0.670	0.584	0	11
# of rooms	7.303	2.241	1	24	7.350	2.229	1	30
# of fireplaces	0.600	0.856	0	11	0.660	0.883	0	10
# of observations	14,298				14,009			

Notes: The estimation sample includes 28,307 housing sales transactions for 2004 to 2013. Sale price and land area enter the regression as their logarithms transformations (*lnValue* and *lnLandArea*). *Distance to nearest metro* is the distance in miles from each house to its nearest metro station. *Distance to city center* is the distance in miles from each house to the city center (represented by the Federal Triangle metro station). *Grade of unit* is a multinomial variable whose value ranges from 1 (poor quality) to 12 (exceptional), with higher value corresponding to higher grade of the house. *Condition of unit* is also a multinomial variable whose value ranges from 1 (poor) to 6 (excellent), with higher value corresponding to better condition of the housing unit. The rest of the structural characteristics include numbers of bathrooms, half bathrooms, rooms, and fireplaces in each housing unit, as well as the age of a housing unit.

Table 3: Descriptive Statistics for Local Consumption Amenity Measures

	pre-Yelp				post-Yelp			
	Mean	*Std Dev*	*Min*	*Max*	*Mean*	*Std Dev*	*Min*	*Max*
N	0.621	0.963	0.014	8.780	1.691	2.174	0.014	15.868
H	0.204	0.487	0	4.565	0.839	1.216	0	8.823
L	0.417	0.511	0.014	4.502	0.851	0.981	0.014	7.358
E	0.037	0.106	0	1.168	0.116	0.264	0	2.218
C	0.584	0.872	0.014	7.668	1.575	1.942	0.014	13.651

N is the distance-weighted number of restaurants. H is the distance-weighted number of restaurants with higher *perceived* amenity. L is the distance-weighted number of restaurants with lower *perceived* amenity. E is the distance-weighted number of restaurants with higher *expected* amenity. C is the distance-weighted number of restaurants with lower *expected* amenity.

Table 4: Capitalization of Local Consumption Amenities

	lnValue		
	Accessibility	*Perceived* Amenity	*Expected* Amenity
	(1)	(2)	(3)
*pre-Yelp*N*	0.065***		
	(0.010)		
*post-Yelp*N*	0.045***		
	(0.004)		
*pre-Yelp*H*		0.068**	
		(0.032)	
*pre-Yelp*L*		0.062**	
		(0.029)	
*post-Yelp*H*		0.078***	
		(0.014)	
*post-Yelp*L*		0.005	
		(0.017)	
*pre-Yelp*E*			0.023
			(0.094)
*pre-Yelp*C*			0.070***
			(0.017)
*post-Yelp*E*			-0.036
			(0.030)
*post-Yelp*C*			0.058***
			(0.006)
Constant	10.640***	10.652***	10.627***
	(0.069)	(0.069)	(0.069)
# of neighborhood-year FE	1,131	1,131	1,131
# of observations	28,307	28,307	28,307
Adjusted R-squared	0.848	0.848	0.848

Notes: *pre-Yelp* refers to 2004-2008, the period before Yelp.com became a popular search site for restaurants in D.C.. *post-Yelp* refers to 2009-2013. N is the distance-weighted number of restaurants. H is the distance-weighted number of restaurants with higher *perceived* amenity. L is the distance-weighted number of restaurants with lower *perceived* amenity. E is the distance-weighted number of restaurants with higher *expected* amenity. C is the distance-weighted number of restaurants with lower *expected* amenity. All regressions include the control variables listed in Table 2, as well as sale season fixed effects and zone code fixed effects. Robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Capitalization of Local Consumption Amenities
(restricted house sample with more than 5 restaurants within one mile)

	lnValue		
	Accessibility	*Perceived* Amenity	*Expected* Amenity
	(1)	(2)	(3)
*pre-Yelp**N*	0.060***		
	(0.010)		
*post-Yelp**N*	0.045***		
	(0.004)		
*pre-Yelp**H*		0.050	
		(0.032)	
*pre-Yelp**L*		0.070**	
		(0.030)	
*post-Yelp**H*		0.074***	
		(0.014)	
*post-Yelp**L*		0.009	
		(0.017)	
*pre-Yelp**E*			-0.005
			(0.095)
*pre-Yelp**C*			0.069***
			(0.017)
*post-Yelp**E*			-0.038
			(0.030)
*post-Yelp**C*			0.058***
			(0.006)
Constant	10.656***	10.664***	10.640***
	(0.072)	(0.072)	(0.072)
# of neighborhood-year FE	1,019	1,019	1,019
# of observations	24,909	24,909	24,909
Adjusted R-squared	0.841	0.841	0.841

Notes: *pre-Yelp* refers to 2004-2008, the period before Yelp.com became a popular search site for restaurants in D.C.. *post-Yelp* refers to 2009-2013. N is the distance-weighted number of restaurants. H is the distance-weighted number of restaurants with higher *perceived* amenity. L is the distance-weighted number of restaurants with lower *perceived* amenity. E is the distance-weighted number of restaurants with higher *expected* amenity. C is the distance-weighted number of restaurants with lower *expected* amenity. All regressions include the control variables listed in Table 2, as well as sale season fixed effects and zone code fixed effects. Robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Capitalization of Local Consumption Amenities
(at a 0.5-mile radius)

	lnValue		
	Accessibility	*Perceived* Amenity	*Expected* Amenity
	(1)	(2)	(3)
*pre-Yelp*N*	0.124***		
	(0.018)		
*post-Yelp*N*	0.074***		
	(0.007)		
*pre-Yelp*H*		0.233***	
		(0.042)	
*pre-Yelp*L*		0.023	
		(0.041)	
*post-Yelp*H*		0.131***	
		(0.018)	
*post-Yelp*L*		0.001	
		(0.022)	
*pre-Yelp*E*			-0.020
			(0.115)
*pre-Yelp*C*			0.139***
			(0.024)
*post-Yelp*E*			0.057
			(0.046)
*post-Yelp*C*			0.076***
			(0.009)
Constant	10.733***	10.761***	10.732***
	(0.068)	(0.068)	(0.068)
# of neighborhood-year FE	1,131	1,131	1,131
# of observations	28,307	28,307	28,307
Adjusted R-squared	0.848	0.848	0.848

Notes: *pre-Yelp* refers to 2004-2008, the period before Yelp.com became a popular search site for restaurants in D.C.. *post-Yelp* refers to 2009-2013. N is the distance-weighted number of restaurants. H is the distance-weighted number of restaurants with higher *perceived* amenity. L is the distance-weighted number of restaurants with lower *perceived* amenity. E is the distance-weighted number of restaurants with higher *expected* amenity. C is the distance-weighted number of restaurants with lower *expected* amenity. All regressions include the control variables listed in Table 2, as well as sale season fixed effects and zone code fixed effects. Robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Capitalization of Local Consumption Amenities
(standard errors clustered at the neighborhood-year level)

	lnValue		
	Accessibility	*Perceived* Amenity	*Expected* Amenity
	(1)	(2)	(3)
*pre-Yelp*N*	0.065***		
	(0.020)		
*post-Yelp*N*	0.045***		
	(0.008)		
*pre-Yelp*H*		0.068	
		(0.054)	
*pre-Yelp*L*		0.062	
		(0.042)	
*post-Yelp*H*		0.078***	
		(0.025)	
*post-Yelp*L*		0.005	
		(0.027)	
*pre-Yelp*E*			0.023
			(0.139)
*pre-Yelp*C*			0.070**
			(0.029)
*post-Yelp*E*			-0.036
			(0.049)
*post-Yelp*C*			0.058***
			(0.011)
Constant	10.640***	10.652***	10.627***
	(0.082)	(0.082)	(0.083)
# of neighborhood-year FE	1,131	1,131	1,131
# of observations	28,307	28,307	28,307
Adjusted R-squared	0.848	0.848	0.848

Notes: *pre-Yelp* refers to 2004-2008, the period before Yelp.com became a popular search site for restaurants in D.C.. *post-Yelp* refers to 2009-2013. N is the distance-weighted number of restaurants. H is the distance-weighted number of restaurants with higher *perceived* amenity. L is the distance-weighted number of restaurants with lower *perceived* amenity. E is the distance-weighted number of restaurants with higher *expected* amenity. C is the distance-weighted number of restaurants with lower *expected* amenity. All regressions include the control variables listed in Table 2, as well as sale season fixed effects and zone code fixed effects. Robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.