Distance decreases with differentiation: Strategic agglomeration by retailers

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Abstract

Theory predicts intense price competition results when firms cluster with rivals. Yet, strong evidence of clustering is found in previous empirical research. Researchers typically measure clustering by comparing observed location patterns to random assignment. The random assignment benchmark does not, however, account for zoning and geography and therefore might overstate the extent of strategic agglomeration. As evidence, we find that public elementary schools cluster more than random, not because of agglomeration economies, but due to demand density and limited location options. We argue that a better measurement of strategic agglomeration is to compare across product markets with similar zoning and other location restrictions but different benefits from agglomeration. We use L-function analysis of five product markets in five cities. We find that retailers with greater ability to differentiate their products are more likely to strategically cluster.

1. Introduction

Business location affects business competition. We examine whether retailers locate near rivals for strategic reasons or because of exogenous factors such as roads, geography and zoning. Furthermore, we examine how the degree of agglomeration depends on firms’ ability to differentiate their products.

Both demand and supply factors influence firms’ incentives to cluster. On the supply side, firms cluster to learn from other firms how to improve manufacturing and research productivity (Glaeser et al., 1992; Shaver and Flyer, 2000; Furman et al., 2006). Alcácer (2006) builds on Ellison and Glaeser (1997) to show that research activities are more likely to cluster than production and sales. Firms also cluster to learn about demand from other firms which decreases the cost of searching for the optimal firm location (Caplin and Leahy, 1998; Ridley, 2008). Firms cluster to pool labor and other inputs (Marshall, 1920; Rosenthal and Strange, 2001). Firm agglomeration can result from spinoffs that locate near parent firms (Buenstorf and Klepper, in press; Klepper, 2007). One cost of agglomeration is that agglomeration also facilitates rivals’ learning which could hurt profits (Shaver and Flyer, 2000).

On the demand side, firms cluster due to lumpy demand, to locate near consumers attracted by the marketing or reputation of rivals (Chung and Kalnins, 2001), to attract consumers searching for optimal product characteristics (Wolinsky, 1983; Fischer and Harrington, 1996; Konishi, 2005), and to provide a credible commitment to low prices (Dudley, 1990). A cost of agglomeration on the demand side is that agglomeration increases price competition (D’Aspremont et al., 1979; Eaton and Lipsey, 1989). Price wars can be avoided by repeated interaction over time (Tirole, 1988) or across retail outlets (Vroom and Gimeno, 2007). Furthermore, price competition can be mitigated by differentiating product offerings (Fischer and Harrington, 1996; Baum and Hayeman, 1997; Fujita and Thisse, 2002; Dranove et al., 2003). If sellers can offer differentiated products, then they can enjoy the benefits of agglomeration without competing too intensely on price.1

In general, empirical agglomeration studies have focused on the supply side, defined markets at a state or national level, and focused
on a single industry. This approach is appropriate for studies of industries that compete on a national scale, such as manufacturing. In contrast, we focus on the demand side, define the market within a city, and compare multiple industries to differentiate between strategic clustering and limited location choices. We argue that our approach is appropriate for studies of localized competition, such as retail markets.

We use precise location data to look inside multiple cities at how retail agglomeration varies across product markets. The product markets we examine have similar zoning, geographic restrictions, and consumer locations, but different incentives to cluster. We examine more than one product market to better identify retailers’ strategic incentives to cluster based on retail type. Furthermore, we examine multiple cities to examine whether effects are city-specific or more general. We examine onsite alcohol retailers (e.g., bars, restaurants) and offshore retailers (e.g., liquor stores, grocery stores) in five geographically dispersed cities in the United States. We also compare these to agglomeration by public elementary schools to illustrate why traditional agglomeration measures can be misleading.

By comparing agglomeration across multiple retail product markets, we can gain a better understanding of whether agglomeration is strategic or results from limited location options. In general, theoretical studies of business location are more supportive of dispersion by firms avoiding intense price competition (Irmen and Thissen, 1998), but empirical studies tend to find more evidence of agglomeration (Netz and Taylor, 2002). We hypothesize that the discrepancy between the theoretical literature which predicts dispersion and the empirical literature which finds evidence of agglomeration might be due in part to the challenge of identifying whether retailers are near one another for strategic reasons, or because zoning, roads, and waterways limit their options. Firms might prefer to disperse (consistent with theory), but appear to cluster in empirical analysis because of a limited location choice set.

We examine retailers with varying degrees of product differentiation. Restaurants have the greatest potential for product differentiation on menu, ambience, and waiting time for service. Bars, like restaurants, have considerable ability to differentiate their products, and have spillover benefits from proximity to rivals if consumers enjoy visiting multiple bars in one evening. At the other end of the spectrum are liquor stores which sell the same high-volume products and have the least potential for product differentiation. Consumers tend to shop for offsite liquor based on location and price, particularly if prices are advertised (Millyo and Waldfogel, 1999).

We focus on the relationship between product differentiation and agglomeration, but as we described above there are other forces that affect retail agglomeration. In the case of alcohol retailers, if people who visit bars are more clustered (in residences or work places) than people who visit liquor stores, then we would expect bars to cluster more. Our theoretical model includes benefits from agglomeration. Our empirical strategy compares across parts of the city to investigate whether the results are driven by a few parts of the city and to control for uneven demand. After accounting for uneven demand we still find evidence that the product differentiation effect persists.

We begin with the assumption that a retailer’s ability to differentiate is exogenous (liquor stores can only do so much to be different from rivals) and business location is endogenous (liquor stores choose to disperse from rivals to avoid price competition). In contrast, Jaffe (1986) and Alcácer and Zhao (2007) assume that manufacturer location is exogenous and manufacturers choose to differentiate their technology based on proximity to other manufacturers.

The remainder of the paper is organized as follows. In Section 2 we use a simple theoretical model to predict which product markets have sellers that are more agglomerated. We hypothesize that retailers cluster more when products are more differentiated, spillovers are positive, and demand is uneven. Section 3 describes L-functions and why we believe it is useful to compare L-functions across product markets when measuring agglomeration. Section 4 describes the location data for five U.S. cities. Section 5 describes the five main results. We include a robustness check that accounts for other reasons for agglomeration beyond product differentiation. We look within a city and find that onsite seller cluster more than offsite sellers in nearly every area of the city. We also look within onsite and offsite sellers and find that bars exhibit the highest degree of agglomeration, followed by restaurants that sell alcohol, then offsite retailers. Section 6 concludes.

2. Simple theory of agglomeration

We develop a simple theoretical model to predict retail agglomeration as a function of product differentiation, positive spillovers, and uneven demand. In the model, an entrant chooses proximity to an incumbent. The closer the firms the more they affect one another’s demand.

Formally, firm 1 observes the location of firm 1 and locates distance $d \in (0, L)$ away. Each firm $i$ then competes a la Cournot by choosing output $q_i$ to maximize profits $p_i = p_i q_i$, where $p_i$ is price.

Inverse demand is in the style of (Dixit, 1979) and (Singh and Vives, 1984): $p_i = \alpha - \beta q_i + (L-d) (c - \varphi q_i)$. Demand differs from these previous studies in that it includes a measure of distance and a benefit from proximity. As firms move closer ($d \to 0$), the fixed (with respect to output) benefit from proximity $\varphi$ and the variable (with respect to output) effect from proximity $q_i$ are magnified. Hence, the model includes agglomeration effects that are fixed and agglomeration effects that vary with output.

For goods that are substitutes ($\gamma = 0$) higher output from a rival decreases market price. There are, nevertheless, fixed benefits from proximity. The model captures the effect that consumers are often attracted to an area with multiple firms, but conditional on being in that area, consumption of one firm’s products can crowd out some consumption of the other firm’s products.

For goods that are fully differentiated in output ($\gamma = 1$) there are still benefits from clustering. For example, consumers that prefer on-stop shopping might be more likely to visit a restaurant that is near a retail store than a restaurant that is isolated.

The degree of product differentiation can be measured by how price depends on rival output relative to own output. Own output elasticity of price relative to rival output elasticity of price gives $\delta = (L-d)^{-2} / (\beta \phi \psi)$. It is more intuitive for products that are more differentiated to have higher values so we use the inverse $1 / \delta = \beta \phi \psi / ((L-d)^2 \psi^2)$.

To find the equilibrium firm output strategy, we start at the end of the game and consider what output a firm will produce given its locations. We differentiate the profit functions with respect to output. The optimal output for firm $i$ given the distance between firms is $q_i(d) = (2 \beta \psi (L-d) \gamma / (\alpha + (L-d) \varphi) / (4 \beta \phi \psi (L-d)^2 \psi^2)$. We then substitute $q_i(d)$ into the profit function and solve for the value of $d$ that maximizes firm 2’s profits.

As in “linear city” models, we find that firms maximize profits by minimizing (Hotelling, 1929) or maximizing (D'Aspremont et al., 1979) the distance between firms. If firm 2 locates next to firm 1 ($d = 0$), then $\pi(q_i(0)) = \beta (L-d) \gamma (L-2 \beta \psi / (\varphi \psi^2 - 4 \beta \phi \psi)^2$. If, however, firm 1 locates distance $L$ away from firm 1, then $\pi(q_i(L)) = \varphi \psi (4 \beta \phi \psi (L-d)^2 \psi^2)$ and we find that firms maximize or minimize the distance between them depends upon the degree of product differentiation (1 / $\delta = \beta \phi \psi / ((L-d^2 \psi^2)$) and the fixed benefit of proximity ($\varphi$). Agglomeration becomes more
profitable if product differentiation increases, if spillovers become more positive, or if demand is higher where the rival locates.

There is a negative relationship between product differentiation and the profitability of geographic distance. This is evident when we difference the profit functions and plot \( \pi(q(L)) - \pi(q(0)) \) as a function of product differentiation \( 1/d = \delta / (L - d)^2 \). If products are less differentiated, it is more profitable for them to be geographically distant. If products are more differentiated, the benefits of distance diminish, even turning negative if there are substantial rewards to proximity (Fig. 1).

We can extend the model to more than two retailers. We briefly sketch the equilibria here. We assume that profits are affected by a firm’s nearest competitor, so \( d \) is the distance to the nearest competitor and \( q \) is the output of the nearest competitor. If products are highly differentiated then firms will cluster in pairs or more. On the other hand, if products are not sufficiently differentiated then one firm will locate at each of the extremes with the other firms spaced evenly between them. Firms with un-differentiated products do not have an incentive to deviate from this even spacing because they will move closer to a rival and earn lower profits.

This simple model illustrates that offsite retailers will choose to be more dispersed than onsite retailers because onsite retailers have differentiated products (and sometimes positive spillovers).

3. Methodology for measuring agglomeration

We use precise location data to look inside cities at how retail agglomeration varies across product markets. We use multiple product markets, because using only a single retail market can be misleading. Almost any spatial pattern of firms will reveal some degree of agglomeration. This reflects the complex set of variables that create human settlements. For example, at a coarse scale of a county, province or state, firms will reveal a clustered pattern which closely corresponds to the distribution of major population centers. At a finer scale of a single city, many firms will reveal agglomeration which reflects the variation in population density and firm-specific or other zoning considerations. At an even finer scale of a single neighborhood, many firms will reveal agglomeration along the road network.

We compare agglomeration for onsite and offsite alcohol retailers. Onsite retailers include bars, restaurants, and private clubs, while offsite retailers include liquor stores, grocery stores, convenience stores, gas stations, and some pharmacies. There are obvious differences in the product mix that each retailer offers within our general classification of onsite and offsite retailers. The importance of alcohol beverage sales as a percentage of total sales also varies widely between types of retailers. In general, however, offsite retailers offer much more homogeneous products than those that sell onsite, even if most of their sales come from products unrelated to alcohol. In other words, a gallon of milk or a pound of sirloin is roughly the same regardless of where the consumer bought them. However, the pleasure of having a steak with a glass of wine will differ sharply among restaurants. Price competition should be more intense for offsite retailers than for onsite retailers.

We identify strategic agglomeration using the difference in agglomeration measures across a range of scales between types of retailers within the same city and within the same ZIP code. Consumer agglomeration, road layouts, and topographic constraints should equally affect both types of retail. Moreover, zoning restrictions on land use are similar across alcohol retailers. For example, for properties zoned commercial in Tampa the correlation between bars and liquor stores is 1, which means that if zoning permits a bar it also permits a liquor store. The zoning correlation between bars and liquor stores is 0.97 for Birmingham, 0.99 for Minneapolis, 1 for St Paul, and 0.99 for Oakland. These correlations decrease when comparing other product markets such as restaurants and grocery stores but are usually above 0.9. Thus, much of the remaining difference in agglomeration can be plausibly attributed to firm strategy which depends on the ability to differentiate products.

We repeat the analysis for five cities. It is not appropriate to compare a given seller type across cities, because cities have different urban forms. It is, however, useful to use multiple cities to repeat the comparison between seller types in order to determine whether the analysis is robust to different urban forms, including cities near the ocean or mountains. Comparing agglomeration between cities is inappropriate, but comparing agglomeration for multiple types of retailers within a city is reasonable because our measurement corrects for sample size.

To illustrate the problem of identifying agglomeration using a single product market, consider establishments in Fig. 2. These establishments might appear to be clustered. In fact, the \( L \)-function, described below, indicates that they are clustered. They are, however, probably not strategically clustered, because these are public elementary schools in the Tampa Area. Planners probably tried to strategically disperse but faced constraints from population distribution and landforms.

A simple mathematical example illustrates the challenge of distinguishing between strategic agglomeration and a limited geographic choice set. Consider three firms locating in three discrete locations: \( (n1, n2, n3) \) where \( n_i \) is the number of firms at location \( i \). A distribution of \( (2,1,0) \) might appear to be agglomeration. Does location 3 lack firms because the firms prefer to cluster or because zoning prohibits locating there? It is difficult for the researcher to identify why firms are absent from location 3. However, by comparing \( (2,1,0) \) to another product market with distribution \( (3,0,0) \), we have evidence that \( (2,1,0) \) might be an example of dispersion rather than agglomeration.

In the simple example above we used a comparison of discrete locations in two product markets in the same city to identify agglomeration. We now apply this approach to continuous measures of agglomeration. In the simple example above, the test for agglomeration proposed by (Rysman and Greenstein, 2005) would be useful. Their test would not, however, be useful for our study of actual retailers locating in a city because their test requires discrete location choices.

In our analysis we use both \( K \) and \( L \)-functions (Section 3.1) and the nearest neighbor index (Section 3.2). The nearest neighbor index allows for comparisons across ZIP codes within a city. By comparing across ZIP codes we can investigate whether the results are driven by a few ZIP codes, driven by certain consumer demographics (e.g., young people living in the area), or are more general. A drawback of mean nearest-neighbor analysis is that is discards considerable information about patterns, including the distribution of values for the nearest-neighbor, as well as information on the second-nearest neighbor and other neighbors. These shortcomings are addressed by more recent methods for measuring distance: the \( K \) and \( L \)-functions which we also use for each city.

Fig. 1. The profitability of distance decreases with differentiation, even becoming negative if products are differentiated and there are rewards to proximity.
3.1. Measuring agglomeration with K and L functions

To measure agglomeration in continuous space, we use K and L functions, types of spatial point pattern analysis from the geography literature. The L-function is a normalization of the K-function which was proposed by Ripley (1976, 1977, 1979, 1988). The K-function is \( K(h) = E(s)/\lambda \) where \( s \) is the number of points within distance \( h \) of an arbitrary point and \( \lambda \) is the overall study-area density of sellers. The ratio of K-functions gives an approximation of the ratio of the number of competitors between industries adjusted for the seller density.

To visualize the calculation of a K, imagine placing circles of radius \( h \) centered on each of the sellers. The other sellers inside each circle of radius \( h \) are counted, and the mean count for all sellers is calculated. This mean count is divided by the overall seller density to give \( K(h) \). This process is repeated for a range of values of \( h \), resulting in the estimator of the K-function:

\[
\hat{K}(h) = \frac{R}{n^2} \sum_{i \neq j} I_h(d_{ij})
\]

where \( n \) is the number of points over an area \( R \), \( d_{ij} \) is the distance between \( i \) and \( j \), and \( I_h(d_{ij}) \) is an indicator function that equals 1 if \( d_{ij} \leq h \) and 0 otherwise.

The K function is normally plotted as the observed value \( K(h) \) versus distance \( h \). Due to the cumulative nature of the K function, the value for \( K(h) \) will either stay constant or increase with increasing distance and will never decrease. The expected value of the K function under the assumption of complete spatial randomness is as follows:

\[
E[\hat{K}(h)] = nh^2.
\]

Since \( nh^2 \) is the area of each circle and \( \lambda \) is the mean density of sellers per unit area, this expected value can be plotted on the same axes as the observed K function. However, both the expected and observed values for \( K(h) \) can become very large as \( h \) increases, making the resulting plot difficult to interpret. To get around this problem the K function has been modified to convert the expected value of \( K(h) \) to zero. The L-function is a normalization of the K function:

\[
\hat{L}(h) = \sqrt{\frac{\hat{K}(h)}{\pi}} - h.
\]

When \( \hat{L}(h) > 0 \), there are more sellers at the corresponding spacing than would be expected under complete spatial randomness. When \( \hat{L}(h) < 0 \), there are fewer sellers than expected. K and L functions are sensitive to edge effects (Yamada and Rogerson, 2003) so we use edge correction (Rowlingson and Diggle, 1993).

If we draw concentric circles around a randomly selected seller and compare the number of competitors relative to what we would expect if stores located randomly, this number would increase as the larger circles included more stores relative to the additional space. Eventually, we would reach an area where the larger circle added more space than stores and the L-function would begin to decrease. Thus, the peak of the L-function would reflect the agglomeration of the city relative to our definition of the city boundaries.

Calculating standard errors for the K and L functions is analytically complex, so we calculate confidence intervals using bootstrapping with edge correction. In this procedure, \( n \) sellers are randomly located in the study region and the K and L functions are derived. This is repeated 100 times or more to allow for the construction of confidence intervals around the expected values for \( K(h) \) and \( L(h) \).

To clarify K and L-functions we illustrate three hypothetical point patterns and the associated L-values: i) random distribution, ii) dispersed distribution, and iii) clustered distribution (Fig. 3). When \( L(h) = 0 \) the point pattern is random; when \( L(h) < 0 \) the point pattern is dispersed relative to complete spatial randomness; and when \( L(h) > 0 \) the point pattern is clustered relative to complete spatial randomness.
Fig. 3. Examples of point patterns and $L$-values.
We use a study area of 1000 by 1000 units with 100 points. Note that the maximum value of radius $h$ is set to 300, approximately one third of the dimension of the study area. For larger values of $h$ the usefulness of the $K$-function is reduced since edge effects can become large. Confidence intervals are calculated using 100 permutations of random point patterns.

The $L$-function for the random point pattern reveals both positive and negative values for $L(h)$ but the entire curve falls within the confidence intervals. The $L$-function for the dispersed point pattern reveals negative value for $L(h)$ and the curve falls below the lower confidence band for value of $h$<100. The $L$-function for the clustered point pattern reveals positive values for $L(h)$ and the curve falls above the upper confidence band for all values of $h$.

The final step in our $K$ and $L$-function cluster analysis is to determine the difference in the $L$ functions for the two types of sellers. We calculate a single $L$-difference curve for each of the five cities.

3.2. Measuring agglomeration with the nearest neighbor index

We measure agglomeration with the nearest neighbor index, in addition to using $K$ and $L$-functions. A strength of $K$ and $L$-functions is that we need not assume a priori that any particular scale is more relevant for cluster analysis. This is, however, a weakness if we want to study whether agglomeration is stronger in certain parts of a study area compared to other parts. The nearest neighbor index allows for comparisons across ZIP codes within a city. By comparing across ZIP codes we can investigate whether one part of the city is driving the results. Furthermore, we can estimate the effects of demographic factors on agglomeration.

We divide the five cities into ZIP codes. For each ZIP code we calculate the nearest neighbor distance (Clark and Evans, 1954):

$$d_{\text{min}} = \frac{\sum_{i=1}^{n} d_{\text{min}}(s_i)}{n}$$

(4)

where $d_{\text{min}}$ is the nearest-neighbor distance for event $s_i$. To determine whether a point pattern is clustered, the observed mean nearest-neighbor distance can be compared to the expected value based on the overall point intensity:

$$E(d) = \frac{1}{2\sqrt{\lambda}}.$$ 

(5)

The ratio $R$ of the observed mean nearest-neighbor distance to this expected value can be used to assess a pattern relative to complete spatial randomness:

$$R = \frac{d_{\text{min}}}{1/2\sqrt{\lambda}} = 2d_{\text{min}}\sqrt{\lambda}.$$ 

(6)

This ratio $R$ is called the nearest neighbor index. If $R$<1 then the nearest neighbor distances are shorter than expected, indicating a tendency to cluster. If $R$>1 then there is a tendency toward even spacing. We determine the significance of the nearest neighbor index values using a Z-score based on the standard error of a random point pattern (Clark and Evans, 1954).

Finally, after dividing each city into ZIP codes and calculating the nearest neighbor distance for each ZIP code, we then subtract the offsite value from the onsite value. Values less than one indicate greater agglomeration, so negative values indicate that onsite sellers are more agglomerated. We can then see whether agglomeration is stronger for onsite establishments compared to off-site establishments for each ZIP code within a city.

4. Data and empirical specification

We obtained 2005 alcohol-licensing data from state liquor control divisions for five cities: Birmingham (defined as Jefferson County), Chicago (Cook, DuPage, and Will Counties), Minneapolis-St. Paul (Anoka, Carver, Dakota, Hennepin, Ramsey, Scott, and Washington Counties), Oakland (Alameda County), and Tampa (Hillsborough County). These five cities create a representative sample of large U.S. cities. In terms of U.S. population rankings, Chicago is third, Oakland is twelfth, Minneapolis-St. Paul is sixteenth, Tampa is twentieth, and Birmingham is forty-eighth. These five cities are very different in terms of population agglomeration, demographic composition, religious beliefs, political inclinations, and other characteristics that might influence zoning, shopping, and alcohol consumption.

The data contain addresses of the alcohol retailers, license numbers, issue dates, expiration dates, and types of licenses. From the type of license, we determined whether the store could sell alcohol to be consumed onsite (bars and restaurants) or offsite (liquor stores, grocery stores, convenience stores, and gas stations). We could also identify whether the stores were able to sell only beer and wine or whether they were also allowed to sell liquor. In Birmingham, all onsite retailers are privately-run, but some of the off-site retailers (those selling distilled spirits) are operated by the state. In the other four cities, alcohol is sold by private retailers.

For purposes of comparison with geographic location of alcohol retailers, we obtained all of the addresses of all the public elementary schools in the five cities. Recall that Tampa’s elementary schools are illustrated in Fig. 2. We use agglomeration data on schools to illustrate strengths and weaknesses of traditional agglomeration measures.

Locations of each alcohol retailer for Tampa appear in Fig. 4. Locations of alcohol retailers for Birmingham, Chicago, Minneapolis-Saint Paul, and Oakland appear in Fig. 5. We matched 95% of Birmingham stores, 89% of Chicago stores, 90% of Minneapolis-St. Paul stores, 93% of Oakland stores, and 92% of Tampa stores. Technical details about alcohol licenses, software for geocoding, and software for calculating $L$-functions appear in Appendix A.

In order to compare agglomeration of onsite retailers to offsite retailers based on demographic factors, we obtained data from Geolytix. Geolytix included ZIP code level data on population density, income, spending, age, and ethnicity.

5. Results and discussion

There is substantial variation among the five cities in the number of onsite and offsite retailers. There are more offsite retailers than onsite retailers in Birmingham and Tampa, while in Chicago, Minneapolis-St. Paul, and Oakland there are more onsite retailers. Oakland has the highest number of onsite retailers per person, and Tampa has the highest number of offsite retailers per person, while Minneapolis-St. Paul the lowest number per person for both onsite and offsite retailers (Table 1).

5.1. Results for $K$ and $L$ functions

The $L$-functions for onsite and offsite retailers are illustrated in Fig. 6. Positive $L$-values indicate agglomeration, zero values indicate randomness, and negative values indicate dispersion. Confidence intervals are determined for each $K$-function but are not plotted in Fig. 6 to improve legibility. For all the $K$-functions for alcohol establishments the $L$-values far exceeded the upper value for the confidence envelope, indicating strong clustering starting at the shortest distances. For example, in the case of Chicago the confidence interval for the $L$-values at a distance of several kilometers falls between –25 and +25, gradually expanding to a range from −100 to +100 at 25 km — this compared to the actual $L$-values which reach over 1000 within the first kilometer. The only exception to this is Oakland, where $L$-values for alcohol establishments eventually come down to values within the confidence interval at distances over 15 km — this is a result of the relatively small size and elongated shape of the Oakland study area, which reduces the meaning of the $L$-values at these distances.
For schools the patterns is slightly different, since for all study areas the \( L \)-values do not increase as rapidly and do not exceed the upper limit of the confidence interval until distances of 1 km. This indicates that elementary schools do not cluster at very short distances (Fig. 6).

These figures provide five interesting results. First, viewed in isolation, Fig. 6 misleadingly indicates agglomeration by onsite retailers, offsite retailers, and public elementary schools. In general, the \( L \)-functions are positive and large. The increasing portion of the \( L \)-function implies that as distance from a retailer increases, the number of competitors increases more rapidly compared to what would have been expected if retailers were randomly located. This finding highlights the fallacy of examining single product markets when measuring agglomeration. \( L \)-functions alone are not sufficient to demonstrate agglomeration. Agglomeration might simply reflect the non-random distribution of residential density, the effects of physical factors (like water bodies, topography) and many social and economic factors that shape urban form. Our strategy is to compare across product markets to identify whether agglomeration is strategic (by choice) or due to limited options and residential agglomeration.

Second, onsite retailers cluster more than offsite retailers at all scales, but more markedly at smaller distances. The \( L \)-function at short distances for onsite retailers increases sharply relative to the \( L \)-function for offsite retailers. In fact, the difference between the \( L \)-functions for onsite and offsite retailers is always positive. It is appropriate to compare onsite to offsite retailers within a city (though not between cities) because the \( L \)-function corrects for sample size. A pattern in the degree of agglomeration is evident. For short distances, onsite retailers are much more clustered than offsite retailers. For example, at 0.2 km in Tampa, the \( L \)-value is 2026 for onsite retailers, but 833 for offsite retailers. Thus, within a radius of 0.2 km in Tampa, the ratio of the \( K \)-values implies that an onsite retailer has 4.64 times more competitors than an offsite retailer.\(^3\) The difference in \( L \)-values is

<table>
<thead>
<tr>
<th>Variable</th>
<th>Birmingham</th>
<th>Chicago</th>
<th>Minneapolis</th>
<th>Oakland</th>
<th>Tampa</th>
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<tbody>
<tr>
<td>Number of counties</td>
<td>1</td>
<td>3</td>
<td>7</td>
<td>1</td>
<td>1</td>
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<tr>
<td>Size (square km)</td>
<td>2911</td>
<td>5552</td>
<td>7711</td>
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<td>2777</td>
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<td>Population (in 2005 est.)</td>
<td>657,229</td>
<td>6,873,609</td>
<td>2,746,987</td>
<td>1,065,266</td>
<td>1,132,152</td>
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<tr>
<td>Population density (people/km(^2))</td>
<td>226</td>
<td>1238</td>
<td>356</td>
<td>2286</td>
<td>408</td>
</tr>
<tr>
<td>Onsite alcohol retailers (#)</td>
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<td>5573</td>
<td>1779</td>
<td>1859</td>
<td>1272</td>
</tr>
<tr>
<td>Onsite per 100,000 people</td>
<td>90</td>
<td>81</td>
<td>65</td>
<td>175</td>
<td>122</td>
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<tr>
<td>Offsite alcohol retailers (#)</td>
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<td>120</td>
<td>43</td>
<td>31</td>
<td>95</td>
<td>128</td>
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</table>


\(^3\) The ratio of onsite to offsite competitors is calculated as follows. First, solve Eq. (3) in terms of \( K \) and insert the \( L \)-values so the \( K \)-value at 200 m for onsite retailers is 15,566,371 and for offsite retailers is 3,352,260. Second, the ratio of \( K \)-values approximates the ratio of the number of competitors between industries adjusted for the industry density so in this case it is 4.64. This is consistent with our calculation that in Tampa at 200 m an onsite retailer has 5.51 competitors on average, while an offsite retailer has 1.23.
statistically significant at the 1% level. A similar pattern is observed at 0.4 km: 2652 vs. 1006 which imply a ratio of 4.71 for the $K$-values. However, at 10 km the differences are much smaller: a ratio of 1.31 for the $K$-values. An onsite retailer in Tampa has 5 times more competitors nearby (at 0.2 or 0.4 km), not because there are more onsite retailers (from Table 1 we see that Tampa has approximately the same number of onsite as offsite retailers), but because onsite retailers are more clustered. For all five cities in the sample, onsite retailers cluster more than offsite retailers at short distances. This finding supports economic theory predicting that firms selling more differentiated products (like full-service restaurants that offer differentiated food and ambience) are less concerned about price competition and more willing to cluster than firms that sell less differentiated products (like liquor stores that sell roughly the same products as rivals).

Fig. 5. Locations of onsite and offsite alcohol licenses in 2005 in Birmingham, Chicago, Minneapolis, and Oakland.
Third, while agglomeration increases at different rates for onsite vs. offsite retailers, agglomeration peaks at roughly the same distance within a city. For both onsite and offsite retailers, as the circle’s radius increases, agglomeration gradually increases, reaches a peak, and then gradually decreases. This result and the next result highlight idiosyncratic differences across cities.

Fourth, while the peak of the $L$-function occurs at approximately the same distance for onsite and offsite retailers within each city, it...
vares across the five cities. In the two northern cities the \( L \)-functions peak at 21 km, in the two southern cities at 16 km, and in Oakland at 6 km. For Oakland, the \( L \)-functions for both onsite and offsite retailers becomes negative after approximately 17 km, because Oakland is surrounded by mountains that are not hospitable to retailers and because spatial differentiation of firms is achieved after reaching a certain scale.

Fifth, we separately calculate the \( L \)-functions for restaurants, bars, offsite sellers excluding liquor stores, and liquor stores in Tampa. Bars exhibit the highest degree of agglomeration, followed by restaurants that sell alcohol, then offsite retailers (Fig. 7). Bars have the highest positive spillovers from proximity so it is not surprising that they show the strongest degree of agglomeration. Restaurants that sell alcohol have smaller benefits from proximity so product differentiation likely plays an important role in their willingness to cluster. Offsite sellers, especially liquor stores, have less ability to differentiate their products and cluster least. Since restaurants cluster more than any type of offsite seller, bar hopping cannot explain the higher agglomeration of onsite establishments.

5.2. Results for the nearest neighbor index

In addition to measuring agglomeration using \( K \) and \( L \) functions, we use the nearest neighbor index. The nearest neighbor index allows us to compare agglomeration across ZIP codes within a given city. By comparing across ZIP codes we can investigate whether the results are being driven by a part of town in which bars are clustered. Furthermore, we can investigate whether the results are driven by demographic factors like population density or number of young people in residence. We calculated the nearest neighbor index for both onsite and offsite locations. In many ZIP codes the sample size is too small so we combined ZIP codes with neighboring ZIP codes that shared the longest boundary. This procedure reduced the sample size relative to the original ZIP codes: Birmingham 53 to 24, Chicago 227 to 105, Minneapolis/St. Paul 149 to 44, Oakland 35 to 22 and Tampa 49 to 29. We then dropped nine that we could not match to demographics, leaving 215.

Of the 215 study areas, 152 have stronger agglomeration for onsite sellers, while only 63 have stronger agglomeration for offsite sellers. The high proportion of ZIP code areas in which onsite sellers are more agglomerated indicate that the results are not being driven just by a few parts of the city with a high concentration of bars and restaurants. Furthermore, the mean nearest neighbor distance is 0.53 for onsite sellers and 0.62 for offsite sellers. Recall from Section 2 that values less than one indicate greater agglomeration. Hence, this is further evidence that onsite sellers are more clustered than offsite sellers.

Table 2 reports the effects of demographic characteristics on the nearest neighbor distance for onsite and offsite establishments and the difference between these two measures. Recall that when the difference between the means is negative, it indicates that onsite sellers are more clustered. Population density has a negative effect on the differential agglomeration between onsite and offsite establishments implying that in more densely populated areas, onsite establishments cluster more than offsite establishments. This result is driven by a positive effect of population density on the nearest neighbor distance for offsite establishments. This indicates that areas with high residential populations tend to have fewer liquor and convenience stores. Buildings with 20 units or more are correlated with agglomeration by off-site retailers. The percentage of young people, Hispanics, blacks, and per capita income are not significant, but in general have the expected sign. Preferences for dining out or eating at home do not appear to explain the difference in agglomeration either. The \( R^2 \)-squared indicates that the demographic factors explain about 16 to 27% of the variation.

In summary, demographic factors alone cannot explain away the difference in agglomeration between onsite and offsite establishments. Differences in ability to differentiate product offerings plausibly explain some of the difference.

6. Conclusions

Recently researchers have argued that agglomeration by auto manufacturers (Klepper, 2007) and tire manufacturers (Buenstorf and

![Fig. 7](image-url) In Tampa, bars are most clustered followed by restaurants, other offsite sellers, liquor stores, and public elementary schools at various definitions of market size.
Klepper, in press) is not necessarily strategic, but due to hysteresis. Agglomeration in these industries results from spinoffs locating near parents. Like manufacturing, retail agglomeration might not be due to agglomeration economies, but due to location limits or lumpy demand. We show that empirical estimates indicate that even public schools cluster more than random location would predict, but this is not necessarily due to agglomeration economies. We argue that school agglomeration is likely driven by geography and demand density. Hence, researchers should be cautious about inferring agglomeration economies in other markets. We identify whether agglomeration is strategic by comparing across multiple product markets with similar location limits and demand density. First, by comparing retail markets with similar location restrictions we can effectively difference out those effects. Second, the alcohol retailers arguably have similar demand densities, but we also account for demand differences by breaking down markets by ZIP code. In some ZIP codes, for example, there might be more young people or attractions that complement certain retail types. We find evidence that retailers cluster strategically based in part on their ability to differentiate their products. We find that liquor stores cluster least, followed by other offsite sellers, restaurants, and bars. Positive spinoffs (e.g., “bar hopping”), might drive bar agglomeration, but so too might product differentiation. Likewise, product differentiation likely facilitates agglomeration by full-service restaurants, and lack of product differentiation likely drives liquor stores apart.

Appendix A. Technical details on data and software

Oakland stores with a license class of 41, 47, and 48 were classified as onsite alcohol retailers, while stores with a license class of 20 and 21 were classified as offsite alcohol retailers. Tampa stores with a license class of 1COP, 2COP, and 4COP were classified as onsite alcohol retailers, while stores with a license class of 1APS, 2APS, and 3APS were classified as offsite alcohol retailers. Minneapolis-St. Paul stores with a license class of 3.2 CMBN, 3.2ONSS, 3.2 ONSS, CT3.2 CMBN, CT3.2ONSS, MWNONSB, MWNONS, CMBN, CMBS, CTCMBS, CTONSS, MCLONSL, MCLONSS, MOCMBN, MOONSS, ONSL, ONSS, and ONSSS were classified as onsite alcohol retailers, while stores with a license class of 3.2 CMBN, 3.2OFSL, BRCOP, CT3.2OFSL, CT3.2 CMBN, CMBS, CMBS, CTCMBS, CTOSFL, MOCMBN, MOOFSL, OFSL, and OFSLFD were classified as offsite alcohol retailers. Chicago stores with a license class of A and C were classified as onsite alcohol retailers, while stores with a license class of B and C were classified as offsite alcohol retailers. Birmingham stores with a license class of 10, 20, 31, 32, 40, and 60 were classified as onsite alcohol retailers, while stores with a license class of 11, 50, and 70 were classified as offsite alcohol retailers.

StreetMap USA within ArcGIS 9 from ESRI is the software used to geocode. We geocoded the addresses of each alcohol retailer in each study area. The geocoded locations for alcohol retailers were re-projected into the appropriate UTM coordinate system to allow for reliable distance estimates. XY coordinates in meters were determined for each retailer and for the area boundaries. We used the Splancs package in R (Rowlingson and Diggle, 1993) to create the K and L functions for each type of retailer within each study area.

References


