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ABSTRACT: We introduce a nonparametric microdata based test for industrial specialization and apply it to a single urban area. Our test employs establishment densities for specific industries, a population counterfactual, and a new correction for multiple hypothesis testing to determine the statistical significance of specialization across both places and industries. Results highlight patterns of specialization which are extremely varied, with downtown places specializing in a number of service sector industries, while more suburban places specialize in both manufacturing and service industries. Business service industries are subject to more specialization than non-business service industries while the manufacturing sector contains the lowest representation of industries with specialized places. Finally, we compare the results of our test for specialization with recent tests of localization and show how these two classes of measures highlight the presence of both industry as well as place specific agglomerative forces.

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1 Introduction

Industry agglomeration has been of interest to economists at least since Marshall (1920)'s treatise on cutlery producers and jewelers in England. Modern examples include information technology firms in Silicon Valley, furniture producers in western North Carolina, and advertising firms in Manhattan. Surveys of the literature in Rosenthal and Strange (2003a) as well as throughout Glaeser (2010) highlight a sizeable number of agglomeration studies contributing to our understanding of both the scale, industrial scope and determinants of industrial concentration. The expanding volume of research on agglomeration is due both to technical advances in the availability and usage of microdata as well as an increasing interest into issues relating to what Krugman (1991b) termed the 'new economic geography'. As regions and countries strive to obtain higher levels of economic growth, policymakers strive to recreate the success of places like Silicon Valley.

As interest in agglomeration has grown, empirically defining industry concentration has received renewed attention. Measures of agglomeration can be bisected into those that capture localization, defined by the overall concentration of specific industries across places, and specialization, defined as the concentration of an industry within a given place. Localization has been the subject of recent research to develop new methodologies for measuring industrial concentration. Ellison and Glaeser (1997) derive a random utility model based index of localization that addresses the concern that perceived industry concentration may be a result of random clustering or the 'Dartboard Effect'. Duranton and Overman (2005) extend the literature by developing a nonparametric based measure of localization that overcomes the Modifiable Areal Unit Problem (MAUP)[1] and provide a statistical test of significance. Our understanding of agglomeration has grown as a result of better detecting localized industries. In the end though, localization is unable to discuss the physical location of industry concentration. Therefore, measures of localization limit our ability to identify the role of place specific agglomerative forces such as access to markets, roads and natural resources.

So we turn to measures of specialization, which assign industry concentration to specific places, but are less evolved methodologically. Existing measures of specialization[2] are limited to location quotients and Herfindahl based indices.[3] These ratio based measures of

[1]MAUP relates to any form of statistical bias that occurs when data is aggregated to spatial units (Openshaw (1984)). In measuring industry concentration, results would be sensitive to both the size and shape of spatial units used for aggregation. Additionally, the boundaries of these spatial units may split up industry clusters thereby underestimating industry concentration.

[2]Empirical methods for measuring specialization are well summarized by Holmes (2004).

[3]Some highly cited empirical applications of these measures of specialization include Krugman (1991a),

concentration rank industrial concentration across places, but are subject to the same shortcomings addressed by Ellison and Glaeser (1997) and Duranton and Overman (2005) in the localization literature. Specifically, existing measures of specialization may be biased due to the MAUP and the 'Dartboard Effect' and are unable to provide a measure of statistical significance.

The current paper contributes to the literature by introducing a statistical test for industrial specialization. Our test utilizes establishment level micro data to control for both the MAUP and the 'Dartboard Effect'. In order to overcome the MAUP, we extend Duranton and Overman (2005) and introduce a bivariate kernel density estimator of industry concentration derived from establishment level data. Our kernel based measure of location specific establishment concentration overcomes the MAUP by creating a continuous surface over the study area which is not defined by geographical units and boundaries. We control for the 'Dartboard Effect' by first creating an empirical null distribution of establishment concentration based on a counterfactual of randomly located industries. We are then able to directly quantify industry concentration at a given place in the form of local p-values by comparing each place's null distribution of establishment density to the density of a specific industry. In order to determine the statistical significance of specialization across industries and places, we must account for the fact that multiple simultaneous hypothesis tests for specialization could lead to 'false positives' under the null hypothesis of randomly located industries. Therefore, we adjust local p-values through a Westfall and Young (1993) based re-sampling routine to ensure that critical values for concluding specialization only occur in *any* place for 5% of randomly located industries.

We confirm that our methodology controls for the dartboard effect and provides unbiased comparisons both across industries and places through a Monte Carlo experiment. With the unbiasedness of the test confirmed, we apply our test of specialization to a single urban area, Denver-Boulder-Greeley CMSA. This highlights a different scale of analysis than has traditionally been incorporated into studies of specialization as well as tests the power of our technique across rural, suburban and urban locations. Our application highlights some new stylized facts about the geographic pattern of industry clustering within a single urban area. The relationship between specialization and urbanization shows that places with greater

who developed an index of regional specialization based on location quotients; Glaeser (1992) who uses location quotients to test the relationship between regional specialization and the growth of cities, and Henderson et al. (1995) who incorporates a Herfindahl based measure of diversity/specialization to test the role of Marshall-Arrow-Romer and Jacobian externalities in the concentration of manufacturing across U.S. cities.

underlying commercial density tend to specialize in more and different types of industries than their lower density counterparts. Across sectors, business services contain the largest portion of industries subject to specialization, while manufacturing contains the least. Empirical results highlight where specialization occurs for individual industries as well as the overall urbanization patterns for different sectors of the economy.

Additionally, our test highlights the relationship between specialization and localization. To illustrate the difference between these two measures of industrial concentration, consider the advertising agency, which is described as heavily concentrated in Manhattan by Arzaghi and Henderson (2008). This industry is localized since the majority of establishments are highly concentrated. At the same time, advertising concentration exceeds its share of general industry concentration in Manhattan indicating that Manhattan specializes in advertising. Therefore, the industry as a whole is both localized and specialized. While specialization and localization often occur together, this may not always be the case. An example of this in our study area is the Offices of Physicians industry (NAICS 6211). The establishments in this industry are concentrated in three suburban clusters just north and southwest of downtown Denver, outside the urban core. These clusters are identified as specialized places since they exceed the expected industrial concentration in these places, but do not represent sufficient establishment concentration across all places to conclude this to be a localized industry. This example illustrates the fact that compared to localization, specialization measures are uniquely suited to detecting within industry agglomerations that occur outside of the dense urban core. Our results support a larger presence of specialization across industries with 62% of our 4 digit NAICS industries subject to specialization in at least one place while only 29% of all industries exhibit significant localization.

Qualitatively, measures of specialization also differ from localization in their ability to identify agglomerative forces. The challenges of using localization measures (Duranton and Overman (2005) and Ellison and Glaeser (1997)) to identify agglomerative forces is evident in a recent paper by Ellison et al. (2009). This innovative paper uses co-agglomeration patterns to identify the role of traditional Marshallian factors as well as natural advantages in industry agglomeration. Results rely on industry level observations and therefore can only indirectly estimate the role of place specific factors. Since specialization is able to describe where industrial concentration is occurring, it is more readily situated to help identify all the determinants of agglomeration, including access to roads, markets and industry specific spillovers.

We continue with Section 2, where we describe our dataset and the range of industry categories we incorporate into our test for specialization. In Section 3, we detail our bivariate kernel density estimator of establishment concentration. In Section 4, we construct local p-values for each place and industry. We then adjust the critical values used to conclude specialization to correct for the fact that we have more than a single hypothesis test in Section 5. Section 6 describes where specialization occurs and Section 7 identifies which industries are subject to specialization. Section 8 discusses the relationship between industrial specialization and localization. Section 9 concludes.

2 Data

Implementing our test for specialization requires spatially disaggregated establishment level business data, for which we use the Quarterly Census of Employment and Wages (QCEW) Program (formerly know as ES-202) dataset. The QCEW is a cooperative program involving the Bureau of Labor Statistics (BLS) of the U.S. Department of Labor and State Employment Security Agencies. The QCEW program produces a comprehensive tabulation of employment and establishments for workers covered by state unemployment insurance laws.[4] Data under the QCEW program represent the number of covered workers who worked during, or received pay for, the pay period including the 12th of the month.

We use establishment level data for QCEW covered firms for the 4th quarter of 2006 that are located in the Denver-Boulder-Greeley CMSA.[5] This urban area contains 2.6 million people over 13,679 square kilometers. In Colorado, most employers are liable for paying into the Colorado Unemployment Insurance Fund and thus covered under the QCEW program. Any business that paid wages of at least $\$1,500$ in a quarter of this year or last year, or a business that employed at least one person for any part of a day for 20 weeks during this year or last year must pay the tax. Others that must pay into the fund include religious, educational, or charitable nonprofit organizations that have four or more employees for 20 weeks during the calendar year, even though they may be exempt from federal unemployment taxes.

This data incorporates geographic information for the physical location of the establishments as well as mailing and corporate headquarters. Physical addresses are transformed

[4] Excluded employees include members of the armed forces, the self-employed, proprietors, domestic workers, unpaid family workers, and railroad workers covered by the railroad unemployment insurance system.

[5] This CMSA includes eight counties: Adams, Arapahoe, Boulder, Broomfield, Denver, Douglas, Jefferson, and Weld.

into points with corresponding latitude and longitude coordinates by the QCEW Program.[6] The dataset has a population of $79,038$ establishments, which represents industries across both the manufacturing and service sectors. In order to provide sufficient establishment representation in a given industry, we conduct our analysis at the 4 digit NAICS industry classification. We examine all industries with NAICS codes 3111 through 8142 (258 industries in our dataset).[7] While the main focus of this paper is on identifying specialization at the 4-digit NAICS level, we group these industries into three main industry sectors for the purpose of exposition: NAICS 3111 through NAICS 3399 is classified as Manufacturing; NAICS 4231 through NAICS 4251 as well as NAICS 4811 through NAICS 6244 as Business Services; NAICS 4411 through NAICS 4543 as well as NAICS 7111 through NAICS 8142 as Non-Business Services. For these three industry sectors, Manufacturing contains 2,706 establishments, Business Services has 56,703 establishments and Non-Business Services includes 19,629 establishments.

3 Measuring Place Specific Establishment Concentration

The intuition behind our test for specialization may be illustrated through a comparison with the most commonly used measure of specialization, the location quotient (LQ). Typically, a location quotient is based on aggregate counts of establishments or employees at Census tract, county, or state geographies.[8] For our discussion, we present the LQ as:

$$LQ_{i,j} = \frac{e_{i,j}/E_j}{e_i/E} \tag{1}$$

The numerator $e_{i,j}/E_j$ represents place i's share of establishment concentration for industry j and the denominator e_i/E is place i's share of total establishment concentration across all industries. Location Quotients above one indicate above average specialization and are defined if $\{E_j, e_i\} \neq 0$. The assumption that $e_i > 0$ is non-trivial, since this limits the spatial

[6]Only 12.1% of establishments did not provide accurate enough geographic information to allow assignment of latitude and longitudes and are thus excluded from analysis. The excluded establishments are spread across industries and more often excluded other data fields.

[7]This includes all manufacturing and service (wholesale trade, retail trade, transportation, and information through other services) industries and excludes agriculture, mining, utilities and construction.

[8]The use of aggregate data may cause location quotients to suffer from MAUP, the severity of which is influenced by both the size and shape of spatial units adopted for aggregation.

units adopted and spatial resolution used for examining establishment concentration.[9] As the number of defined locations increases holding the number of establishments constant, as would be the case of a high resolution microdata framework, arguments for the use of a LQ become untenable since the majority of locations will have an undefined location quotient. Overall, the location quotient illustrates two properties that are necessary for correctly defining specialization. First, the measure must account for the likelihood that a randomly drawn establishment from a given industry would locate in a given place (the numerator). Second, the measure must control for the likelihood that a randomly drawn establishment from any industry would locate in this place (the denominator).

In measuring specialization across an urban area with a variety of commercial centers that vary in both size and density, any configuration of spatial units will likely violate both of Arbia (1989) and Amrhein and Reynolds (1997)'s data conditions[10] necessary for no distortion due to MAUP. Therefore, we begin our test for specialization by creating a measure of establishment concentration that controls for the MAUP. Specifically, we estimate a kernel density function[11] based on the physical location of individual establishments. This generates a nonparametric and continuous measure of establishment location. By adopting the kernel estimator, we generate a weighted average at a given location based on neighboring point intensity. This allows resulting establishment density to be insensitive to the location of administrative or other geographic borders. This estimator may be interpreted as the probability that a randomly chosen establishment is found in a given location across the study area. If this probability is conditioned on industry, then the surface is comparable to the numerator of our LQ since both of these measures represent the establishment density of an industry at a given location. Additionally, the kernel surface is continuous and unbounded, ensuring that the probability that an establishment is located at any point is never actually equal to zero.[12]

[9] Specifically, places must be drawn such that they contain at least one establishment to avoid undefined LQs. This partitioning of places creates a mix of spatial units given the segregation of commercial and residential land-use within most urban areas.

[10] Condition 1 is the equivalence of spatial units in terms of size, shape and neighboring structure and condition 2 is the absence of spatial autocorrelation.

[11] The kernel smoothing of establishment location data has been justified in the agglomeration literature for several different reasons. Kernel smoothing may aid in overcoming data inaccuracies in establishment location due to measurement error (McMillen and Klier (2008) and Duranton and Overman (2005)). As discussed by Duranton and Overman (2005) and Ellison et al. (2009), industry spillovers may be a decreasing function of distance from an establishment, and therefore a kernel estimator is well suited to capture this effect. The use of kernel smoothing can also be justified to deal with the inexact nature of establishment location, where the actual location that an establishment selects may by proximate to its ideal location due to site availability.

[12] Beyond concern about MAUP, there are several other reasons why the literature has justified the use

To estimate a kernel density across our study area, we must choose both the kernel function and bandwidth. We base the kernel estimator on a bivariate Gaussian[13] density function and use a smoothed cross validation (SCV) procedure to estimate the bandwidth.[14] The kernel density estimator sums the values of the kernel functions generated at each establishment point and then divides by the total number of establishments in the sample. In our case, we define $\mathbf{x} = (x_1, x_2)$ as corresponding latitude and longitude coordinates for the N establishments in a given sample. Correspondingly, the set of points incorporated into the kernel estimator at each $\mathbf{x}$ are given by $\mathbf{X}_\ell = (X_{\ell,1}, X_{\ell,2})$ for $\ell = 1, 2, ..., N$. Together, the bivariate Gaussian function $K(\mathbf{x})$ and the 2×2 bandwidth matrix $\mathbf{H}$ determine the shape of the kernel density estimator $\hat{f}(\mathbf{x}; \mathbf{H})$ defined in Equation 2.

$$\hat{f}(\mathbf{x}; \mathbf{H}) = N^{-1} \sum_{\ell=1}^{N} |\mathbf{H}|^{-1/2} K(\mathbf{H}^{-1/2}(\mathbf{x} - \mathbf{X}_\ell)) \tag{2}$$

$$\mathbf{H} = \begin{pmatrix} h_1^2 & h_{1,2} \\ h_{2,1} & h_2^2 \end{pmatrix} \tag{3}$$

The choice of $\mathbf{H}$ is debated in the literature[15] and may have a significant impact on estimates of $\hat{f}(\mathbf{x}; \mathbf{H})$. In economic applications of kernel density estimation, scholars (e.g. Duranton and Overman (2005), McMillen and Klier (2008) and Ellison et al. (2009)) incorporate the *rule of thumb* bandwidth selection based on Section 3.4.2 of Silverman (1986). However, this type of bandwidth selection procedure may not be the best choice in our case because it assumes zero covariance and as discussed by Wand and Jones (1995) may oversmooth the data, thus masking the presence of multipeaked surfaces. These two issues are relevant to our data and study area. First, off-diagonal elements of the bandwidth matrix should be non zero when establishments are aligned with physical features such as roads or rivers which can be oriented in directions other than north-south or east-west. In our study area, this is true for a number of establishments which are located on the US 36 corridor

of kernel smoothing. McMillen and Klier (2008) and Duranton and Overman (2005) justify the use of kernel smoothing to help overcome data inaccuracies in establishment location due to measurement error. Additionally, kernels may be a good way to capture industry spillovers which are a decreasing function of distance from an establishment (Duranton and Overman (2005) and Ellison et al. (2009)).

[13] As discussed by Waller and Gotway (2004) and Duong and Hazelton (2005a), the choice of functional form for kernel estimation generates small differences in estimated densities, but the choice of bandwidth has significant consequences.

[14] In the context of the Gaussian kernel, the bandwidth is analogous to the covariance matrix.

[15] See Wand and Jones (1995)), Scott (1992) and more recently Duong and Hazelton (2005a) and Hall and Kang (2005) for discussions on the different methodologies for selecting $\mathbf{H}$.

between Denver and Boulder. Second, since we incorporate downtown Denver as well as the surrounding areas such as Boulder and Greeley, and the Denver tech center, the study area is not single peaked.[16]

Therefore, we estimate $\mathbf{H}$ using the smoothed cross validation (SCV) technique introduced by Hall et al. (1992), which has been shown by Duong and Hazelton (2003) and Duong and Hazelton (2005b) to have a low Mean Integrated Square Error (MISE) for a range of target density shapes, an excellent convergence rate for small sample sizes, and an ability to accurately estimate the off-diagonal elements of the bandwidth matrix. The SCV bandwidth selection procedure is more formally discussed in Appendix 6.

Once we determine the appropriate bandwidth for a given sample, $\widehat{\mathbf{H}_j}$, is substituted into Equation 2 to produce a kernel density estimate across our study area for industry j. Since the kernel smooths point data and is unbounded, the surface will necessarily cross the boundaries of the study area. We account for this by imposing a simple 2-dimensional modification of Silverman (1986)'s reflection method. This technique reflects smoothed data for values of (x_1, x_2) outside the study area back into the study area and then assigns zero values to (x_1, x_2) outside the study area.[17] Karunamuni and Alberts (2005) discuss the potential pitfalls of various reflection algorithms, but in practice any bias imposed by reflection on our bivariate kernel density estimation is minimal because of the large amount of undeveloped and sparsely developed land on the fringes of our study area. Reflection concerns are further mitigated by the fact that any statistical test using our kernel estimate involves a counterfactual generated from a kernel estimated with the same reflection method.

A graphical example of a bivariate kernel density estimate for the full population of all $79,038$ establishments in the population is shown in Figure 1. The main area of establishment concentration is centered on downtown Denver and extends to secondary commercial centers in the south, west and northwest which represent the Denver Technology Center, Golden and Boulder. The figure also highlights the discretization that we employed by creating a grid that encompassed our study area comprised of cells of approximately 5 square kms.[18]

[16] Redfearn (2007) and McMillen (2001) find the presence of multiple commercial centers of varying sizes within most large U.S. urban areas.

[17] Specifically, for $\hat{f}(x_1 < min(x_1), x_2)$, where x_1 is outside the study area, we assign its density to $(x_1 = (min(x_1) + (min(x_1) - x_1)), x_2)$ and replace $\hat{f}$ with zero. Correspondingly, we assign density values to zero for locations where $(x_1, x_2 < min(x_2))$ and the density is given to $(x_1, x_2 = (min(x_2) + (min(x_2) - x_2)))$. This process is replicated for all densities where $(x_1 > max(x_1), x_2)$ and $(x_1, x_2 > max(x_2))$ and densities are assigned to $(x_1 = (max(x_1) - (x_1 - max(x_1))), x_2)$ and $(x_1, x_2 = (max(x_2) - (x_2 - max(x_2))))$ correspondingly.

[18] Conceptually, results should be similar as the size of the grids change. We formally tested this result by applying our test for specialization to the case when we discretize the study area into larger 15 square km grid cells and results find the same number and composition of four digit industries that are subject to

The resulting grid of 51 by 51 cells is then overlaid onto our bivariate kernel density with the kernel density values assigned to the centroid of each grid cell and represent the density estimate for a given place.

In the first stage of our test, we apply the kernel density and discretization algorithm to the population of establishments in each 4 digit industry. As one would expect, there is a large amount of variation in establishment density across industries. Figure 2 provides examples for two specific industries, NAICS 5411 - Legal Services, and NAICS 5417 - Scientific Research & Development Services. It is clear from the industry population kernels that Legal Services contains multiple dense centers in downtown areas, while Scientific Research & Development Services contains lower density centered on Boulder and Denver.

4 Local P Values

The denominator of the LQ illustrates the need to scale the place specific industry concentration by the population concentration. Therefore, the next step in the construction of our estimator is to compare the kernel density estimate of a individual industry at a given place to what would potentially be observed from random draws of the population. We do this by first identifying a population counterfactual based on randomly located industries and then estimating the full distribution of potential establishment concentrations across places for an industry. Finally, we compare the results to the actual industry concentrations to generate a base measure of statistical significance in the form of local p-values.

Similar to Duranton and Overman (2005), our sampling procedure to determine the counterfactual of randomly located industries has two specific criteria: 1) the sample should be drawn from the set of locations where a establishment could potentially locate, and 2) the sample size used in constructing the counterfactual must be equal to the number of establishments in the industry. Since our data contains two distinct types of establishments, manufacturing and service, we split our counterfactual accordingly.[19] We assume that an establishment in a given service industry (NAICS 4000 to NAICS 8142) such as a grocery store or a dental office can reasonably locate in any service site. The same holds for specific manufacturing industries (NAICS 3000 to NAICS 3999) and all manufacturing sites. This strategy helps control for potential zoning regulations as well as other unobservable

specialization by at least one place.

[19]Using all establishments as a counterfactual, we would expect more specialization because of the use of infeasible sites in determining the benchmark of random location. Therefore, our counterfactual is a more conservative measure for concluding specialization.

constraints on industrial location for manufacturing and service industries.[20]

For each industry, j, we construct a counterfactual based not only on potential establishment locations but also on an industry's establishment count, N_j.[21] We then randomly select N_j locations from the set of possible service or manufacturing establishment sites without replacement. The resulting point data is then smoothed with the kernel function and densities are assigned to the corresponding grid cells. We apply the $\mathbf{H_j}$ derived for each industry to that industry's corresponding counterfactual in order to provide a consistent bandwidth when comparing industry densities to our counterfactual.[22] We repeat this process of random point selection and kernel density estimation 50,000 times to create the empirical null distribution.

For each place $i = (1, .., I)$ in our study area, we compare the industry establishment density to the relevant empirical null distribution to create local p values (p_i^{local}). Our local p values represent the probability of falsely rejecting the null hypothesis of no specialization for each place and thus represent a single test for specialization at place i. For each industry, each grid cell contains a unique p_i^{local} based on the corresponding null distribution. This p_i^{local} is a pivotal statistic, which allows one to compare results within a given industry across all places irrespective of the underlying heterogeneity in null distributions by location.

Figure 3 displays local p-values for our example industries of Legal Services and Scientific Research & Development Services. We scale the p-values as $(1 - p_i^{local})$ to ease visual comparison to earlier population kernels. Therefore, areas of greater specialization relative to the empirical null distribution correspond to higher values on the z-axis. Corresponding contours for these p-values are provided in Figure 4. Darker areas in this figure indicate places of higher establishment concentration for an industry relative to randomly located industries. Legal Services are characterized by a multitude of higher and lower p-values across the study area, indicating that Legal Services tend to locate in multiple spatially concentrated clusters. These clusters follow population centers for this study area. For Scientific Research & Development Services, the bottom of Figure 4 shows corresponding p-value contours with relatively more concentration (darker areas) in/around Boulder and relatively less in Denver compared to the counterfactual. Referring to the population density

[20]For example, it is unlikely that a concrete plant could reasonably locate in a strip mall with neighboring retail establishments.

[21]Restricting out counterfactual to the same number of establishments as our industry of interest accounts for any variation in the estimated density due to the sample size of the point process.

[22]We considered estimating $\mathbf{H}$ uniquely for each estimated kernel (industry or counterfactual), but wanted to demonstrate that differences in kernel bandwidths between our industry and counterfactual kernels were not influencing our results.

shown in Figure 2, we can see that the population kernel is captured in two peaks, one over Boulder and the other over Denver. The place specific local p-values highlight that kernel densities in Boulder and Denver for Scientific Research and Development Services are more likely to represent non-random clustering in Boulder than in Denver.

5 Global P-Values

Lower local p-values provide greater evidence that a place specializes in a given industry. However, if we are interested in evidence that an industry is specialized in *any* place, then inference based upon local p-values will overstate the amount of specialization. For example, assume that we define a standard critical local p-value of 0.05, and then perform hypothesis tests for an industry across all 2,601 places that encompass our study area. Even if establishments were just randomly distributed across the study area, we would still expect to find 130 places where we reject the null hypothesis of no specialization for a given industry. This would lead us to naively conclude that all industries are subject to specialization in multiple places. This issue has been termed the multiple hypothesis testing problem. Though well established in statistics and biostatistics, economists have only recently began to recognize and properly correct for the flawed inference due to Type I errors under multiple hypothesis testing in empirical research. In recent work, Romano and Wolf (2005) stressed the need to minimize empirical data snooping for 'false positives' by controlling for familywise error rates (p^{FWE}). This entails adjusting the critical values for each of the individual hypothesis tests to ensure that the probability of rejecting the null for *any one* of the multiple hypothesis tests is approximately equal to the p^{FWE}.[23] Therefore, we define a familywise error rate (here we choose 5%) and adjust the threshold (p^{adj}) upon which we conclude statistical significance so that a false positive test for specialization only occurs in a prespecified percent of randomly located industries.

The Bonferroni correction is a classic and simple method for deriving the threshold value p^{adj} from a predetermined familywise error rate (p^{FWE}). This procedure divides the desired p^{FWE} by the number of hypothesis tests to find p^{adj}.[24] For our study area, with 2,601 individual hypothesis tests, the Bonferroni correction defines $p^{adj} = .00002$. This adjusted

[23] Some examples of recent economics papers that adopt FWE corrections include Anderson (2005), Kling et al. (2007), Bifulco et al. (2008) and Ross et al. (2008)

[24] The logic behind this test is that each of the I places has a probability p^{adj} of being less than a critical value. The probability of *all* places being greater than p^{adj} is $(1-p^{adj})^I$. Therefore, the familywise error rate is defined as the probability that at least one place is less than the critical value is $p^{FWE} = 1 - (1 - p^{adj})^I$. For small levels of p^{adj}, this can be approximated as $p^{adj} = p^{FWE}/I$.

p-value is simple to compute, but it overcorrects if the hypothesis tests are correlated. In order to see this, consider a case where all of the hypothesis tests were perfectly correlated, then the correct choice for p^{adj} would be exactly equal to p^{FWE}. In our case, where p-values are derived from smoothed and generally spatially correlated data, the Bonferroni method is too conservative and will underestimate specialization.

The failure of the Bonferroni method to account for correlation across hypothesis tests has resulted in a myriad of alternative strategies, ranging from parametric tests that explicitly define the nature of the correlation, random field methods which are are based on the topological characteristics of Gaussian random variables[25], to nonparametric bootstrap and permutation techniques based upon the re-sampling procedures of Westfall and Young (1993).[26] For the purpose of testing for specialization, the permutation based methods are best suited to control for spatial correlation without needing to make parametric assumptions on the shape of the empirical null distributions across places.

Again, our goal to is to determine a critical value p^{adj}, which will result in a positive test for *any* place across the study area due to randomness only 5% of the time (the familywise error rate). An outline to create the correct p^{adj} is defined as follows and is based on Westfall and Young (1993) Algorithm 2.5. First, we randomly sample $N_{\tilde{j}}$ establishments without replacement in order to generate a randomly located industry, which we term pseudo industry $\tilde{j}$. Next, we apply our kernel density estimator $\hat{f}$ to our $N_{\tilde{j}}$ establishments and assign the estimated density to each place $i = 1, .., I$. We then construct our empirical null using 50,000 replications of the pseudo industries from the relevant counterfactual[27] of $N_{\tilde{j}}$ random establishment sites. The empirical null determines local $p^{local}_{i,\tilde{j}}$ for pseudo industry $\tilde{j}$. We then select $\overline{p_{\tilde{j}}} = min_{1 \leq i \leq I}\ p^{local}_{i,\tilde{j}}$. This represents one pass of our routine.

This algorithm is repeated $\tilde{j} = 1, .., \tilde{J}$ times and generates $\tilde{J}$ values of $\overline{p_{\tilde{j}}}$. Sorting these values generates a distribution of global p-values. In order to determine the p-value which satisfies the familywise error rate, we select the $\overline{p_{\tilde{j}}}$ for which only 5% of the ranked $\overline{p_{\tilde{j}}}$ are

[25]These are based on the underlying topology of the region used for hypothesis testing, and are much less computationally intensive than resampling procedures. See Adler et al. (2009) for an excellent introduction to random field based derivations of global confidence levels for any geometric region. A necessary condition for random field techniques is that the distribution of the empirical null distribution at each place follows a Gaussian distribution. We tested if this assumption is valid for our dataset. We found a large number of places with non-normal distributions, which therefore invalidates the use of random fields based methods.

[26]Of these three procedures, Nichols and Hayasaka (2003) finds that the nonparametric re-sampling procedures outperformed a series of parametrically defined Bonferroni and random field based critical values using simulated data.

[27]As the number of places increases, more replications are required to ensure that a sufficient number of decimal places can be captured for resulting p-values.

smaller. The resulting global critical p-value is given by $p^{adj}_{N_j}$ and is determined uniquely for every possible industry size in our dataset. $p^{adj}_{N_j}$ is significantly smaller that the 0.05 naively determined critical value that ignores the problem of multiple hypothesis testing and greater than the .00002 defined by the Bonferroni correction.

To verify that our test adequately controls for industry size and is equally able to detect specialization in urban and rural locations, we conduct a Monte Carlo experiment upon randomly located (pseudo) industries. We use the fact that our $p^{adj}_{N_j}$ are set such that 5% of pseudo industries exhibit at least one specialized place in order to examine the distribution of specialized places for randomly located industries. We apply $p^{adj}_{N_j}$ to 5,000 pseudo industries for industry sizes of 5, 10, 100 and 500 establishments and record which places never experienced specialization.[28] In order to later test the statistical significance of Monte Carlo results, we repeat this experiment twenty times. We also categorized each place into quartiles based on the full population kernel density with Quartile 1 being the least dense (rural areas) and Quartile 4 being the most dense (urban areas).[29]

Table 1 provides our results and reported values are based on the median count of our twenty Monte Carlo experiments. The first column indicates the number of non-specialized places in total for each industry size. Results show an even distribution of non-specialized places (with median values between 1,304 and 1,380)[30] across industry sizes with no relationship between industry size and the number of non-specialized places. This even distribution holds across quartiles with a range of between 319 and 359 non-specialized places by quartiles and sample sizes. We formally test these results using a Kruskal and Wallis (1952) test. This nonparametric test uses the ranking of the number of non-specialized places for each pseudo industry across industry sizes or quartiles to test the equality of population medians among the groups. The null hypothesis is that all groups are drawn from identical distribution functions. We implement this test separately across the four industry sizes and four quartiles within each industry size and report the results in Table 1. The fact that none of our Kruskal-Wallis tests can reject the null hypothesis indicates that our test for specialization

[28] Due to the large computational burden in implementing this Monte Carlo experiment, we made some simplifying assumptions on the kernel bandwidth by adopting a product kernel based on the 'rule of thumb', which assumes no off-diagonal elements. Furthermore, we select pseudo industries from all service and manufacturing sites.

[29] These quartiles of density capture heterogeneity in empirical null distributions across places due to our random sampling of establishments in generating our counterfactual.

[30] Given that $p^{adj}_{N_j}$ allows 250 psuedo industries to be subject to specialization in at least one place, we expect at the minimum to find at least one specialized place per industry. We find considerably more specialized places and thus fewer non-specialized places because of the spatial dependence in our measure of industry concentration.

is insensitive to industry size as well as the population density of places.[31] These properties are important in order for us to compare our results for specialization across industries as well as between downtown, suburban and rural places.

Figure 5 provides results of the global test for specialization for our two example industries. Areas of black indicate areas where $p^{local}_{i,j} < p^{adj}_{N_j}$ for place i in industry j. Areas of white indicate where we accept the null hypothesis of no specialization. Legal Services experiences three distinct clusters spread across the study area. These correspond closely with the cities of Denver, Boulder and Greeley. Scientific Research & Development Services exhibits significant specialization in multiple neighboring places northwest of Denver (along US-36 and in Boulder).

6 Spatial Composition of Specialization

Since the composition of economic activity varies both across and within urban areas, patterns of specialization are likely influenced by both city specific characteristics as well as the varying forces of urbanization within a city. The theorized relationship between urbanization and specialization was pioneered with the development of Christaller (1966)'s Central Place Theory, which predicts that different sized cities produce and specialize in different types of goods. A number of empirical studies[32] offer support for this theory and most conclude that in moving to larger, more urbanized areas, specialization increases in both the scale of production as well as types of goods. Henderson (1996) and Henderson (1983) find that larger urban areas tend to specialize in higher technology or evolving industries, while smaller urban areas specialize in more traditional manufacturing. To our knowledge, none of this empirical literature focuses on the relationship between specialization and urbanization within an urban area.

We begin by summarizing the overall spatial composition of specialization for all industries in Figure 6. Downtown Denver is in the center and contains the places with the greatest number of industries subject to specialization. Secondary commercial centers such as Boulder in the Northwest, the Denver Technology Center to the South and Greeley to the North also contain a number of industries subject to specialization. However, specialization is not confined to only the most dense urban areas. A number of specialized places

[31] Again, the notion of multiple testing comes into play here, since we are performing 8 different hypothesis tests. In fact, using a basic Bonferroni correction we would expect to find a p value < 0.1 from the 8 tests 57% of the time.

[32] Berry (1968), Henderson (1988) and Sveikauskas (1975).

extend radially along transportation corridors and the vast majority of places in our study area specialize in at least one industry. Overall, the presence and scope of specialization has a positive relationship with the location of commercial centers in this urban area. This pattern is statistically and economically significant, since our Monte Carlo results predict that if establishments are randomly drawn from the population, the presence or absence of specialization should not correlate with the commercial density of a place.

The relationship between specialization and urbanization is described in Table 2, which provides the frequency of industries subject to specialization by quartiles of population density. We adopt a simple measure of urbanization based on the quartiles of kernel density estimates from our full population shown in Figure 1. The first two rows of the table compare the distribution of places across quartiles for non-specialized and specialized places. Comparing the distributions of non-specialized places versus specialized places highlights a positive relationship between urbanization and specialization. Specialized places have a greater representation in the densest quartile while non-specialized places have greater representation in the least dense quartile. As shown by the Monte Carlo experiment for psuedo industries, the ratio of non-specialized places found in the most dense to the least dense locations is between .92 and .99, while with our actual industry data, this ratio is 0.3. This pattern also holds true for the actual counts of specialized places. Overall, 26% of all places in the study area do not specialize in any industry and 43% of places specialize in only one or two industries.

The final column of Table 2 indicates that the first quartile is more likely to not specialize or to specialize in only one industry and places that specialize in two or more industries have a greater representation in the 4th quartile. From the most dense quartile, one sees that places that specialize in a large number of industries are almost exclusive to more urbanized places. Supporting a larger number of industries likely requires a sufficient concentration of commercial activity.[33] For places in the first quartile, 39% of places do not specialize in any industry and 47% of places specialize in only one industry. Correspondingly, only 14% of places in the densest (fourth) quartile are not specialized in any industry. The second quartile finds 27% and the third quartile finds 24% of their places to not specialize in any industry. The second and third quartiles represents a number of suburban places and contain the greatest concentration of places that specialize in between one and four

[33] One may be concerned that a high commercial density is required for us to conclude that a place has a large number of specialized industries. This is not due to the nature of our test for specialization, for which concluding a place to specialize in one industry does not influence the test for specialization in another industry.

industries. Suburban places appear well suited to specialize in a few industries.

The relationship between specialization and urbanization may also vary by industry sector. We provide the number of specialized places for each industry aggregated to 2 digit industry sectors and the distribution of these places across quartiles of population density in Table 3.[34] Across industry sectors, places specializing in industries in the Finance & Insurance and Professional & Scientific & Technical Services are more often located in the densest places, while Accommodation & Food Services and Arts, Entertainment & Recreation have the smallest presence in the most dense places. Places in denser commercial areas almost never specialize in Arts, Entertainment & Recreation industries and this industry sector is heavily specialized in suburban or secondary commercial centers (61% of the specialization in this sector occurs in the third quartile). Industries in Manufacturing, Transportation & Warehousing , Information, Administrative & Waste Services and Accommodation & Food Services have a number of specialized places across quartiles and highlight a strong presence in both downtown as well as suburban places. Information and Manufacturing contain some higher technology industries and tend to locate along suburban transportation corridors and industrial parks between Boulder and Denver as well as south of Denver in the Denver Technology Center.

We next examine the relationship between specialization and urbanization for specific four digit industries. For ease of exposition and comparisons across four digit industries, we assign each specialized place a ranking based on its population density. We rank places from least to most dense[35] and compute summary statistics based on these rankings across all specialized places within a given four digit industry. We provide results for the industries located in the least dense, most dense and highest variance in density specialized places. We also identify the number of distinct sets of specialized places for each industry, where we define a set of specialized places as a single grouping of contiguous places.[36]

In the top panel of Table 4, we identify the top ten industries based on specialized places in the least dense locations. One of these industries is Lawn & Garden Equipment & Supplies Stores, which is shown in the top panel of Figure 7. The bottom panel of this figure plots the rank of specialized places on the x-axis and their corresponding population density on the y-axis. This figure displays a dot for each specialized place in this four digit industry and highlights the presence of a number of specialized places in the low density areas. Low density

[34] Percentages in columns are based on the number of specialized places for each 2 digit industry sector.

[35] The least dense place is given a rank of 1 and the most dense place a rank of 2,601.

[36] For example, Figure 5 shows that NAICS 5411 contains 3 distinct sets varying in size from a single place to a set of 15 contiguous places.

specialization also occurs for Recreational Vehicle Parks & Recreational Camps, which locate in/around national wilderness areas in the foothills of the Rocky Mountains on the western edge of our study area. Some residential based industries on this list are Elementary & Secondary Schools and Agents & Managers for Public Figures. The former includes private education institutions and the latter incorporates a number of home businesses. Other Support Services includes a number of industrial based business support services which would require large tracts of land and likely serve businesses across the urban area. A number of four digit manufacturing industries such as Waste Collection and Agricultural Chemical Manufacturing are often located away from denser commercial areas due to the fact that they produce negative externalities in production.

The second panel of Table 4 shows the top 10 industries based on specialized places in the most dense locations. All ten industries are specialized in a single part of the urban area as given by the presence of only one set of specialized places. Figure 8 highlights the Advertising & Related Services, which contains a set of specialized places in downtown Denver.[37] Two main types of industries populate this list. First, Other Investment Pools & Funds and Professional, Scientific & Technical Services represent the large presence of financial and professional services in downtown Denver, which serve a number of central city businesses. Second, Social Advocacy; Business, Professional & Labor Organization and Grant making & Giving Services locate in order to access officials in the state capital, which is located in downtown Denver. The first group of industries likely benefit from both own industry as well as other industry concentration while the second group concentrates to access the state capital.

As shown in the bottom panel of Table 4, variance in the population density of specialized places occurs for a range of industries and is exclusive to industries with multiple sets of specialized places. The mix of denser and sparser specialized places highlight that specialization is not exclusive to certain commercial densities for these industries. Figure 9 displays Management of Companies and Enterprises, which captures establishments that contain equity interest in companies and may serve as administrative or corporate offices. This figure displays four distinct sets of specialization of which two are in higher density places and two in lower density places. These establishments tend to locate in both downtown and suburban areas. Waste Collection serves both residential and business locations. Other Personal Services, which include such diverse activities as bail bonding, parking lot/garages as well as

[37]The results are consistent with Arzaghi and Henderson (2008)'s discussion of advertising agency concentration in Manhattan.

dating services, generates a range of specialization and commercial densities.[38] The two air transportation industries are located proximate to airports and also along interstates and thus contain a mix of suburban locations.

7 Industrial Composition of Specialization

Table 5 presents the results of our test for specialization summarized across all four digit NAICS industries as well as just the manufacturing, business services, and non-business services sectors. We find that 62.0% of all industries contain *as least* one place with significant specialization, with business services containing the highest portion of industries subject to specialization at 71.5%. The manufacturing sector contained the fewest portion of industries with 41.0%, while 70.2% of non-business service industries where found to be specialized in at least one place. The large representation of business service industries is consistent with perceptions of technology and professional clusters like Route 128 in Boston and Research Triangle Park in North Carolina. The smaller representation for manufacturing industries is consistent with our use of a single urban area, which limits such agglomeration benefits as labor matching/pooling or access to specialized inputs.

Table 5 also describes the number of distinct sets (groups) of specialized places. We find that 24.0% of all four digit industries are subject to specialization in more than one set of places and 9.7% of industries are in three or more sets of specialized places. Manufacturing is the least likely of the broad industry classifications to be subject to specialization, and when specialization occurs, it is concentrated in one portion of the urban area, with only 10.3% of all industries being in more than one set of specialized places. In contrast to Manufacturing, 24.6% of Non-Business Services and 32.5% of Business Services locate in more than one set of specialized places. The presence of approximately a quarter of industries containing multiple sets of specialized places in these two classifications suggests that agglomerative forces are present at varying scales across industries.

To further explore the industrial composition of specialization, Table 6 provides the percent of four digit industries with any specialized places for more detailed industry sectors. Focusing only on the column for specialization highlights some variation in trends within the business and non-business service sectors. Eight of the nine four digit NAICS technology and professional industry classifications (NAICS 54) are subject to specialization. Other highly

[38] In essence, some of the multiple sets of specialized places may just be a result of industry classification. This highlights a problem that is endemic to this literature, the mismatch between industry classifications (e.g. NAICS, SIC) and industry categorizations that best capture agglomerative forces.

specialized sectors are Wholesale Trade, Real Estate & Rental & Leasing and Accommodation & Food Services. These industries are not commonly discussed in the agglomeration literature. Their specialization may be due to industry specific spillovers, but place specific amenities such as access to highways or consumer markets likely matter. Service industries often not subject to specialization include Educational Services and Arts, Entertainment & Recreation. These industries are highly consumer dependent and competition between establishments providing similar products and services likely weaken agglomerative forces.

8 Comparison of Agglomeration Measures

The relationship between specialized places for a specific industry and that industry's overall degree of localization may highlight the role of industry specific as well as place specific agglomerative forces. Therefore, we implement a test for localization in order to highlight the relationship between specialization and localization across each industry. Duranton and Overman (2005) provide a well established test for localization that incorporates some similar characteristics as our test for specialization. We begin by replicating the Duranton and Overman (2005) methodology using our Colorado dataset with our full set of industry classifications and note any modifications in our application.

8.1 Duranton & Overman Test for Localization

The first step in implementing the Duranton and Overman (2005) test for localization is to estimate a univariate kernel density based on $\frac{n*(n-1)}{2}$ unique pairwise Euclidean distances for all n establishments in a given industry.[39] This kernel may be defined for areas where the pairwise distance is less than zero, so data reflection is done following the Silverman (1986) technique. Kernel bandwidths are set along one dimension, the pairwise distance, using the Silverman (1986) 'rule of thumb' procedure. The counterfactual of randomly located industries is based on randomly sampling from all manufacturing or service establishments analogous to the methodology described in Section 4. We simulate a full empirical null distribution of kernel smoothed pairwise distances using 2,000 replications. Finally, local critical values are determined from the empirical null distribution for all possible pairwise

[39]One practical issue with this methodology is the exponential growth in pairwise matches for industries with a large number of establishments. To avoid computational problems for large industries, we randomly draw a subset of establishments equal to 200 for any industry or counterfactual with more than 200 establishments.

distances.

The Duranton and Overman (2005) solution to the multiple testing problem is to create global confidence bands based on null distribution kernels. This is done by sorting kernels at each pairwise distance such that 95% of the kernels lie entirely below the upper confidence band. The envelope of kernel density values that satisfy these criteria provide the global confidence band for each pairwise distance. These global confidence bands are conceptually similar to our globally adjusted p-value because they dictate that 95% of randomly located industries accept the null hypothesis of no localization at any pairwise distance.[40] We calculate the median pairwise distance in our dataset (25.6 km)[41] and conclude localization when an industry specific kernel exceeds the global upper confidence band for any distance less than or equal to 25.6 km. Correspondingly, we conclude dispersion for distances greater than 25.6 km.[42]

The graphical results of the Duranton and Overman (2005) test for localization in our two sample industries are shown in Figure 10. For Legal Services, the test concludes localization because the industry kernel exceeds the global upper confidence band given by the dotted line for all distances less than approximately 10km. A second significant range of distances occurs from 35 to 40 km, and represents the distance between clusters of establishments. In other words, the first peak defines the intensity of existing clusters and the second peak represents the distance between the clusters. In the lower panel of Figure 10, the industry based kernel for Scientific Research & Development Services exceeds the global confidence band at distances of 35 to 55 km, which is in a range greater than the median pairwise distance of 25.6km. Therefore, no localization is concluded for this industry.

8.2 Specialization and Localization

We provide the results for four specific industries, which highlight the range of results across our 258 industries upon which we test for specialization as well as localization. Each set

[40]The main applied difference is that we generate local p-values so that a single p-value provides a global critical value instead of the Duranton & Overman global confidence bands, which vary across pairwise distances.

[41]The maximum pairwise distance in our dataset occurs around 120 km.

[42]This is a modification from Duranton and Overman (2005) who only look at pairwise distances less than or equal to the median pairwise distance and use an upper and lower confidence band. In Duranton and Overman (2005), pairwise distances that exceed the upper global confidence are concluded as localized and distances that fall below the lower global confidence threshold are designated dispersion. Both methods should provide similar results since the kernel density integrates to one over the full range of pairwise distances. We make this modification because we later test the sensitivity of concluding localization for distances other than the median distance in our dataset.

of figures provides an industry's population kernel, globally significant specialized places, plots of specialization by commercial density and the Duranton & Overman estimate of localization for comparison. Figure 11 provides results for NAICS - 3118 Bakeries & Tortilla Manufacturing. Comparing our results with Duranton & Overman show that this localized industry contains one specialized place. Panel (c) of Figure 11 shows that this specialized place is located in a medium density commercial center just east of Downtown Denver. An example of an industry with multiple sets of specialized places is given by NAICS 5171 - Wired Telecommunications Carriers in Figure 12. Results emphasize the presence of two sets of specialized places in denser portions of the study area. According to Duranton & Overman, this industry would be characterized as localized at two different scales, less than 4 km and also between 19 and 22 km. Figure 13 provides results for NAICS 4841 - General Freight Trucking and indicates the presence of multiple sets of specialized places in sparser locations along Interstates 25, 70 and 76. Duranton & Overman's test would not find this industry to be localized. An industry that provides neither specialized places nor localization is NAICS 4422 - Home Furnishing, which is given in Figure 14.

These graphical examples highlight elements of industry concentration that may be undetected or masked in existing tests for localization. The presence of a large number of specialized places in General Freight Trucking highlights industrial concentration that is statistically significant for a large number of places, yet insignificant for the industry as a whole. This result may highlight the importance of interstate access for this industry. Of course, patterns of specialization can vary even for similar measures of localization. A pattern of specialization for fewer places and/or different regions of the urban area may indicate the role of different agglomerative forces and/or place based amenities. The presence of both specialization and localization can also highlight the dual role of industry specific spillovers and place based amenities. For example, a set of specialized places exists around Denver International Airport for the localized industry of NAICS 4811 - Scheduled Air Transportation. Likely both access to an airport as well as industry spillovers matter for this industry. In essence, patterns of specialization with measures of localization may help disentangle the agglomerative forces leading to the concentration of an industry.

Table 6 directly compares our estimates of specialization with those of localization by two digit industry sector. For the set of all industries, the differences are substantial. We find that 62.0% of all industries are subject to specialization in at least one place while only 28.7% of industries are localized.[43] This difference is maintained for most two digit industry

[43] The substantially fewer localized industries than industries subject to specialization is minimally influ-

sectors. In Duranton & Overman 's study of national level U.K. manufacturing, they found that 52% of industries are localized. Using Duranton & Overman's measure we find only 15% of manufacturing industries are localized. The smaller estimate for manufacturing in our study area relative to the U.K. dataset is consistent with the scale of our dataset being limited to a single urban area. This scale of analysis limits such localization benefits as labor matching/pooling and access to specialized inputs.

Eighteen of the nineteen Wholesale Trade industries (94.7%) are subject to specialization, while only 52.6% of Wholesale Trade industries are localized. This difference may be attributed to specialized places with low establishment concentrations and/or the presence of a large number of specialized places, which may not generate a sufficient concentration of small pairwise distances to conclude localization under the Duranton & Overman test. Wholesale Trade industries likely locate away from traditional downtown commercial centers given their large scale operations and lack of walk-in traffic. In Retail Trade, 74.1% of four digit industries are in at least one specialized place while only 25.9% are localized. Large retail and strip malls may generate specialization, but likely do not represent enough overall industry concentration to conclude localization. One of the most striking differences between industry findings for specialization and localization is in Professional, Scientific & Management Services where eight of nine industries are in specialized places, but only four are considered localized. These higher technology industries are located in downtown Denver, secondary commercial centers in Boulder, Golden and along US-36 connecting Denver to Boulder as well as in the Denver Technology Center in the southern portion of the study area. Specialization in multiple portions of the urban area appear too spread out to conclude localization. Accommodation & Food Services industries locate across the study area and contain the largest difference between industries subject to specialization and industries found to be localized.

To compare and contrast patterns of specialization and localization, we break down results by those industries which are found to contain specialized places, but are not localized as well as those industries which are localized, but do not contain any specialized places. Eighty-seven industries contain specialized places, yet are not localized. This is not a relationship endemic to particular industries or sectors. By definition, specialization is based on place specific industrial concentration and thus each place only marginally contributes to a measure of localization. Therefore, specialized places may not contribute enough to overall

enced by the pairwise distance used to classify localization and dispersion. For example, our finding that 28.7% of industries are localized increases to 33.3% and 40.3% if one adopts the 75th percentile of pairwise distances (40.5 km) and the 95th percentile of pairwise distances (69 km) for concluding localization.

industry concentration to be considered localized. If this is true, then specialized places in non-localized industries should be located in lower density places than specialized places in localized industries.

We formally test if industries with low density specialized places are less likely to be localized. Across all industry sectors, 72 four digit were both localized and specialized, with an average specialization place rank of 2420 or in the top 7% most dense places for our study area. Of the 87 industries which were specialized but *not* localized, the average specialization rank was 2133 or in the top 18% most dense places.[44] Implementing a bootstrapped t-test for differences in means between the average population density[45] for specialized places between the two groups finds that they are statistical different from one another (t=5.74). These results show that our test for specialization detects a number of industries with clustering in low density places that do not contribute enough to overall industry concentration to conclude localization for those industries. Furthermore, if one looks at the top ten industries by density of specialized places in Table 4, nine of these industries are identified as localized. This compares to only two localized industries out of the ten industries with the lowest density for specialized places.

9 Conclusion

In this study, we develop a new statistical test for specialization which is able to identify not only where specialization occurs, but also which industries are subject to specialization. We implement our test by constructing a bivariate kernel density estimator of establishment concentration within a given industry. We use establishment density estimates and a permutation based empirical null distribution of randomly located industries to assign probabilities of non-random clustering across places in our study area. Our technique derives a new global estimator for significant departures from randomness that accounts for spatial dependence across hypothesis tests and is unbiased for small samples. This methodology yields a measure of specialization that can be applied to econometric studies of agglomeration, yet still allow for statistical tests of the significance of specialization and controlling for the Modifiable Areal Unit Problem (MAUP).

Results indicate a positive relationship between urbanization and specialization with dense commercial places more likely to specialize and to do so in more industries. Industry

[44] Only two industries tested positive for localization, but not for specialization.

[45] The average population density for specialized places in non-localized industries is 0.00141 and for specialized places in localized industries is 0.00056.

results show that 62% of all industries contain specialized places and a quarter of these industries contain multiple sets of specialized places within a single urban area. When examining the relationship between specialization and localization, we show that a number of industries are specialized but not localized and these specialized places occur in sparser commercial areas. By industry sectors, results indicate the presence of suburban industry concentration in non-localized industries. This highlights the concern that simply identifying an industry as localized may miss meaningful agglomeration that aids in our understanding of specialized places like Silicon Valley.

Future research points toward econometric studies to isolate the benefits due to industry specific external economies from place specific amenities using this new test for specialization. Econometrically, studies have incorporated the localization measures of Duranton and Overman (2005) and Ellison and Glaeser (1997), but given the nature of localization, analysis is restricted to industry level observations (see Ellison and Glaeser (1999) and Ellison et al. (2009)). A number of papers on the determinants of agglomeration measure clustering based on counts of proximate establishments or employment.[46] Without a formal test to rule out random location, factors that influence overall industrial concentration may confound estimates. By detecting specialized places, subsequent research into the determinants of agglomeration can highlight the role of both industry and place specific factors. Additionally, one can imagine extending this research to highlight patterns of co-specialization and identify sets of industries subject to specialization in the same places. A rich understanding of the patterns of specialization and co-specialization should improve our understanding of the relationship between localization and place specific amenities and their role in local economic growth and development.

[46] For examples of this research, see Arzaghi and Henderson (2008), Rosenthal and Strange (2003b) and Holmes (1999).

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10 Appendix: Smoothed Cross Validation Bandwidth Estimator

The smoothed cross validation bandwidth estimator represents a modification of a least squares cross validation (LSCV) technique. Therefore, we begin with describing the standard LSCV, which is given by,

$$LSCV(\mathbf{H}) = \int_{\mathbb{R}^2} \hat{f}(\mathbf{x})^2 dx - 2n^{-1} \sum_{\ell=1}^{N} \hat{f}_{-\ell}(\mathbf{x}) \tag{4}$$

$$\hat{f}_{-\ell}(\mathbf{x}) = (N-1)^{-1} \sum_{\ell \neq k}^{N} |\mathbf{H}|^{-1/2} K(\mathbf{H}^{-1/2}(\mathbf{x} - \mathbf{X}_k)) \tag{5}$$

This technique involves estimating $\mathbf{H}$ based on minimizing $LSCV(\mathbf{H})$, which directly estimates Mean Integrated Squared Error (MISE), using a leave-one-out estimator ($\hat{f}_{-\ell}$). This technique is extended to smoothed cross validation (SCV)[47] by pre-transforming the data in order to allow better estimation of $\mathbf{H}$ under the large sampling fluctuations in estimates that often occur using standard cross validation techniques. Specifically, we estimate an unconstrained version of SCV with a pre-sphering data transformation. These attributes are shown to improve kernel density estimation even with non-coordinate alignments of point patterns (Duong 2007). The pre-sphering transforms the original data $\mathbf{X}_1, \mathbf{X}_2$ to $\mathbf{X}_1^*, \mathbf{X}_2^*$ by

$$\mathbf{X}^* = \mathbf{S}^{-1/2}\mathbf{X}$$

where $\mathbf{S}$ indicates a full covariance matrix of the untransformed data. The optimal bandwidth $\mathbf{H}$ is determined for each industry by minimizing the following expression using the transformed data $\mathbf{X}^*$.

$$argmin_{\mathbf{H}} \quad SCV(\mathbf{H}) = \int_{\mathbf{R}^2} \hat{f}(\mathbf{x}^{*2}) dx - 2n^{-1} \sum_{\ell=1}^{N} \hat{f}_{-\ell}(\mathbf{x}^*) \tag{6}$$

reported values are based on the median count of our twenty Monte Carlo experiments

[47] See Hall et al. (1992) for more details.

Industry Size (N)	All Places	Least Dense → Most Dense 1st	2nd	3rd	4th	Kruskal-Wallis Test ($\chi^2_{(3)}$)
5	1,380	349	359	344	328	6.7 (0.08)
10	1,370	350	355	341	324	3.4 (0.34)
100	1,304	331	327	319	327	1.6 (0.66)
500	1,377	359	336	352	330	4.2 (0.24)
Kruskal-Wallis Test ($\chi^2_{(3)}$)	4.5 (0.22)	1.2 (0.75)	6.4 (0.10)	3.6 (0.31)	1.3 (0.74)	

Based on $p^{adj}_{N_j}$, 5% of psuedo industries contain at least one specialized place. p-values in parenthesis.
Each row provides the results of our test for specialization on 5,000 psuedo industries of size N_j and
each cell indicates the median count of non-specialized places based on 20 repetitions of these 5,000 psuedo industries.
1st → 4th indicate quartiles of the full population kernel density.

Table 1: Non-Specialized Places for Psuedo Industries

# Industries Subject to Specialization	All Places	Least Dense → Most Dense 1st	2nd	3rd	4th	4th / 1st
0	678	256	178	156	88	0.3
> 0	1,923	394	472	494	562	1.4
0	678	256	178	156	88	0.3
1	760	306	217	136	101	0.3
2	371	55	89	113	114	2.1
3	202	18	31	75	78	4.3
4	149	10	56	47	36	3.6
5	85	2	24	32	27	13.5
6- 10	245	3	54	72	116	38.7
11- 15	48	0	1	11	36	-
16- 20	32	0	0	4	28	-
21- 25	14	0	0	2	12	-
26- 30	11	0	0	2	9	-
31- 49	6	0	0	0	6	-
50- 258	0	0	0	0	0	-
Total Places	2,601	650	650	650	651	

The final column provides the ratio of the number of places in the 4th quartile to the number of places in the 1st quartile.

Table 2: Specialization by Urbanization

NAICS Code	Industry Sector	# Specialized Places	Least Dense → Most Dense 1st	2nd	3rd	4th
31-33	Manufacturing	1,563	8%	22%	28%	41%
42	Wholesale Trade	980	2%	10%	23%	65%
44-45	Retail Trade	350	0%	4%	18%	78%
48-49	Transportation & Warehousing	1,547	6%	27%	33%	34%
51	Information	323	12%	20%	13%	55%
52	Finance & Insurance	188	1 %	1 %	7 %	92 %
53	Real Estate & Rental & Leasing	183	1%	13%	31%	55%
54	Professional, Scientific, & Technical Services	232	0%	1%	14%	85%
55	Management of Companies & Enterprises	20	15%	10%	5%	70%
56	Administrative & Waste Services	297	14%	30%	20%	35%
61	Educational Services	27	0%	0%	22%	78%
62	Health Care & Social Assistance	301	0%	10%	21%	70%
71	Arts, Entertainment & Recreation	97	13%	8%	61%	18%
72	Accommodation & Food Services	521	36%	20%	23%	21%
81	Other Services (except Public Administration)	293	1%	8%	22%	70%

The number of specialized places are based on aggregating 4 digit results to 2 digit industry sectors and percentages in columns are based on the number of specialized places.

Table 3: Specialization by Urbanization for Industry Sectors

NAICS	Industry Name	Sets of Specialized Places	Min	Max	Mean	Std Dev
Industries in Least Dense Specialized Places						
5619	Other Support Services	1	11	117	61.9	34.6
6111	Elementary & Secondary Schools	2	278	297	287.5	13.4
7212	Recreational Vehicle Parks & Recreational Camps	2	18	1739	760.9	431.5
4442	Lawn & Garden Equipment & Supplies Stores	1	510	1203	821.6	215.5
3253	Agricultural Chemical Manufacturing	1	235	1790	880.3	404.4
7114	Agents & Managers for Public Figures	1	474	1655	918.6	350.7
5174	Satellite Telecommunications Services	1	74	2017	962.2	476.6
3159	Apparel Manufacturing	1	421	1596	1020.5	344.2
3365	Railroad Rolling Stock Manufacturing	1	737	1542	1054.7	182.9
5621	Waste Collection	4	235	2420	1097.1	673.1
Industries in Most Dense Specialized Places						
5151	Radio & Television Broadcasting	1	2597	2601	2599.2	1.7
7111	Performing Arts Companies	1	2590	2601	2595.2	4.6
5259	Other Investment Pools & Funds	1	2582	2601	2594.2	6.8
5418	Advertising & Related Services	1	2582	2601	2592.8	6.1
5414	Professional, Scientific & Technical Services	1	2581	2601	2592.5	6.2
8133	Social Advocacy Organizations	1	2561	2601	2590.8	10.8
4421	Furniture Stores	1	2590	2590	2590.0	0.0
6243	Vocational Rehabilitation Services	1	2561	2601	2588.9	10.1
8139	Business, Professional & Labor Organizations	1	2560	2601	2588.2	12.0
8132	Grantmaking & Giving Services	1	2550	2601	2585.0	13.7
Industries with Highest Variance in Density of Specialized Places						
5511	Management of Companies & Enterprises	4	549	2600	1984.9	846.5
5629	Remediation & Other Waste Management Services	2	507	2508	1654.4	732.5
3161	Leather & Hiding Tanning & Finishing	1	22	2238	1142.9	717.4
4812	Nonscheduled Air Transportation	2	541	2566	1665.1	699.3
5161	Internet Publishing & Broadcasting	3	543	2449	1714.1	696.4
8129	Other Personal Services	3	882	2601	1878.2	696.0
5621	Waste Collection	4	235	2420	1097.1	673.1
5324	Commercial, Industrial Machinery Rental	2	854	2546	1779.8	652.7
4842	Specialized Freight Trucking	4	19	2508	1317.3	614.7
4881	Support Activities for Air Transportation	3	219	2539	1362.4	611.2

Values for Min, Max, Mean and Std Dev are based population density of all specialized places in a given industry. The most dense place is given a rank of 2,601 and the lease dense place a rank of 1.

Table 4: Specialization by Urbanization for Specific Industries

	All Industries	Manufacturing	Business Services	Non-Business Services
Percent of 4 digit NAICS Industries with any Specialized Places	62.0%	41.0%	71.5%	70.2%
Percent of 4 digit NAICS Industries with Multiple Sets of Specialized Places	24.0%	10.3%	32.5%	24.6%
Percent of Industries by Number of Distinct Sets of Specialized Places				
Zero	38.0%	59.0%	28.5%	29.8%
One	38.0%	30.8%	39.0%	45.6%
Two	14.3%	7.7%	21.1%	8.8%
Three	6.2%	2.6%	4.9%	14.0%
Four or More	3.5%	0.0%	6.5%	1.8%
Number of Industries	258	78	123	57

We define a distinct set of specialized places as a unique grouping of contiguous specialized places.

For example, Figure 5 shows that NAICS 5411 contains 3 distinct sets varying in size from a single place to a set of 15 contiguous places.

Table 5: Specialization for 4 Digit NAICS Industries

NAICS Code	Industry Name	No. 4 digit Industries	% of 4 digit Industries Subject to Specialization	% of 4 digit Industries Localized
31-33	Manufacturing	78	41.0%	15.4%
42	Wholesale Trade	19	94.7%	52.6%
44-45	Retail Trade	27	74.1%	25.9%
48-49	Transportation and Warehousing	23	69.6%	39.1%
51	Information	16	56.3%	37.5%
52	Finance & Insurance	11	72.7%	54.5%
53	Real Estate & Rental & Leasing	8	75.0%	25.0%
54	Professional, Scientific & Technical Services	9	88.9%	44.4%
55	Management of Companies & Enterprises	1	100.0%	100.0%
56	Administrative, Waste & Remediation Services	11	63.6%	18.2%
61	Educational Services	7	42.9%	14.3%
62	Health Care & Social Assistance	18	66.7%	27.8%
71	Arts, Entertainment & Recreation	9	55.6%	22.2%
72	Accommodation & Food Services	7	85.7%	14.3%
81	Other Services (except Public Administration)	14	64.3%	42.9%
	Total	258	62.0%	28.7%

Percent Localized is based on the methodology described in Section 8.1 and described in more detail by Duranton and Overman (2005)

Table 6: Specialization and Localization

Figure 1: Population Kernel - All Industries

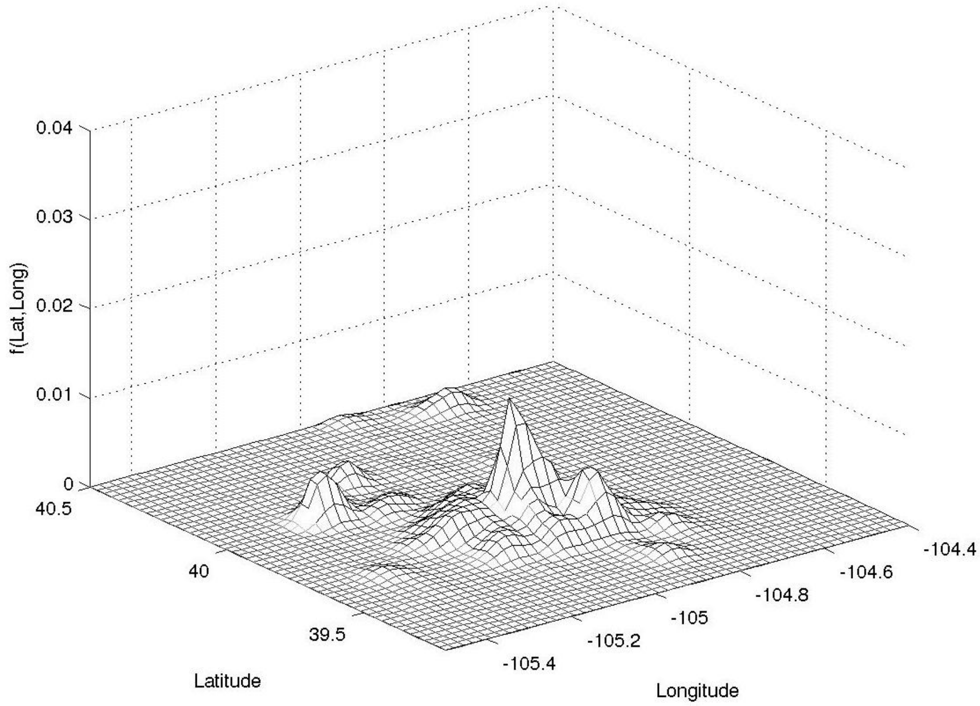
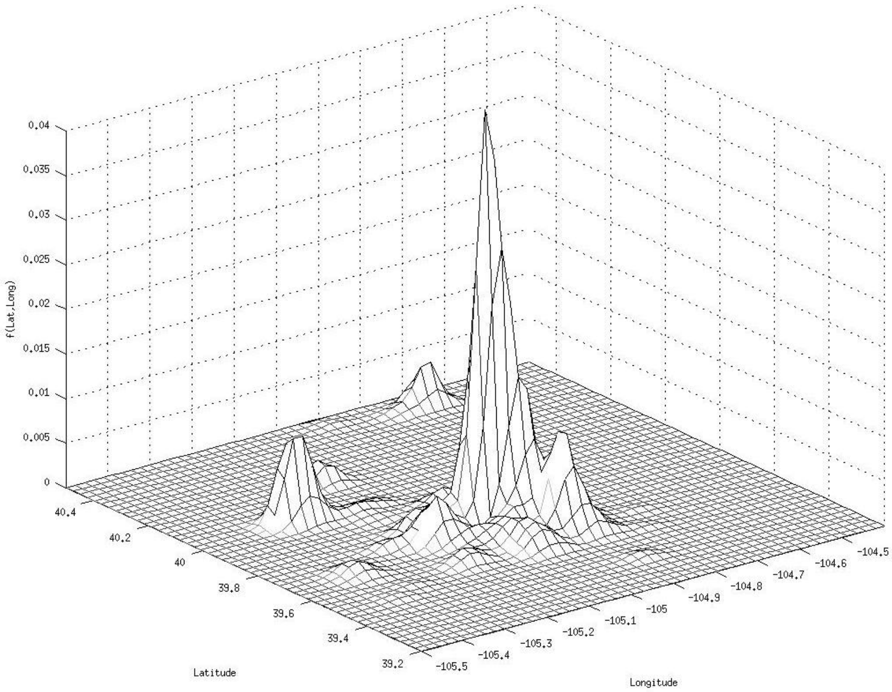
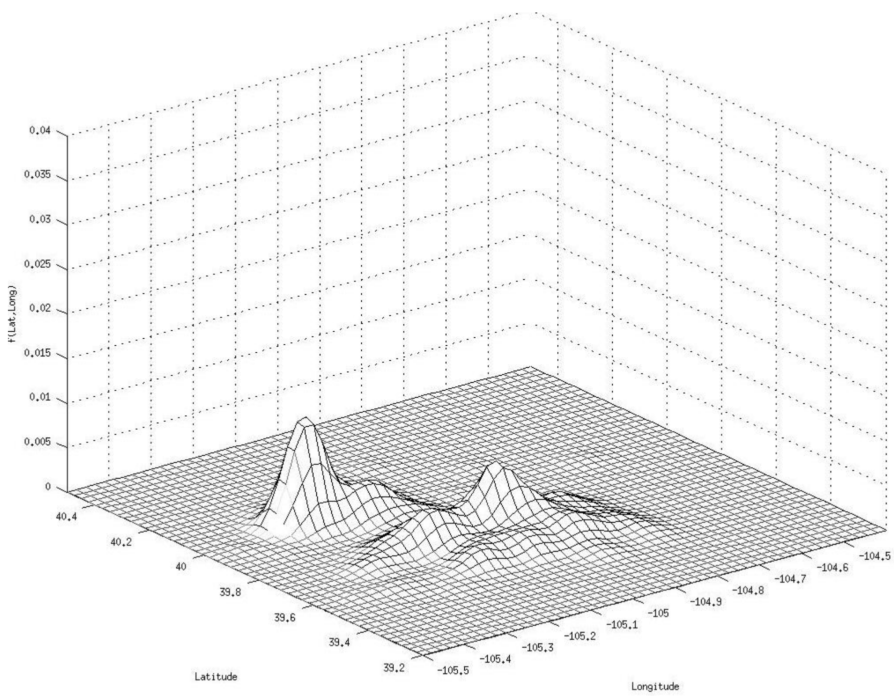


Figure 2: Population Kernels

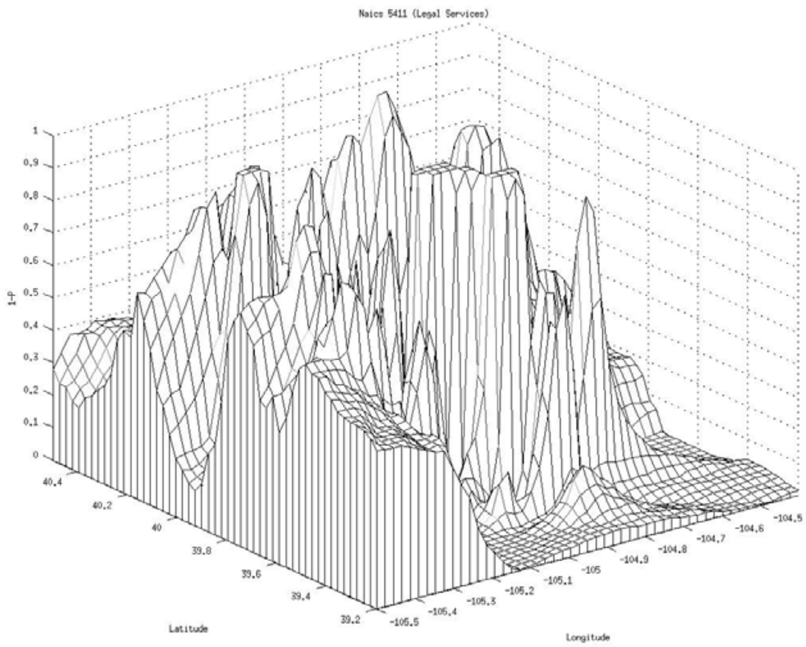


(a) NAICS 5411 Legal Services

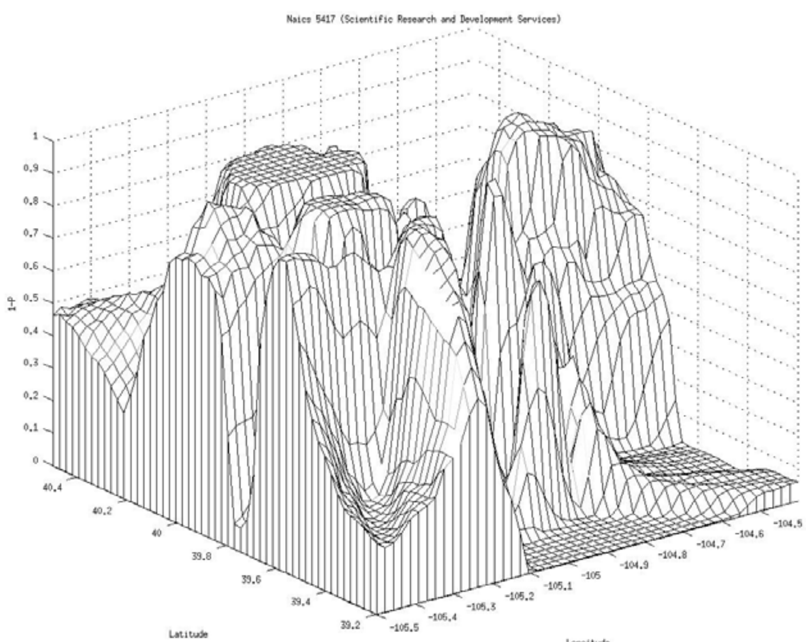


(b) NAICS 5417 Scientific Research and Development Services

Figure 3: Local P-values $(1 - p_i^{local})$

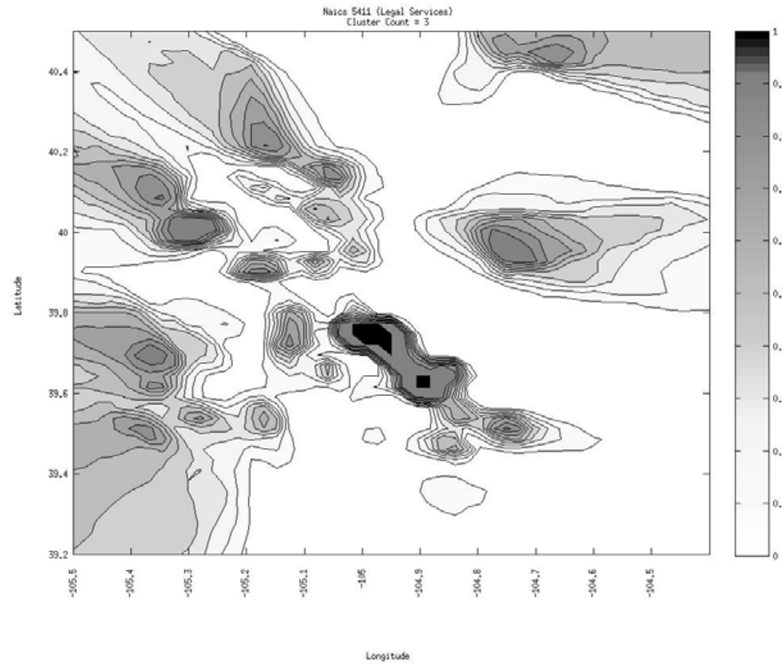


(a) NAICS 5411 Legal Services

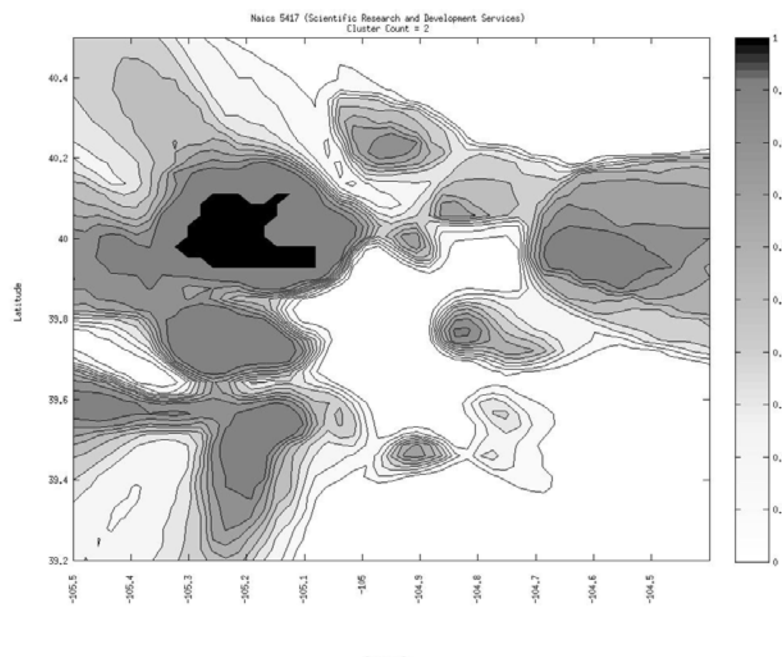


(b) NAICS 5417 Scientific Research and Development Services

Figure 4: Local P-value Contours

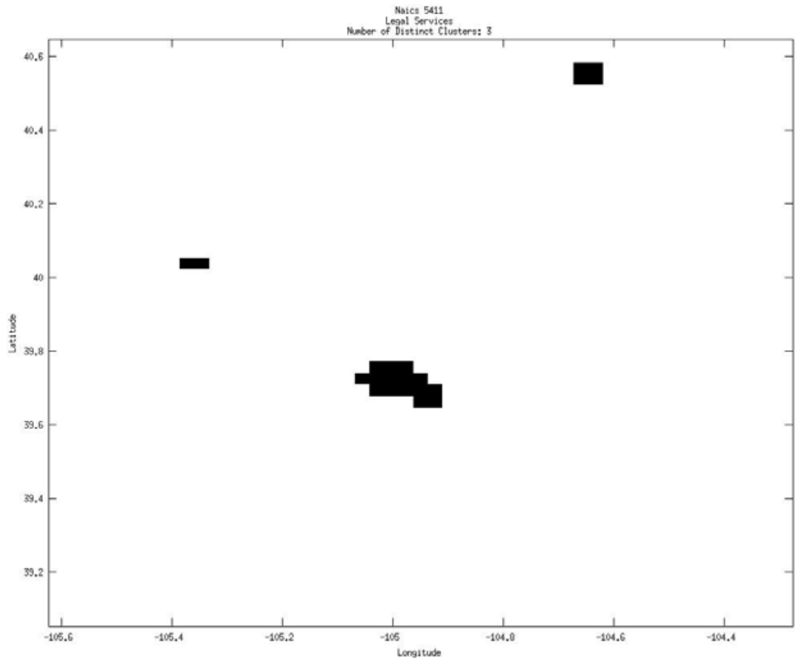


(a) NAICS 5411 Legal Services

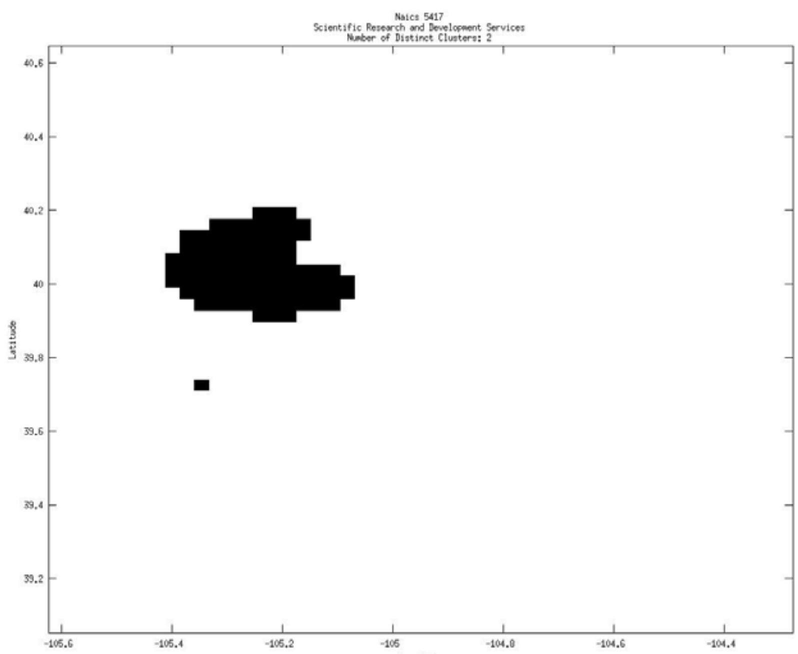


(b) NAICS 5417 Scientific Research and Development Services

Figure 5: Globally Significant Specialized Places



(a) NAICS 5411 Legal Services



(b) NAICS 5417 Scientific Research and Development Services

Figure 6: Total Number of Industries Subject to Specialization by Place

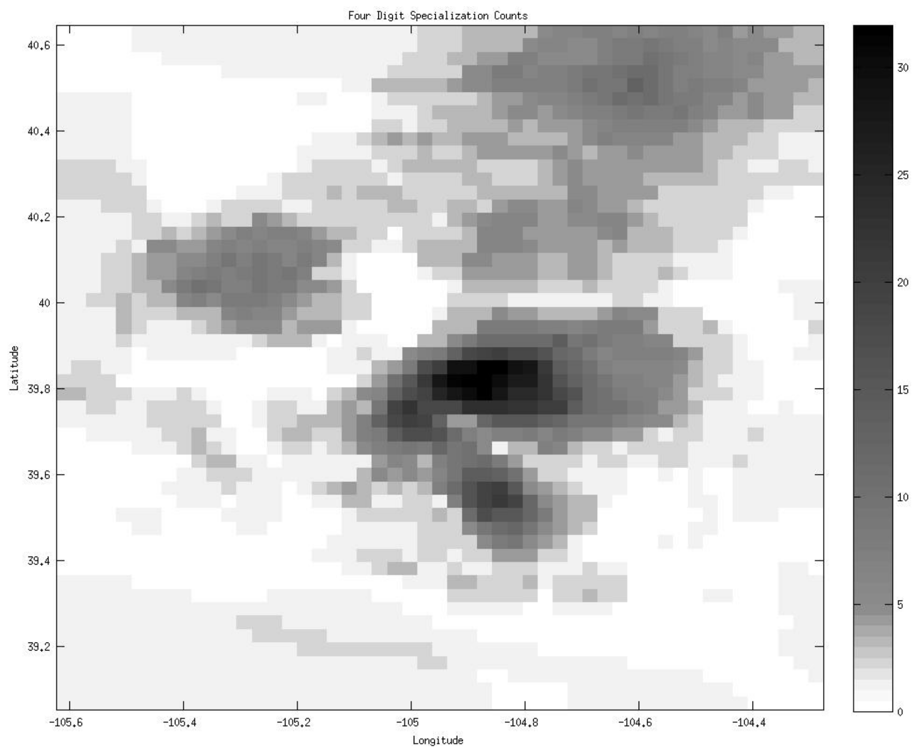
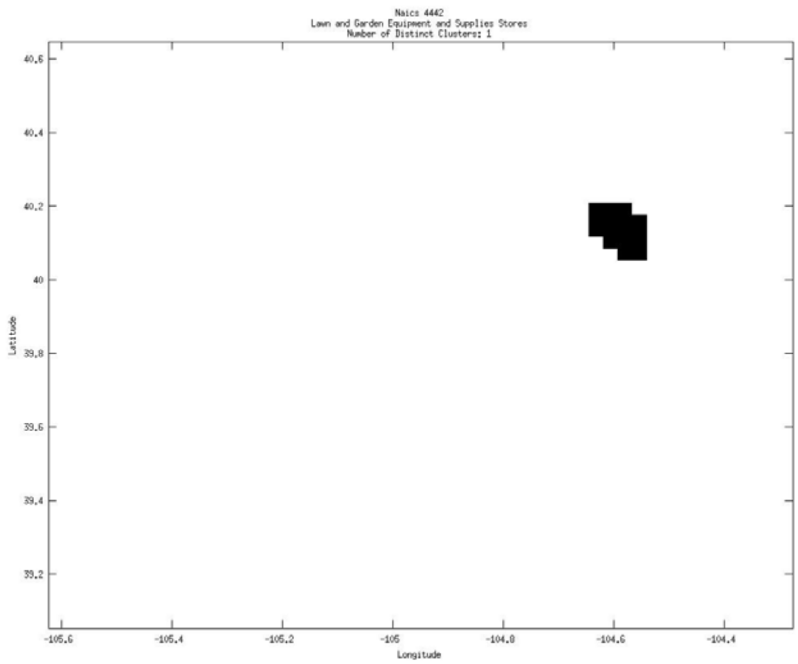
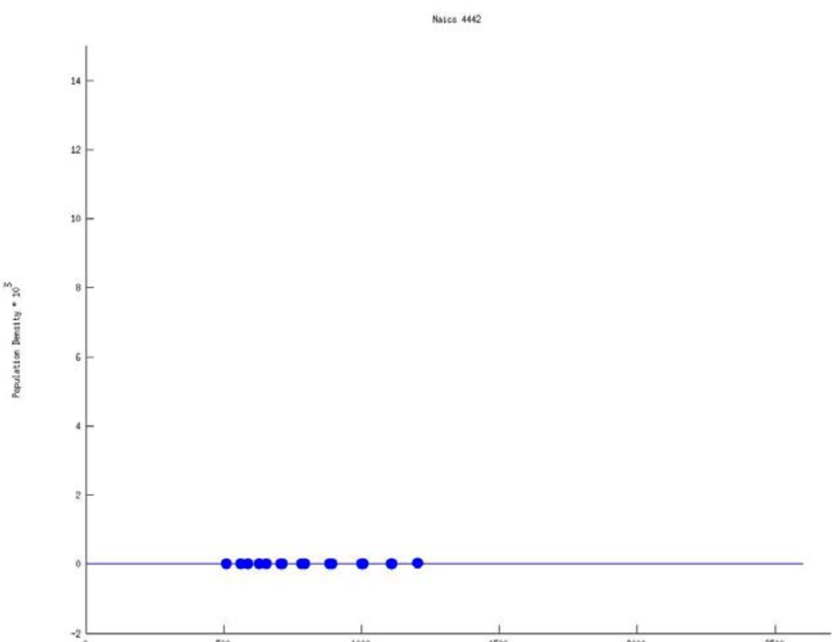


Figure 7: Lawn & Garden Equipment & Supplies Stores

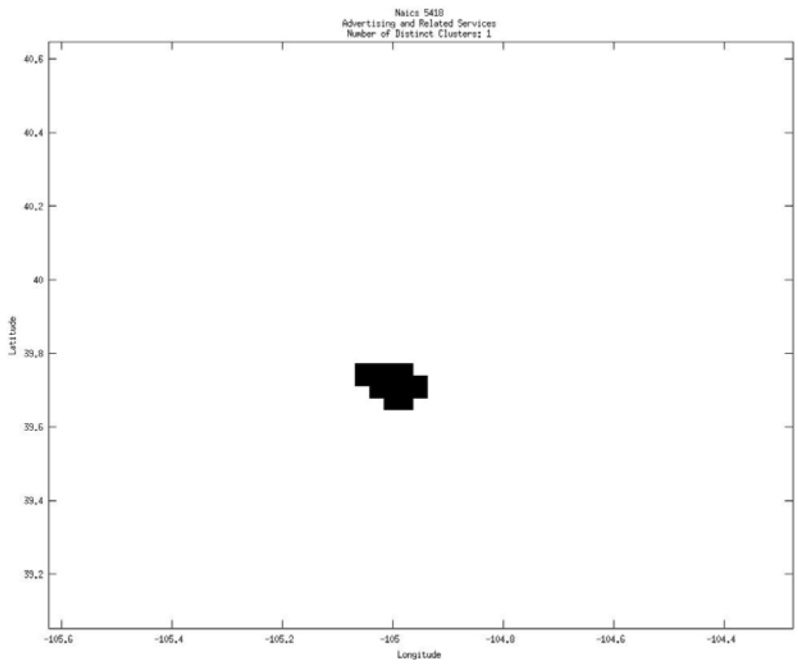


(a) Specialized Places

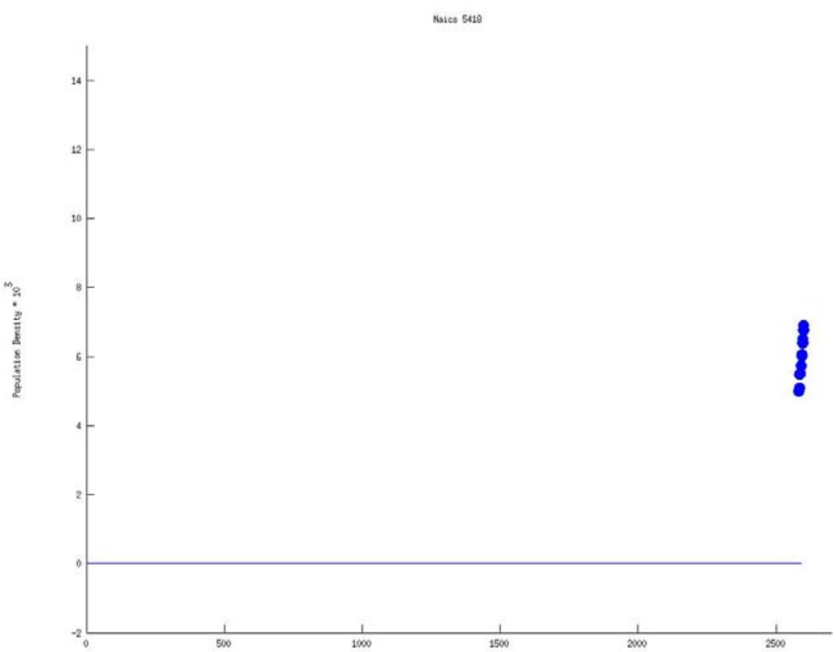


(b) Specialized Places Intensity Rank

Figure 8: Advertising and Related Services

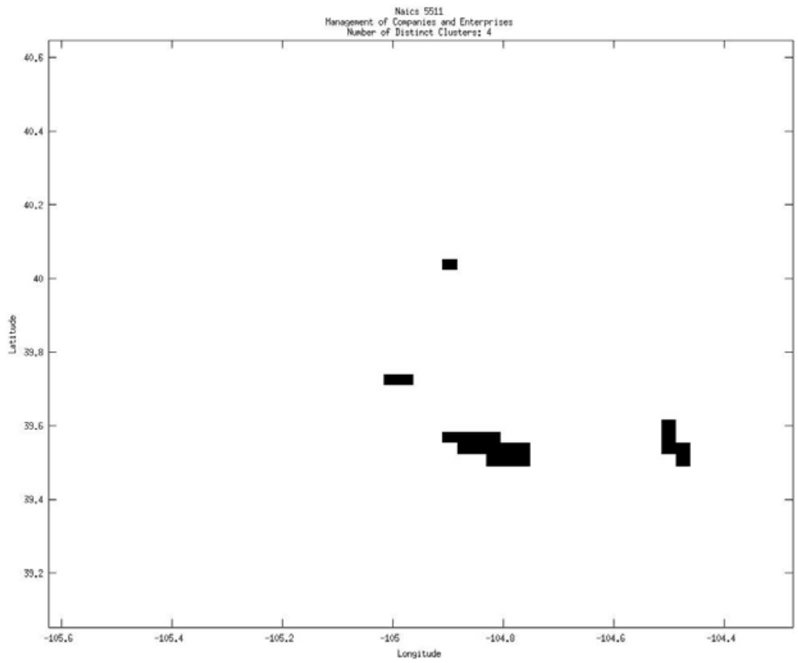


(a) Specialized Places

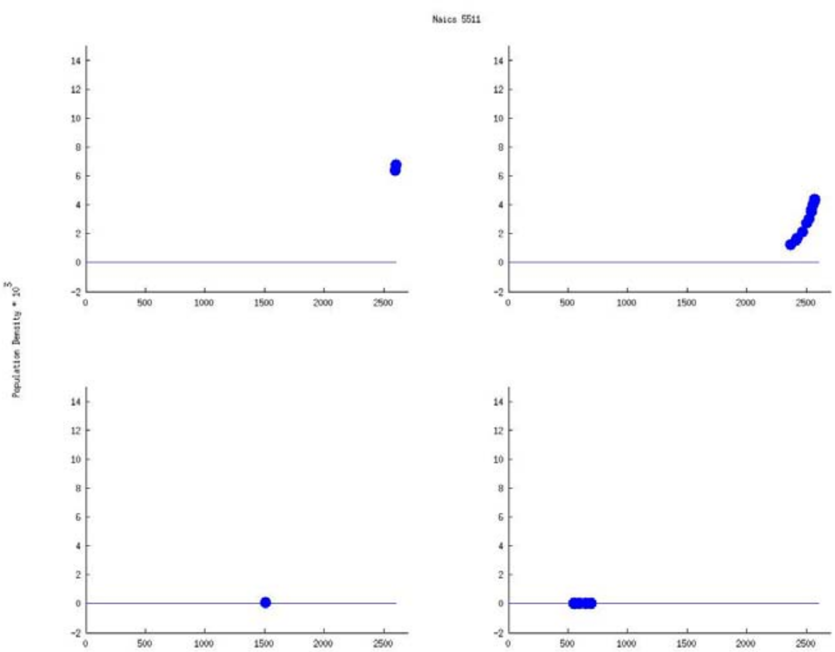


(b) Specialized Places Intensity Rank

Figure 9: Management of Companies & Enterprises

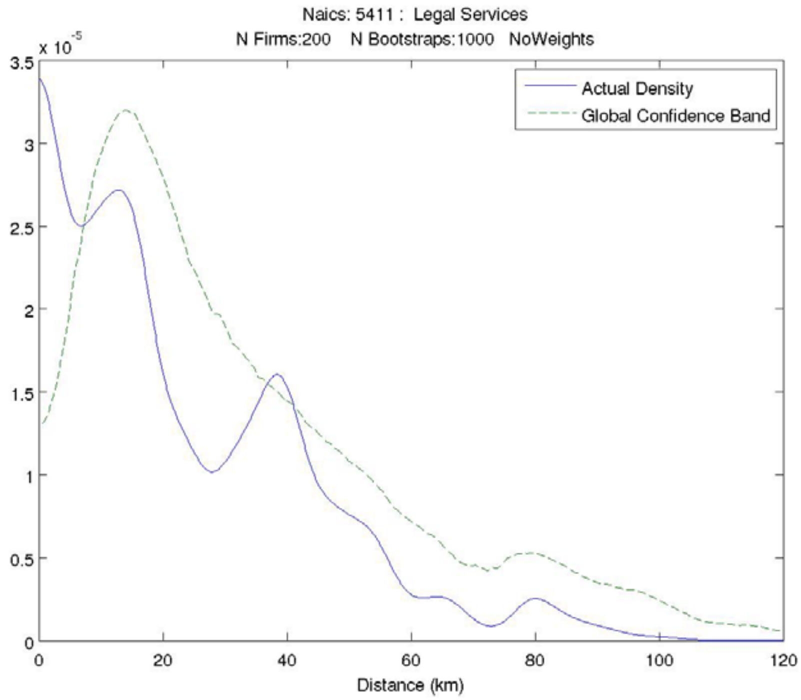


(a) Specialized Places

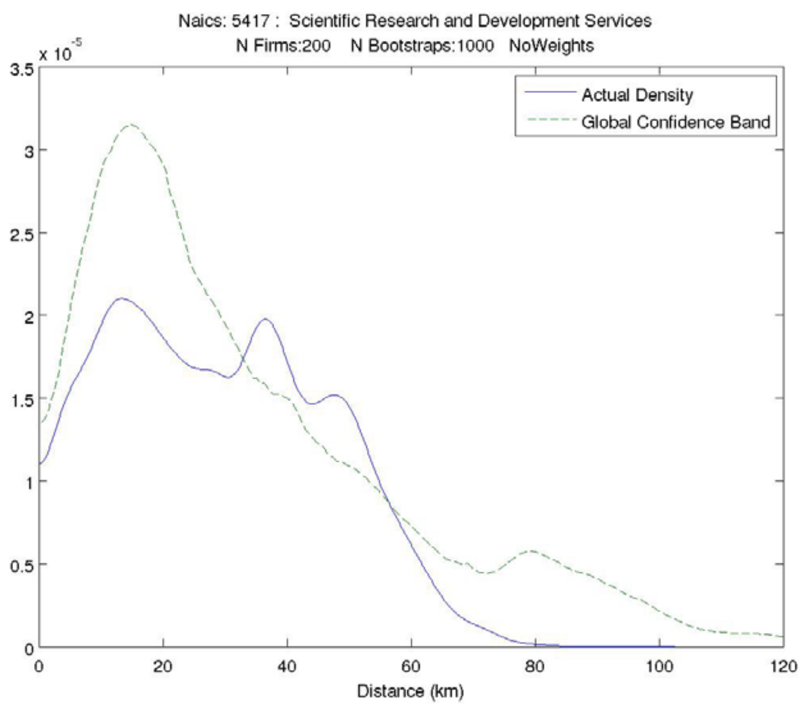


(b) Specialized Places Intensity Rank

Figure 10: Duranton & Overman Test for Localization

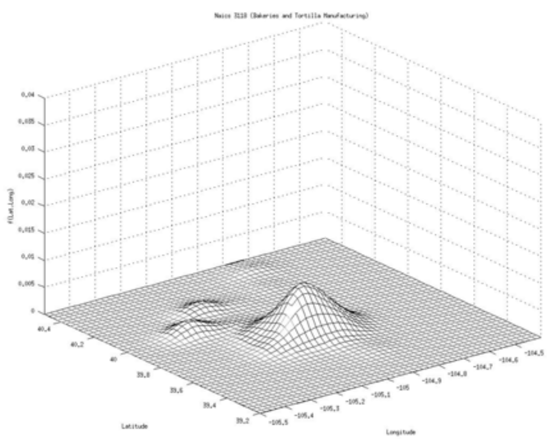


(a) NAICS 5411 Legal Services

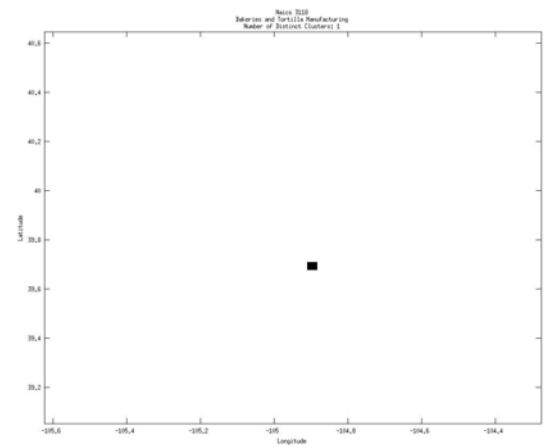


(b) NAICS 5417 Scientific Research and Development Services

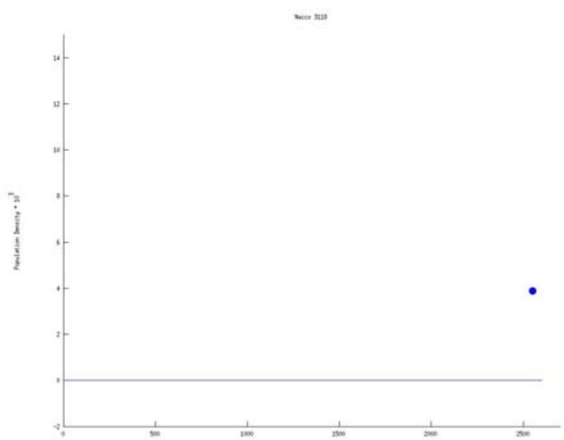
Figure 11: NAICS 3118 Bakeries & Tortilla Manufacturing



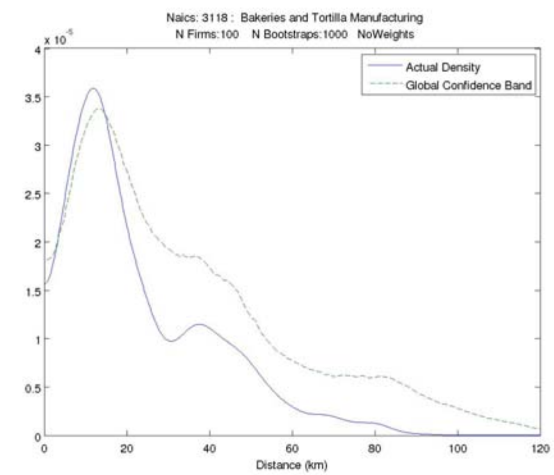
(a) Industry P Values



(b) Globally Significant Specialized Places

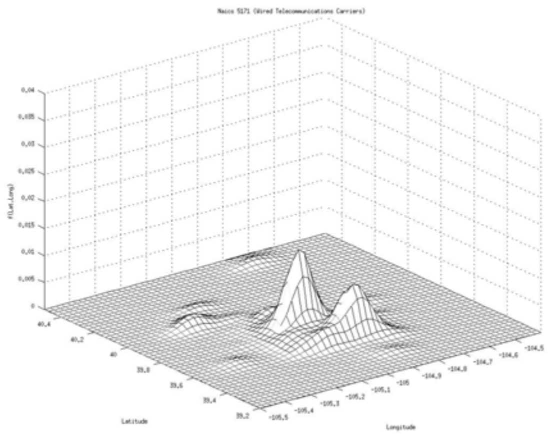


(c) Specialized Places Plots

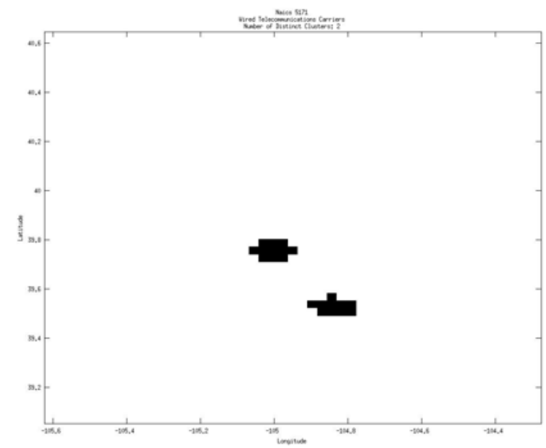


(d) Test for Localization

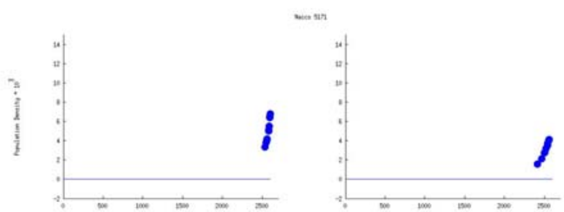
Figure 12: NAICS 5171 Wired Telecommunications Carriers



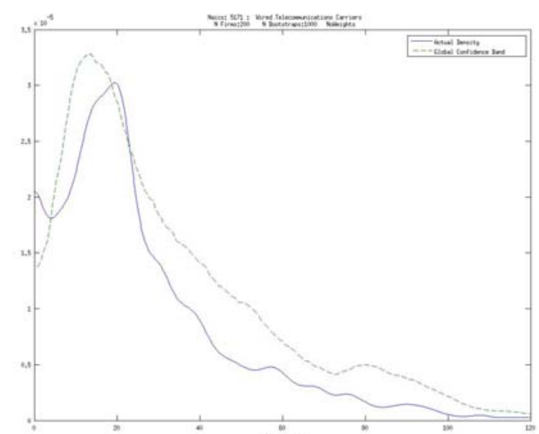
(a) Industry P Values



(b) Globally Significant Specialized Places

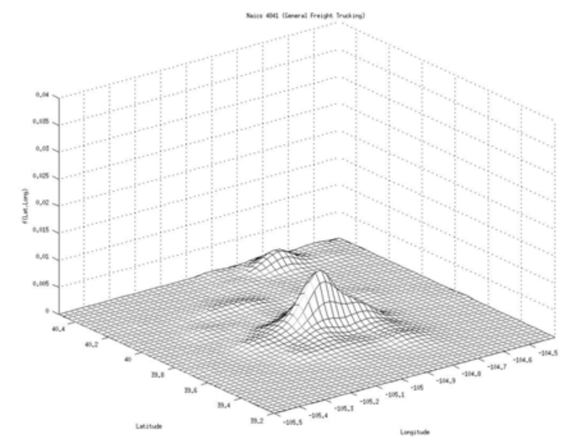


(c) Specialized Places Plots

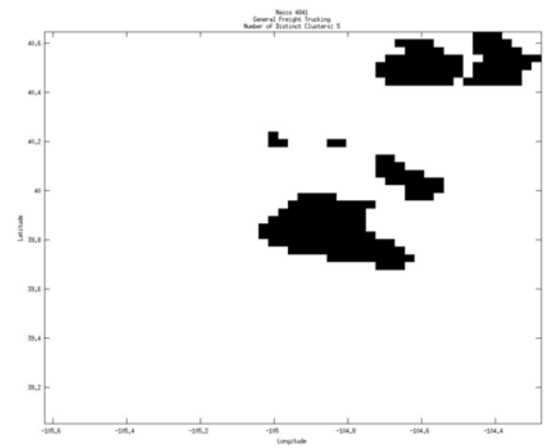


(d) Test for Localization

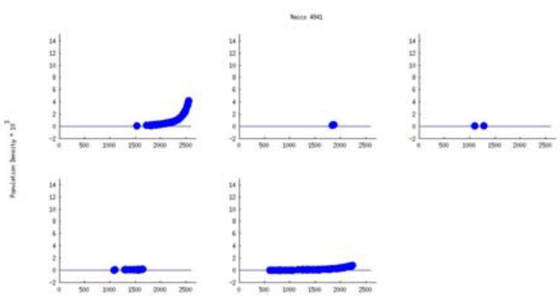
Figure 13: NAICS 4841 General Freight Trucking



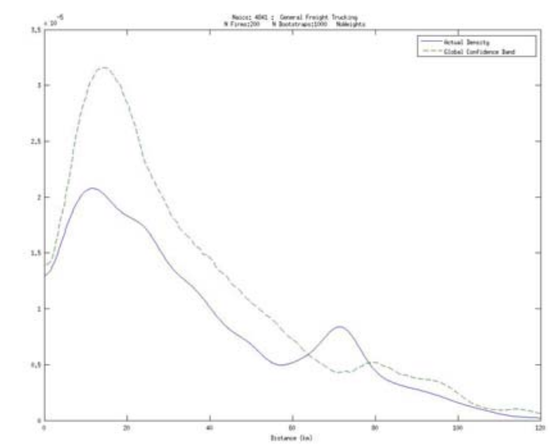
(a) Industry P Values



(b) Globally Significant Specialized Places

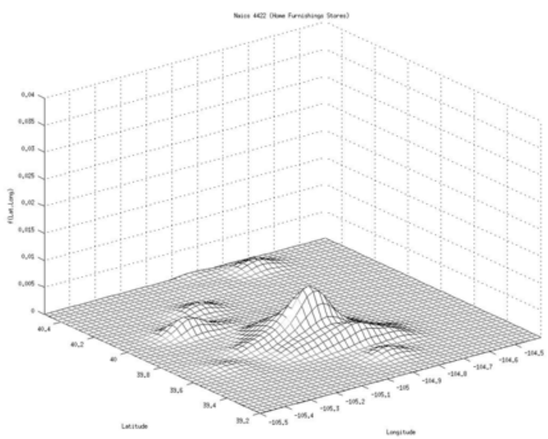


(c) Specialized Places Plots

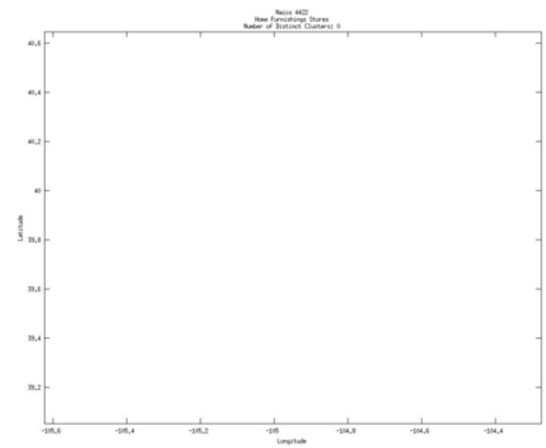


(d) Test for Localization

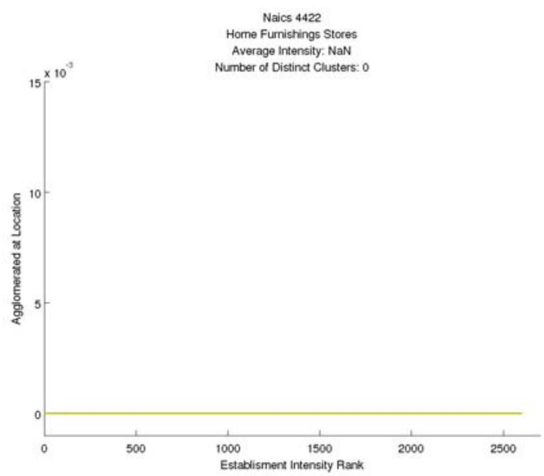
Figure 14: NAICS 4422 Home Furnishing Stores



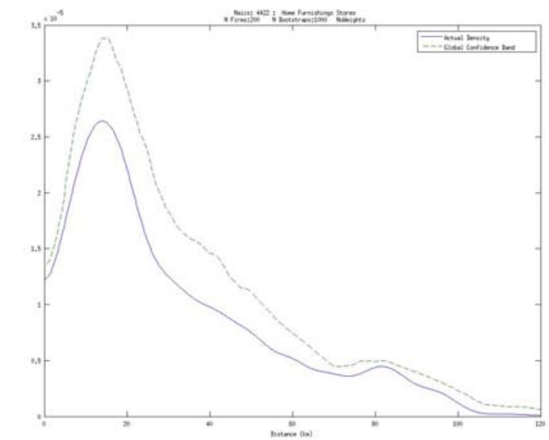
(a) Industry P Values



(b) Globally Significant Specialized Places



(c) Specialized Places Plots



(d) Test for Localization

2009

2009/1. Rork, J.C.; Wagner, G.A.: "Reciprocity and competition: is there a connection?"
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