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Dartboard Tests for the Location Quotient

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Abstract

In this paper we reinterpret the location quotient, the commonly employed measure of regional industrial agglomeration, as an estimator derived from Ellison & Glaeser's (1997) dartboard framework. This approach provides a theoretical foundation on which to build statistical tests for the measure. With a simple application, we show that these tests provide valuable information about the accuracy of the location quotient. The tests are relatively easy to implement using regional employment and establishment data.

JEL classification: R10, R12, C12

1 Introduction

First introduced by Florence (1939), the location quotient is often employed to quantify industrial concentration in regions. In fact, its popularity is so widespread that the U.S. Bureau of Labor Statistics has added a tool for calculating location quotients to their web site.[1] Moreover, the location quotient has long been applied to estimate the strength of regional economic impacts and export (economic-base) activities [Isserman (1977); Isserman (1980)]. Typically constructed with employment data, the measure is the ratio of two shares: the employment share of a particular industry in a region and the employment share of that industry in a wider area, such as a country. Researchers usually assume that if the quotient is above one, then the industry is concentrated in the region. Yet they do not have any suitable statistical tests to determine whether location quotients provide evidence of an excessive degree of geographic concentration of an industry. Thus, the measure remains a widely applied empirical technique without a solid theoretical and statistical foundation.

Location quotients purport to reveal distinct specializations in regional activities based on natural assets like coastal locations, along with other comparative and competitive advantages, including the positive agglomeration economies of existing local industry clusters. Obviously, they must reflect firm location decisions. Yet, as stressed by Duranton & Overman (2005), industry location is in part a random phenomenon. Firms may exhibit some level of spatial concentration by chance. This idea can be illustrated using the well-known dartboard example of Ellison & Glaeser (1997). If 10 firms

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[1] The location calculator is available at http://www.bls.gov/cew/home.htm .

choose their locations by throwing darts at a map with 10 equally sized regions the probability of ending up with a single firm in each region is very small. Most likely, in some regions by chance pockets of concentration will occur and that is perfectly compatible with the idea that firms' decisions were independent and random. The location quotient is unable to account for this problem. Because of the discrete nature of the phenomena it is possible to observe spurious concentration; that is, concentration that occurs by chance alone.

Hence, industry concentration (or localization) indices should offer an indication of the statistical significance of the results. To our knowledge, the only attempts to provide statistical properties for the location quotient are O'Donoghue & Gleave (2004) and Moineddin, Beyene & Boyle (2003). In the former, the approach consists of a set of rules designed to elicit the empirical regularities of the data, without a clear rationale for the proposed methodology. Likewise, the latter paper's methods are *ad hoc*, with standard deviations for location quotients calculated, without any reference to an underlying theory (in this case, applied to health care utilization, not industry location). The essential problem persists in the literature: The location quotient lacks a theoretically based statistical foundation. Without one, it cannot account for the inherent randomness of the underlying location decisions.

In this paper we reinterpret the location quotient as an estimator derived from Ellison & Glaeser's (1997) dartboard location model. This approach has the distinct advantage of providing a theoretical basis on which to build statistical tests for the measure. Importantly, in this framework, the location quotient is derived from a probabilistic model. It is then possible to account for sampling uncertainty, an important concept in statistical inference.

The rest of the paper is structured as follows. In the next section we show how to derive the location quotient as an estimator in the context of the Ellison & Glaeser's (1997) dartboard location model. In section 3, we develop statistical tests for the measure. Section 4, shows, using a simple application, how to implement the tests, and section 5 concludes.

2 The location quotient as an estimator derived from the Ellison-Glaeser framework

Our reference is an economy with J distinct regions. Following the natural advantage model of Ellison & Glaeser (1997)[2] we assume that the spatial distribution of firms in a given industry, say industry k, reflects their profit maximizing location choices. Profits for firm i in industry k, if it locates in region j, are given by:

$$\log \pi_{ijk} = \log \overline{\pi}_{jk} + \eta_{jk} + \varepsilon_{ijk} \ . \tag{1}$$

The term $\overline{\pi}_{jk}$ reflects the expected profitability of locating in region j, while η_{jk} is a variable that captures the strength of external economies and (or) natural advantages specific to that region that attract firms from that particular industry. As we will see below, the location quotient may be interpreted as a estimator of the term reflecting the importance of these external

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[2] Note that the fact that we base the discussion on the model of natural advantages of Ellison & Glaeser (1997) is not crucial. Observationally this model is equivalent to the spillover version also developed by the authors.

economies and (or) natural advantages of the region [or, more precisely, an estimator of $\exp(\eta_{jk})$]. The term ε_{ijk} is a random effect that picks all other idiosyncratic factors that also affect firm i's profits. Under the assumption that the ε_{ijk} are i.i.d. with an Extreme Value Type I distribution then, conditional on a realization of $\boldsymbol{\eta}_k = (\eta_{1k}, \eta_{2k}, ..., \eta_{Jk})$, we can use McFadden's (1974) well-known result to derive an expression for the probability that a firm from industry k will locate in region j:

$$p_{jk|\boldsymbol{\eta}_k} = \frac{\exp(\log \overline{\pi}_{jk} + \eta_{jk})}{\sum_{j=1}^{J} \exp(\log \overline{\pi}_{jk} + \eta_{jk})} \ . \tag{2}$$

As in Ellison & Glaeser (1997), we assume that the spatial distribution of firms will, on average, replicate the distribution of overall economic activity. Also, following common practice, we take total manufacturing employment to represent the distribution of overall economic activity. Following the reasoning in Ellison & Glaeser (1997) this means that the expected value of $p_{jk|\boldsymbol{\eta}_k}$ (calculated over the multivariate distribution of $\boldsymbol{\eta}_k$) equals:

$$E(p_{jk}) = \frac{x_j}{\sum_{j=1}^{J} x_j} = \frac{x_j}{x} \ , \tag{3}$$

where x_j is total manufacturing employment in region j and x is total manufacturing employment in the economy. We also admit as valid an additional assumption, introduced in Figueiredo, Guimarães & Woodward (2007), requiring that on average the effect of the η_{jk}'s cancel out in such a way that:

$$E(p_{jk}) = \frac{\overline{\pi}_{jk}}{\sum_{j=1}^{J} \overline{\pi}_{jk}} \ . \tag{4}$$

Guimarães, Figueiredo & Woodward (2007) show that this happens when the η_{jk}'s follow a gamma distribution. This assumption allows us to rewrite the location probabilities in terms of the known x_j,

$$p_{jk|\boldsymbol{\eta}_k} = \frac{\exp(\log x_j + \eta_{jk})}{\sum_{j=1}^{J} \exp(\log x_j + \eta_{jk})} = \frac{x_j \exp(\eta_{jk})}{\sum_{j=1}^{J} x_j \exp(\eta_{jk})} \ . \qquad (5)$$

Based on the argument put forth in Figueiredo et al. (2007) we can treat the realizations of η_{jk} as constants that need to be estimated. To see how this is implemented suppose that there are n_k plants in industry k. We assume that these correspond to a total of n_k independent location decisions. This means that we can construct the likelihood of observing a particular spatial distribution of investments as the product of all location probabilities, each decision weighted by a factor of w_{jk}. Hence, the likelihood function for a given sector is:

$$L_k = \prod_{j=1}^{J} p_{j|\boldsymbol{\eta}_k}^{w_{jk}} = \prod_{j=1}^{J} \left(\frac{x_j \exp(\eta_{jk})}{\sum_{j=1}^{J} x_j \exp(\eta_{jk})} \right)^{w_{jk}} \ . \qquad (6)$$

Notice that by introducing weights we are allowing for the possibility that two location decisions in the same region offer different contributions to the likelihood function. For example, it may be argued that the location decision of larger plants should be given more importance. To account for this, we can make the weights proportional to employment or any other measure of firm size. In any case, if weights are used, then their sum across regions, w_k, should be normalized to equal the number of location decisions observed in the sector.[3]

Maximization of the likelihood function in (6) is straightforward. The individual elements of the vector $\mathbf{s}$ containing the first order conditions for maximization with respect to η_{jk} are generically given by:

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[3] For example, if the weights are proportional to employment then $w_{jk} = (x_{jk}/x_k) \times n_k$.

$$s_{jk} \equiv \frac{\partial \ln L_k}{\partial \eta_{jk}} = w_{jk} - w_k \frac{x_j \exp(\eta_{jk})}{\sum_{j=1}^{J} x_j \exp(\eta_{jk})} \tag{7}$$

In turn, the generic elements of the Hessian matrix, **H**, are given by,

$$h_{jlk} \equiv \frac{\partial^2 \ln L}{\partial \eta_{jk} \partial \eta_{lk}} = \begin{cases} -w_k \frac{x_j \exp(\eta_{jk})}{\sum_{j=1}^{J} x_j \exp(\eta_{jk})} \left(1 - \frac{x_j \exp(\eta_{jk})}{\sum_{j=1}^{J} x_j \exp(\eta_{jk})} \right) \ , & j = l \\ -w_k \frac{x_j \exp(\eta_{jk})}{\sum_{j=1}^{J} x_j \exp(\eta_{jk})} \frac{x_l \exp(\eta_k)}{\sum_{j=1}^{J} x_j \exp(\eta_{jk})} \ , & j \neq l \end{cases} . \tag{8}$$

The first order conditions lead to an indeterminate solution, because the η_{jk}'s are not identifiable. To solve the problem we need to introduce a restriction on the parameters. Hence, for identification purposes, we add the restriction that:

$$\sum_{j=1}^{J} x_j \exp(\eta_{jk}) = x \ . \tag{9}$$

With this restriction in place we now have a metric for the η_{jk}'s. This restriction also makes intuitive sense. From (5) we see that if the parameter η_{jk} for region j equals 0 that means that the actual location probability equals its expected value and thus industry k is not localized in region j. Solving the first order conditions we obtain the following maximum likelihood estimator:

$$\widehat{\eta}_{jk} = \log L_{jk} \ , \tag{10}$$

where $L_{jk} = (w_{jk}/w_k) \, / \, (x_j/x_\bullet)$ is a location quotient for industry k in region j. The structure of weights given to the location probabilities determines the different types of location quotients that are constructed. If we assume that the contribution of each firm to the likelihood function should be weighted by its size (say employment) then we obtain the traditional employment location quotient. On the other hand, if we assume that all firms have identical contributions then we get a location quotient that is based on plant counts.[4]

This derivation of the location quotient–now seen as an estimator obtained from a probabilistic model–provides a convenient framework to construct hypothesis tests. However, we should bear in mind that hypotheses should be formulated in terms of the η_{jk}'s; that is, in terms of the unknown variables that capture the locational advantages of the specific regions.

3 Tests based on the Location Quotient

3.1 Testing the hypothesis of non-localization of one industry in a region

Consider the general expression for the Wald test of a linear combination(s) of the η_{jk}'s given by:

$$W = (\mathbf{R}\widehat{\boldsymbol{\eta}} - \mathbf{q})'[\mathbf{RVR}']^{-1}(\mathbf{R}\widehat{\boldsymbol{\eta}} - \mathbf{q}) \ , \tag{11}$$

where $\mathbf{R}$ is a matrix containing the coefficients of the linear combination(s), $\mathbf{q}$ is a vector of constants, $\widehat{\boldsymbol{\eta}}$ are the maximum likelihood estimates of $\boldsymbol{\eta}$ and $\mathbf{V}$ is the estimated variance-covariance matrix associated with $\widehat{\boldsymbol{\eta}}$. This test follows a chi-squared distribution with degrees of freedom equal to the number of restrictions being tested. To calculate $\mathbf{V}$ we use the inverse of the negative of the Hessian evaluated at the maximum likelihood estimates. Taking advantage of the first order conditions, we can rewrite (8), the expression

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[4] Figueiredo et al. (2007) argued that if the objective is to measure the intensity of localization economies, then this should be the preferred approach.

for the generic elements of the Hessian, as:

$$h_{jlk} = \begin{cases} -w_k \frac{w_{jk}}{w_k}\left(1 - \frac{w_{jk}}{w_k}\right) & , \ k = l \\ -w_k \left[\frac{w_{jk}}{w_k}\frac{w_{lk}}{w_k}\right] & , \ k \neq l \end{cases} . \tag{12}$$

Or, in matrix form, as:

$$\mathbf{H} = -w_k(\mathrm{diag}(\widetilde{\mathbf{w}}) - \widetilde{\mathbf{w}}\widetilde{\mathbf{w}}') \ , \tag{13}$$

where $\widetilde{\mathbf{w}} = (w_{1k}/w_k, w_{2k}/w_k, ..., w_{Jk}/x_k)$ is a vector containing the regional shares of the variable used to weight the location probabilities. The expression for the negative of the Hessian, $-\mathbf{H}$, is the same as the variance-covariance matrix of the multinomial distribution. This allows us to use the result of Tanabe & Sagae (1992) to obtain the generalized inverse of $-\mathbf{H}$ which we denote by $\widehat{\mathbf{V}}$. Thus,

$$\widehat{\mathbf{V}} = w_k^{-1}(\mathbf{I} - \frac{1}{J}\mathbf{i}\mathbf{i}')[\mathrm{diag}(\widetilde{\mathbf{w}})]^{-1}(\mathbf{I} - \frac{1}{J}\mathbf{i}\mathbf{i}') \ , \tag{14}$$

where $\mathbf{I}$ is the identity matrix and $\mathbf{i}$ is a $J \times 1$ vector with elements $(1, 1, ..., 1)$. Using $\widehat{\mathbf{V}}$ in place of $\mathbf{V}$ we can now test for any linear combinations of the η_{jk}'s. Of particular interest is the test of the hypothesis that $\eta_{jk} = 0$, which can be interpreted as a test of non-localization of an industry in a region.[5] Without loss of generality assume that $j = 1$. This means that $\mathbf{R} = [1, 0, 0, ..., 0]$ and $\mathbf{q} = [0]$. Replacing these vectors into (11) and simplifying we obtain the statistic:

$$W_{jk} = \frac{J\left[\log(L_{jk})\right]^2}{(J-2)w_{jk}^{-1} + \overline{w_k^{-1}}} \ , \tag{15}$$

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[5] Note that the relevant alternative hypothesis, the existence of localization, is H_a : $\eta_{jk} > 0$. Hence, in subsequent applications we will use one-sided tests.

which is asymptotically distributed as chi-square with one degree of freedom. The term $\overline{w_k^{-1}}$ is the average of all w_{jk}^{-1}. In a similar fashion we could implement other tests using the general expression in (11).[6]

3.2 Testing the hypothesis of non-localization of one industry across a set of regions

Another test that can be implemented based on the location quotient is a score test of the hypothesis that the η_{jk}'s are identical for all the regions. If that is the case then the location probabilities for the industry will coincide with the share of each region in overall manufacturing employment. This can be seen as a test of whether or not one industry is localized across a set of regions and should lead to similar conclusions as other tests for localization of an industry, such as Ellison & Glaeser (1997), Maurel & Sedillot (1999), Mori, Nishikimi & Smith (2005) and Guimarães et al. (2007). To implement the test, let $\boldsymbol{\eta}_r$ denote the value of $\boldsymbol{\eta}$ under the null hypothesis. Then, Rao's score test is obtained by the statistic:

$$T = -\mathbf{s}'(\boldsymbol{\eta}_r)\left[\mathbf{H}(\boldsymbol{\eta}_r)\right]^{-1}\mathbf{s}(\boldsymbol{\eta}_r)\ , \tag{16}$$

which is known to be asymptotically distributed as chi-square with degrees of freedom equal to the number of restrictions being tested. In the above formula, $\mathbf{s}(\boldsymbol{\eta}_r)$ is the score vector evaluated under the null hypothesis and

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[6] For example, to test the hypothesis of equality of the degree of localization of industry k in two regions, $\eta_{jk} = \eta_{lk}$, the Wald statistic becomes:

$$W_{jk} = \frac{\left[\log(L_{jk}) - \log(L_{lk})\right]^2}{w_{jk}^{-1} + w_{lk}^{-1}}\ ,$$

which is also asymptotically distributed as chi-square with one degree of freedom.

$\mathbf{H}(\boldsymbol{\eta}_r)$ is defined similarly. Thus, the generic element of $\mathbf{s}(\boldsymbol{\eta}_r)$ equals:

$$s_j(\boldsymbol{\eta}_r) = w_{jk} - w_k \frac{x_j}{x} \ , \tag{17}$$

and the Hessian matrix is,

$$\mathbf{H}(\boldsymbol{\eta}_r) = -w_k(\mathrm{diag}(\widetilde{\mathbf{x}}) - \widetilde{\mathbf{x}}\widetilde{\mathbf{x}}') \ , \tag{18}$$

where $\widetilde{\mathbf{x}} = (x_1/x, x_2/x, ..., x_J/x)$ is a vector containing the regional shares of total manufacturing employment. Replacing the elements in (16) by the expressions derived above, and using again the result of Tanabe & Sagae (1992) to calculate the inverse of the Hessian, we arrive at the following test statistic for an industry localization across a set of regions expressed in terms of location quotients:

$$T_k = \sum_{j=1}^{J} w_{jk} \frac{(L_{jk} - 1)^2}{L_{jk}} \ . \tag{19}$$

The above statistic follows (asymptotically) a chi-square distribution with $J - 1$ degrees of freedom. This statistic makes intuitive sense. If most location quotients are around one then the industry does not exhibit any degree of localization, but the further apart the location quotients are from 1 the more likely the evidence is in favor of localization.

4 An Illustration

We now illustrate the implementation of the tests developed above using a simple study of industry localization in the state of Connecticut. Connecticut is suitable for our purpose because with only 8 counties it makes for a simple example with almost all required data fitting in a few tables. We use employment based location quotients because this is common practice among applied researchers.

The questions that we want to answer are:

(1) Compared with the U. S. average, is any manufacturing sector localized in the state of Connecticut?

(2) If so, is this sector localized within Connecticut?

(3) And, in which counties is this sector localized within Connecticut?

To do this we needed data on employment and number of establishments by manufacturing sector for the 50 U.S. states and the district of Columbia, as well as for the 8 counties in Connecticut.[7]

In Table 1, we present location quotients calculated at the state level for the 21 industries of the 3-digit North American Industrial Classification System (NAICS). We find that location quotients are above one for 7 of the 21 industries in Connecticut. Next, we use the statistic in (15) to check whether these location quotients provide evidence of geographic concentration in excess of what would be expected to arise randomly.[8] This statistic is asymptotically distributed as chi-square with one degree of freedom and thus the critical value for the one-sided test is 2.71 for a level of significance

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[7] We obtained the data from the web page of Thomas J. Holmes at the University of Minnesota. The data are for the year of 2000 and is taken from the U.S. Census Bureau, *County Business Patterns* (CBP). The county data in the CBP have a large number of disclosure problems. The advantage of the Holmes data is that the author used an imputation procedure to fill all the empty cells. The data can be found at www.econ.umn.edu/~holmes/data/cbp .

[8] Note that with the exception of column 8, Table 1, all calculations can be replicated using the employment and establishment data shown in the tables. It is also worthy to note in Table 1, column 6, that some sectors are not present in all the regions. This is a problem likely to show up in applied work. In these instances, when computing the tests, we can overcome the problem by subtracting from J the regions with missing sectors.

of 95 percent. An inspection of Table 1 shows that only 5 of the 7 industries with location quotient above the unity pass the test. Hence, with reference to the United States, we can conclude that Chemicals, Fabricated Metal Products, Electrical Equipment & Components, Transportation Equipment, and Miscellaneous Manufacturing are localized in Connecticut.

[insert Table 1 about here]

Next, in Table 2, we examine whether Transportation Equipment (the industry with the highest statistically significant location quotient in Table 1) is localized within Connecticut. To answer this question, we calculate location quotients for this industry at the county level and use the statistic in (19). Since this statistic follows (asymptotically) a chi-square distribution with $J - 1$ degrees of freedom, the critical value is 14.07 for a level of significance of 95 percent. Given that we obtained 42.74 for this statistic, we conclude that Transportation Equipment is localized within Connecticut.

[insert Table 2 about here]

Finally, in Table 3, we address our last question: Within the set of Connecticut counties, where is Transportation Equipment localized? To find out, we again used the statistic in (15). The results in Table 3 indicate that Transportation Equipment is localized within Connecticut in the county of New London (using a level of significance of 95 percent). It should be noted that this industry (NAICS code 336) includes Ship and Boat Building (NAICS code 33661). At this level, it is not surprising to find that a strong localization exists for Transportation Equipment within Connecticut. The town of

Groton in New London county is the "submarine capital" of the world–which includes a highly concentrated manufacturing hub based on the area's legacy of ship-building and sustained by large government contracts.[9]

[insert Table 3 about here]

5 Conclusion

The location quotient professes to assess industry localization in a particular region. Researchers usually assume that if the calculated location quotient is above one, then the industry is concentrated in that particular region. They do not, however, have any suitable statistical technique to determine whether the measure provides evidence of geographic concentration in excess of what would be expected to arise randomly. Despite its practical popularity, then, the location quotient has lacked a theoretical basis. In particular, it can not account for the inherent randomness of underlying location decisions. Even if plants are randomly distributed across locations, by chance pockets of concentration are likely to emerge.

In this paper we construe the location quotient to be an estimator derived from Ellison & Glaeser's (1997) dartboard location model. This approach has the advantage of providing a framework on which to build statistical tests. For the first time, the location quotient is derived from a probabilistic model. It is then possible to account for sampling uncertainty, an important concept in statistical inference. Estimates for the parameter without an associated

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[9] Clearly, in any calculation of location quotients, it helps to have disaggregated data. In this illustration, however, we restricted the analysis to 3-digit NAICS codes, because we wanted to make available to the readers in a few tables the data required for the tests.

level of significance (as usually reported in location quotient analysis) are of little value. In reporting point estimates for the location quotient, statistical tests should be given in future work.

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Table 1: **Compared With the U. S. Average is Any Manufacturing Sector Localized in the State of Connecticut**?

NAICS	Employment		Establishments	L_{jk}	J	w_{jk}^{-1}	$\overline{w_k^{-1}}$	W_{jk}
	U.S.	Connecticut	U.S.					
311- Food	1,451,633	7,978	17,927	0.38	51	-	-	-
312- Beverage & tobacco	168,651	449	2,225	0.18	51	-	-	-
313- Textile mills	332,036	2,910	3,179	0.61	50	-	-	-
314- Textile product mills	213,512	1,645	4,380	0.54	51	-	-	-
315- Apparel manufacturing	507,236	1,256	6,856	0.17	51	-	-	-
316- Leather & allied products	68,111	197	1,469	0.20	50	-	-	-
321- Wood products	592,443	1,871	13,247	0.22	50	-	-	-
322- Paper	550,212	5,718	4,590	0.72	51	-	-	-
323- Printing & related support activities	805,271	12,354	14,706	1.07	51	0.004	0.016	0.88
324- Petroleum & coal products	106,604	676	1,783	0.44	50	-	-	-
325- Chemicals	860,534	15,178	10,374	1.23	51	0.005	0.062	6.37
326- Plastics & rubber products	1,041,322	9,625	10,221	0.64	50	-	-	-
327- Nonmetallic mineral products	518,138	3,144	12,393	0.42	51	-	-	-
331- Primary metal manufacturing	600,995	5,289	5,423	0.61	50	-	-	-
332- Fabricated metal products	1,777,533	40,848	29,744	1.60	51	0.001	0.031	108.64
333- Machinery	1,360,732	22,341	20,421	1.14	51	0.003	0.246	2.24
334- Computer & electronic products	1,559,624	21,011	11,460	0.94	51	-	-	-
335- Electrical equipement & components	586,219	13,976	5,538	1.66	51	0.008	1.112	8.75
336- Transportation equipment	1,875,332	52,009	9,841	1.93	51	0.004	0.180	61.00
337- Furniture & related products	628,944	3,176	10,998	0.35	51	-	-	-
339- Miscellaneous manufacturing	727,169	13,475	15,472	1.29	51	0.003	0.021	16.98
Total manufacturing	16,332,251	235,126	212,247	-	-	-	-	-

Source: U. S. Census Bureau, *County Business Patterns*, 2000 (as in Thomas J. Holmes web page).

Table 2: **Is NAICS 336 Localized Within Connecticut**?

County	Employment		Establishments	L_{jk}	w_{jk}	T_k
	NAICS 336	Total Manufacturing	NAICS 336			
Fairfield	12,085	58,045	6	0.94	31.369	
Hartford	21,203	68,049	11	1.41	55.037	
Litchfield	1,638	15,387	37	0.48	4.252	
Middlesex	2,506	11,390	7	0.99	6.505	
New Haven	4,171	51,359	7	0.37	10.827	
New London	9,621	18,867	11	2.31	24.973	
Tolland	180	3,930	31	0.21	0.467	
Windham	605	8,099	25	0.34	1.570	
Total Connecticut	52,009	235,126	135	-	-	42.74

Source: U. S. Census Bureau, *County Business Patterns*, 2000 (as in Thomas J. Holmes web page).

Table 3: **In Which Counties is NAICS 336 Localized Within Connecticut**?

County	L_{jk}	w_{jk}^{-1}	$\overline{w_k^{-1}}$	W_{jk}
Fairfield	0.94	0.0319	-	-
Hartford	1.41	0.0182	0.4186	1.7801
Litchfield	0.48	0.2352	-	-
Middlesex	0.99	0.1537	-	-
New Haven	0.37	0.0924	-	-
New London	2.31	0.0400	0.4186	8.4714
Tolland	0.21	2.1403	-	-
Windham	0.34	0.6368	-	-

Source: U. S. Census Bureau, *County Business Patterns*, 2000 (as in Thomas J. Holmes web page).

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