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DO MANUFACTURING PLANTS CLUSTER ACROSS RURAL AREAS? EVIDENCE FROM A PROBABILISTIC MODELING APPROACH

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Abstract

A statistical procedure for detecting "contagious" location patterns for manufacturing establishments is presented. Manufacturing industries' establishment clustering tendencies are ranked based on the "dispersion parameter" of the negative binomial distribution. Establishment data are for three-digit SIC manufacturing industries, nonmetro counties of BEA Component Economic Areas, 1981 and 1992. Findings indicate that virtually all manufacturing industries cluster establishments in nonmetro areas. Approximately two-thirds of the industries had dispersion parameters indicating a high or moderate level of spatial concentration. The propensity to cluster plants in nonmetro CEAs was evident for both 1981 and 1992, though weaker in 1992. Much of the industry clustering in nonmetro areas appears to be attributable to local "natural advantages" and not inter-firm spillovers.

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Introduction

The new economic growth theory of Romer, Krugman, and Venables has stimulated a renewed interest in the spatial concentration of industrial activity and the advantages that concentrations provide member establishments. The focus of this recent research is the extent of industry clusters or agglomerations at state or metro levels and evidence of static and/or dynamic locationalization economies attributable to these concentrations.[1] Research on industry clusters in nonmetropolitan areas is also available but currently limited to case studies of specific industries (Rosenfeld) and analysis of the association between nonmetro concentrations and industry employment growth (Henry and Drabenstott) and wage rates (Gibbs and Bernat). Yet industry clusters may be especially important to nonmetro areas if these agglomerations provide (through external economies) the means to overcome disadvantages inherent with nonmetro locations (sparse local markets, geographic isolation, and lack of economic diversity).

The purpose of this study is to provide an overview of establishment clustering tendencies and trends for nonmetropolitan manufacturing industries (three-digit SIC level). Three research questions are of particular interest. Do manufacturers cluster establishments in nonmetro areas, and if so, are these agglomeration propensities relatively strong? Which manufacturing industries exhibit the greatest or least spatial concentration in nonmetro areas? Have nonmetropolitan clustering propensities increased or decreased over time for manufacturers? Answers to the above questions will provide insights into the determinants of industry clustering in nonmetropolitan areas (natural advantages versus inter-industry spillovers). Documentation of industries' agglomeration tendencies also will be useful to nonmetro communities that are attempting to develop or expand industry clusters through targeted industrial recruitment efforts. The development of an industry cluster provides greater local economic development benefits than a less focused industrialization strategy because establishment clustering promotes external economies, facilitates industrial restructuring, stimulates inter-firm networking, and permits greater focusing of public resources (Barkley and Henry). However, all industries are not equally attractive candidates for industry clusters, and industry cluster development programs will have greater success if the targeted industries tend to spatially concentrate their establishments.

In this paper, industry clustering is addressed through analysis of a statistical measure of geographic dispersion based on the spatial distribution of nonmetro establishments in three-digit SIC manufacturing industries. Thus, an industry cluster is defined to be a group of establishments in the same or closely related industry, located in close proximity to one another. As noted by Bernat, this definition represents an intermediate view of industry clusters. Broader interpretations include other industries linked to the "core" industry through actual or potential buy or sell relationships. Narrower interpretations, on the other hand, restrict industry clusters to establishments in close proximity that are closely connected through networks. Bernat notes, however, that neither intra-industry buy- or sell-linkages nor networking are necessary for the existence of establishment clusters since establishments may be responding to cluster-related externalities provided through the market.

Our analysis of nonmetro establishment concentrations is organized as follows. First, we provide a summary of the reasons why establishments in an industry may locate near one another. Second, we present a statistical methodology for detecting "contagious" establishment location patterns, and rank industries' nonmetro clustering tendencies based on the "dispersion parameter" of the negative binomial distribution. Third, industries with high or low establishment concentrations are compared to provide insights into the determinants of nonmetro clusters and implications for nonmetro industrial development policy.

Why Do Industry Establishments Cluster?

Ellison and Glaeser find widespread evidence of industry clustering and attribute this to two principal forces: industry-specific spillovers and natural advantages. Industry-specific spillovers are economies external to the firms but internal to the regional industry cluster. These external economies are referred to as static localization economies if they are attributable to the current scale (e.g. employment or number of establishments) of the industry cluster or Marshall-Arrow-Romer (MAR) dynamic externalities if they result from a historical presence and regional specialization in a particular industry. More specifically, Henderson (1986) attributes static localization economies to:

(1) economies of intra-industry specialization where increased industry size permits

greater specialization among industry firms in addition to a greater availability of specialized intermediate input suppliers, business services, and financial markets.

(2) labor market economies resulting from a larger pool of trained, specialized workers and reduced search costs for firms looking for workers with specific skills.

(3) scale for networking or communication among firms to take advantage of complementarities, exploit new markets, integrate activities, and adopt new innovations.

(4) scale in providing public goods and services tailored to the needs of a specific industry.

Alternatively, Marshall-Arrow-Romer externalities are derived from the accumulation of knowledge and knowledge spillovers among local firms in the same industry (Glaeser et al.; Henderson, Kuncoro, and Turner). The build-up and sharing of knowledge among area firms in the industry are enhanced by a local legacy of and specialization in a particular industry.

Both static and dynamic externalities encourage the clustering of industry establishments in a limited number of locations. Yet, Ellison and Glaeser (p. 921) suggest that "some of the most extreme cases of concentration are likely due to natural advantages." Natural advantages include climate, topography, proximity to location-specific inputs, locations that minimize transportation costs associated with shipping inputs and outputs, and locations with access to pools of labor with desired characteristics (e.g., lower labor costs or amenities attractive to skilled labor). McCann suggests that spatial industry agglomerations resulting from "natural advantages" may be purely the incidental result of individual firm optimizing behavior. The presence of other establishments in the industry at the location may not provide any benefits in terms of external economies.

Insights into the role of industry-specific spillovers versus natural advantages in nonmetro clusters may be provided by an investigation of clustering propensities across industries. A comparison of alternative methodologies for estimating spatial concentration is presented in the following section.

Methodology for Measuring Industry Agglomerations

Estimating Spatial Concentrations. Four principal indices are used in previous research to measure the spatial concentration of industrial activity: spatial concentration ratio, spatial Hirschman-Herfindahl index, locational Gini coefficient, and the Ellison and Glaeser concentration index. The spatial concentration ratio is generally the percentage of an industry's employment in the most concentrated four or eight geographic areas (e.g., states, metro areas, or counties). Spatial concentration ratios provide only limited information on differences in the spatial distributions of industries because the industry's ratios may be sensitive to the number of regions selected and information on the distribution of employment outside the selected four or eight regions is not considered.

The spatial Hirschman-Herfindahl index is preferred to the concentration ratio because the index includes information from all relevant regions. The Hirschman-Herfindahl index generally is estimated as:

$$g_j = \sum_{i=1}^{n} \left(s_i - x_i\right)^2 \tag{1}$$

where j = industry

i = region

n = number of regions

s_i = share of industry $j's$ employment in region i

x_i = share of total employment in region i

The spatial Hirschman-Herfindahl index has a value of zero if the regional distribution of industry j's employment is identical to the distribution of total employment. Index values greater than zero are interpreted to indicate a spatial concentration of industry activity.

The spatial Hirschman-Herfindahl index has two inherent limitations for detecting and measuring the spatial concentration of manufacturing establishments. First, the index does not distinguish between random and non-random distributions of establishments. Second, the index is sensitive to the number of establishments in an industry if establishment numbers are less than the number of regions. That is, an industry with a relatively small number of establishments may have a relatively high index value since $s_i = 0$ for many regions simply because the number of regions exceeds the number of establishments. Thus, a small number of establishments will inflate an industry's index value, making comparisons across industries problematic.[2]

The locational Gini coefficient is a summary measure of spatial dispersion derived from a spatial Lorenz curve. The locational Gini coefficient for an industry *m* is calculated as:

$$Gini_m = \frac{D}{4u} \qquad (2)$$

where $$D = \frac{1}{n(n-1)} \sum_{i=1}^{n} \sum_{j=1}^{n} | x_i - x_j |$$

$i, j =$ regions ($i \ldots j$)

u = mean of x_i

$x_{i(j)} = \dfrac{\text{Region } i\text{'s } (j\text{'s}) \text{ share of employment in } m}{\text{Region } i\text{'s } (j\text{'s}) \text{ share of total employment}}$

n = number of regions

The locational Gini coefficient has a value of zero if employment in industry *m* is distributed identically to that of total employment, and a value of .50 if industry employment is concentrated in one region. The Gini coefficient has the same limitations as the Hirschman-Herfindahl index when regional industry activity is measured by establishment counts — inability to distinguish between random and non-random distributions and sensitivity to number of establishments in the industry

Ellison and Glaeser recognize that some spatial clustering of industry employment may result from a random distribution of establishments and traditional measures of spatial concentration do not reflect whether the observed level of industry concentration is greater than would be expected to arise randomly based on a “dartboard” approach to locating employment. In Ellison and Glaeser's simplest model, the estimated spatial Hirschman-Herfindahl index for industry j (g_j) is compared with the expected value of g_j $[E(g_j)]$, the index value that would arise, on average, if plants selected locations randomly and no spillovers or natural advantages were present. The expected value of g_j was estimated as

$$E(g_j) = \left(1 - \sum_{i=1}^{n} x_i^2\right) \sum_{k=1}^{m} z_k^2 \qquad (3)$$

where x_i = share of total manufacturing employment in region i

z_k = share of industry employment in plant k

n = number of regions

m = number of plants in industry j

Ellison and Glaeser, using state-level employment data, found that the estimated Hirschman-Herfindahl index (g_j) was larger than $E(g_j)$ for 446 of 459 four-digit SIC manufacturing industries and this difference was more than twice its standard deviation in 369 of the 446 industries. They concluded that the level of raw concentration exceeds what would be expected to arise randomly, thus indicating the influence of natural advantages and spillovers on plant locations.

Ellison and Glaeser's dartboard approach is a significant improvement over earlier concentration measures because employment concentration attributable to randomness is considered. However, the dartboard approach is not appropriate for our study of establishment concentrations because the equation provided for the $E(g_j)$

appears to underestimate the mean spatial Hirschman-Herfindahl index for a distribution of establishments where establishment counts are less than the number of regions.

For example, assume there are five plants of equal size in an industry, and ten regions of equal total employment. There are 2002 number of ways in which five indistinguishable plants may be distributed among the ten regions. The expected value of the Hirschman-Herfindahl index for the 2002 combination is .247 while Ellison and Glaeser's $E(g_j)$ = .180.[3] Similarly, for the 715 possible combinations of four plants among 10 regions, Ellison and Glaeser's $E(g_j)$ of .225 is less than the expected value of the Hirschman-Herfindahl index (.286). The above examples demonstrate that the use of $E(g_j)$ to distinguish random plant distributions from non-random may overestimate the number of industries classified as non-random, and thus, overstate the importance of agglomerations in establishment location patterns.

In response to shortcomings in the above measures of spatial concentration, we selected a methodology developed by statisticians for determining whether events (such as insects per acre, bacteria per colony, or defects per production facility) are spatially distributed in regular, random, or contagious patterns (Figure 1). In general, this methodology follows three steps for detecting and measuring contagious patterns in the spatial distribution of events (in this study, the events are the presence of manufacturing establishments in nonmetropolitan areas).

Step one, the distribution of establishments among the regions is analyzed to determine if the distribution is regular, random, or non-random. If every region were exposed equally to the chance of containing an establishment (i.e., plant locations are independent random variables), the distribution of establishments across regions would follow the Poisson distribution.[4] Observed establishment distribution frequencies are compared with the values predicted by the Poisson model under the null hypothesis of "independent" counts of establishments across regions. If the observed and predicted values are significantly different, the null hypothesis of a random distribution is not accepted.

Step two, if the observed values are neither uniformly or randomly distributed, then the observations are said to exhibit "contagious" behavior or to "cluster" in space. The industry establishment distributions exhibiting contagious behavior are fitted to the negative binomial distribution, a probabilistic model developed to account for distributions in which the variance is significantly larger than the mean. Next, tests are conducted to determine if the predicted values provided by the negative binomial distribution closely match the observed values.

Step three, if the observed spatial distribution of establishments for an industry are approximated by the negative binomial distribution, then the exponent k of the negative binomial distribution (referred to as the dispersion parameter) may be used as a measure of the extent of contagious behavior among the establishments. The estimated k values are used to classify industries according to their nonmetro agglomeration propensities and investigate changes in these propensities over time.[5]

Data Sources. The focus of this study is the distribution of manufacturing establishments among nonmetropolitan areas. County-level establishment data for 140 three-digit SIC manufacturing industries for 1981 and 1992 were obtained from the Enhanced County

Business Patterns. Establishment counts were collected for only the nonmetropolitan counties of the BEA's multi-county Component Economic Areas (CEAs).[6] Multi-county CEAs were selected as the appropriate geographic scale because nonmetro industry concentrations generally are not confined to a single nonmetro county (Rosenfeld).

Testing for Non-Randomness of Locations. For each industry, a frequency distribution was constructed providing the number of nonmetro CEAs containing $x = 0, 1, 2, 3 \ldots n$ establishments. If every region were exposed equally to the chance of containing an establishment, the distribution of establishments would follow a Poisson series, where the expected frequency (E_x = expected number of CEAs with x establishments) is computed as:

$$E_x = n \cdot P_x = n \cdot e^{-m} \left(\frac{m^x}{x!} \right) \tag{4}$$

where n is the total number of regions, x is number of establishments in a region, P_x is the probability of finding a number of establishments equal to x, and m is the mean number of establishments per region.

Next chi-square goodness-of-fit tests are used to determine whether observed counts are consistent with expected counts calculated under the hypothesis that the Poisson probability model is representative. Experience has shown that the expected counts per category (in this case, expected number of regions with x establishments) should be greater than five in order that the chi-square distribution provides an adequate approximation. Thus, a pooling of categories may be required to attain expected CEA numbers greater than five.

An example of the application of the Poisson distribution to establishment count data is provided for the regional distribution of establishments in SIC 382 (Measuring and Controlling Devices). In 1992, SIC 382 had 384 nonmetro establishments in the 280 nonmetro CEAs, and the observed and expected frequency distribution of establishments among the CEAs are provided in table 1, part a. The observed distribution of establishments for SIC 382, compared to the expected distribution based on the Poisson, had a relatively large number of CEAs with no establishments, a relatively large number with four or more establishments, and a relatively small number of CEAs with one, two, or three establishments. The null hypothesis that establishments in SIC 382 were randomly distributed was rejected.

Tests for randomness of establishment locations were conducted for the 140 3-digit SIC manufacturing industries. Non-random distributions of establishments were found for 119 industries for 1992, the establishments in SIC 385 (Ophthalmic goods) were distributed randomly among nonmetro CEAs, and 20 industries were non-testable because of too few establishment observations. For 1981, non-random distributions of establishments were found for 112 manufacturing industries, and 28 industries had too few establishments to test for randomness using this procedure.[7]

<u>Negative Binomial Distribution</u>. The results of the previous statistical analysis indicate that the geographic distribution of manufacturing establishments in nonmetro CEAs is contagious, i.e., non-random concentrations or agglomerations are evident for

most three-digit manufacturing industries. A measure of the extent of contagious behavior for each industry is provided by "fitting" the industry's establishment distribution data to the negative binomial distribution.

Each negative binomial distribution is defined by two parameters--the population mean (m) and the exponent k (the dispersion parameter). The variance (v) of the negative binomial distribution is

$$v = m + m^2/k \tag{5}$$

Note that as k ÷4, v approaches the mean m and the distribution approaches Poisson. On the other hand, as k ÷o from above, the variance increases indicating a contagious distribution. Thus, the parameter k of the negative binomial distribution may be used to indicate the "spatial affinity" that establishments in an industry have for one another.

Estimates of the exponent k (provided by maximum likelihood methods) are acceptable measures of agglomeration propensities only if the industry establishment data fit the negative binomial distribution. The standard test of adequacy of the negative binomial distribution in representing a non-random distribution is the similarity between the observed number of CEAs with x establishments (O_x) and the expected number of CEAs (E_x) as computed from the statistics of the sample (m and k). For example, the first expectation, E_o for $x = 0$ is determined as

$$E_o = \frac{n}{q^k} \quad where \quad q = 1 + p = \frac{m+k}{k} \tag{6}$$

and the succeeding entries for $x = 1, 2, 3, \ldots$ as

$$E_x = \frac{(k+x-1)R}{x} E_{x-1} \quad where \quad R = \frac{p}{q} = \frac{m}{k+m} \tag{7}$$

The observed and expected frequencies are compared using the chi-square test.

An example of fitting the negative binomial distribution to manufacturing establishment data for nonmetro CEAs is provided in table 1, part b for SIC 382 (Measuring and Controlling Devices). In contrast with the previous test, the frequencies predicted by the negative binomial distribution approximate the observed values. Thus, we cannot reject the null hypothesis that the spatial distribution of establishments in SIC 382 has a negative binomial distribution.[8]

In sum, the negative binomial distribution approximated the observed establishment distributions for 113 of the 119 industries that we found to be non-randomly distributed in 1992. For the 1981 establishment data, 107 of the 112 non-random distributions were represented by the negative binomial distribution. The results of the maximum likelihood estimation of the exponent *k* for the 113 1992 establishment distributions and the 107 1982 distributions are provided in Appendix Table 1.

Different Sized Regions. The theory of negative binomial distributions assumes that numbers of events are counted on sample regions of equal geographic and economic size, that is, each region is equally exposed to the chance of containing an event. For the previous estimates of the exponent *k*, the number of industry establishments are counted for each nonmetro CEA assuming that the CEAs are the same size or equally exposed to establishment locations.

Yet nonmetropolitan CEAs vary significantly in terms of geographic and economic size, and the "equal exposure" assumption may not be appropriate.[9] Variations in region size may be accommodated in the negative binomial model through the introduction of a variable representing the relative size of each region (Bissell). Specifically, Bissell proposed using the weight (w_i) representing the ratio of the size of the ith region (a_i) to the mean size of all regions.

$$w_i = \frac{a_i}{\sum_{i=1}^{n} a_i / n} \tag{8}$$

Bissell described maximum likelihood estimators for a negative binomial model with different sized regions. Consider a set of n regions yielding a set of establishment counts x_i $(i = 1, \ldots n)$, represented by X_n. The relative sizes of the n regions are denoted by w_i $(i = 1, \ldots, n)$, similarly represented by W_i. The probability of observing x_i establishments in a region of size w_i from a negative binomial distribution with dispersion parameter kw_i and mean mw_i is given by

$$Pr\left(x_i | w_i\right) = \left(\frac{k}{m+k}\right)^{kw_i} \left(\frac{m}{m+k}\right)^{x_i} \prod_{j=1}^{x_i} \left(\frac{kw_i + j - 1}{j}\right) \tag{9}$$

For a set of establishment counts $\{X_n\}$ from a sample of nonmetro CEAs of size n with region sizes $\{W_n\}$, the log likelihood function is

$$L(X_n|k,m,W_n) = k \sum_{i=1}^{n} w_i \log\{k/(m+l)\} + \sum_{i=1}^{n} x_i \log\{m/(m+k)\}$$

$$+\sum_{i=1}^{n} \sum_{j=1}^{x_i} \log \{(kw_i + j - 1)/j\} \qquad (10)$$

Using the above log likelihood function, the maximum likelihood estimators for k can be obtained through an iterative process as follows:

$$\hat{m} = \left(\frac{1}{n}\right)\sum_{i=1}^{n} x_i \text{ ; given } \hat{m}\text{, solve the following for } \hat{k}$$

$$0 = n \log\left\{ \hat{k} / (\hat{m} + \hat{k}) \right\} + \sum_{i=1}^{n} \sum_{j=1}^{x_i} w_i (\hat{k} w_i + j - 1)^{-1} \qquad (11)$$

For this study, three sets of weights (w_a, w_e, and w_t) were used to adjust for differences in regions' sizes.

w_a = weight based on nonmetro CEA area size (square miles)

w_e = weight based on nonmetro CEA manufacturing employment in 1981 or 1992.

$w_{t,}$ = weight based on nonmetro CEA total employment in 1981 or 1992.

Table 1 in the Appendix provides the maximum likelihood estimates of the dispersion parameter k for (1) no adjustments for differences in the sizes of nonmetro CEAs,

$k = k^{*}$; (2) weights used to adjust for differences in CEA geographic size, $k = k^{a}$; (3)

weights used to adjust for the differences in CEA manufacturing employment, $k = k^{e}$; and (4) weights used to adjust for differences in total employment, $k = k^{t}$.[10]

The findings presented in Appendix Table 1 for k^*, k^a, k^e, and k^t indicate that our measures of dispersion may be sensitive to the weights selected to account for region size. The introduction of weights for geographic size had little impact on the estimates of the exponent *k* relative to the estimates provided in the unweighted model. The estimated *k* values for manufacturing industries were relatively low for both the unweighted and "weighted-by-area" models, indicating extensive concentration for establishments in these industries. Moreover, the rank-order of *k* values provided by the unweighted and weighted-by-area models were very similar (correlation coefficient = .950). Industries with low (high) *k* values in the unweighted model also had low (high) *k* values in the weighted-by-area models.

The introduction of weights for economy size (as measured by manufacturing or total employment) resulted in greater changes in the estimate *k* values. The *k* values in the weighted-by-employment estimations were generally higher and had greater variation than those estimated for the unweighted and weighted-by-area models. Thus, manufacturing establishments were less concentrated among the nonmetro CEAs when CEA size was measured (weighted) by manufacturing or total employment. Larger *k* values (less spatial clustering) when CEA size was measured by employment (manufacturing or total) were expected since the use of Bissell's weighting procedure treats "large" regions as if they were multiple "average" regions. That is, a region with employment twice the average regional employment is treated as two regions in the maximum likelihood estimations of *k*. The "larger" regions must have proportionately more establishments than "average" regions if the dispersion parameter *k* is to remain relatively unchanged after weighting for size (see, for example, SICs 221 and 228). However, if the number of establishments does not increase proportionately with region size, then the distribution becomes more dispersed and *k* values increase relative to the unweighted estimates (for example, SIC 254).[11]

Interpretations of Exponent *k*

As noted earlier, the exponent *k* of the negative binomial distribution is a summary measure of the extent of concentration or contagious behavior among establishments in an industry. The possible range of the exponent *k* is 0 to $+4$. A *k* value close to zero indicates that the industry is highly concentrated, while a large *k* value indicates that the distribution of establishments is relatively dispersed. The sensitivity of the spatial distribution of establishments to changes in *k* and the total numbers of establishments is discussed below.

<u>Changes in *k* with Total Establishments Held Constant</u>. Figure 2 provides an example of establishment distributions that would be associated with different *k* values but the same total number of establishments. The hypothetical data for this figure are derived for an industry with 1,700 establishments in the 280 nonmetro CEAs in 1992.

The numbers of expected CEAs in figure 2 are calculated by changing the value of *k* with the total number of establishments held constant. The hypothetical distributions show that if *k* is small (e.g., $k = .50$ or .10), there are many regions with no establishments and a few CEAs with a very large number of establishments. As *k* increases, the number of empty regions decreases and the number of CEAs with large numbers of establishments also decreases. Thus an increase in *k* indicates that establishments are distributed more randomly, with a greater number of regions having establishment numbers closer to the CEA mean ($m = 6.07$). And negative binomial distributions with $k > 1.50$ begin to take a shape similar to a Poisson distribution (that is, a skewed normal distribution). Based on the distributions displayed in figure 2, we shall adopt the convention of referring to industries with $k < .50$ as highly concentrated spatially and industries with $k > 1.50$ as exhibiting weak concentrations.

Changes in Establishment Numbers with *k* Held Constant. The negative binomial distribution is defined by two parameters, the mean *(m)* number of establishments per region and the exponent *k*. Thus, two industries with the same *k* but different numbers of establishments (and *m* values) will have different distributions of establishments among CEAs. Figure 3 provides examples of establishment distributions among nonmetro areas that are associated with different *m* values but the same estimated value for the exponent *k*. The three industries selected (SICs 281, 286, and 365) have the same estimated exponent *k* ($k^* = 0.545$) but different numbers of nonmetropolitan establishments (SIC 365 — 86; SIC 286 — 186; and SIC 281 — 276). As expected, the distribution of establishments among the 280 CEAs was sensitive to the total number of establishments in the industry, *k* held constant. An increase in industry establishment numbers was associated with a slight "flattening" of the distribution--fewer regions with zero establishments and more regions with a large number of establishments. However, the shape of the distribution remained relatively unchanged in response to changes in *m* as compared to changes in *k* (Figure 1). Thus comparisons of *k* parameters across industries of different sizes provide significant insights into which industries have similar and dissimilar spatial distribution patterns.

Summary of Findings

Prevalence of Industry Concentrations. The statistical procedures applied in this study indicate that the propensity to concentrate manufacturing establishments in nonmetro CEAs was pervasive. Contagious establishment location patterns were found for 119 of the 120 3-digit manufacturing industries for which sufficient observations were available for statistical analysis. These findings of non-random location patterns for nonmetro plants are consistent with those of Ellison and Glaeser's state-level employment distributions for 4-digit SIC manufacturing industries.

The extent of spatial concentration among nonmetro manufacturing establishments may be appreciated by analyzing the estimated dispersion parameters for 1981 and 1992. For discussion purposes, we will focus on k^t, the dispersion parameter weighted by total nonmetro CEA employment. Histograms illustrating the frequency distributions of k^t for 1981 and 1992 are presented in figure 4. In each figure, the bars represent the number of 3-digit SIC industries for which k^t lies in an interval -.10 to

+.10 of the value on the horizontal axis for all k^t less than 3.00. For k^t values 3.00 and greater, the interval is -.50 to +.50 of the value on the horizontal axis.

The histogram for 1992 k^t estimates indicates that the propensity to concentrate establishments in nonmetro areas varied widely among manufacturing industries. The mean dispersion parameter value was 2.51 and the median value was 1.08. Only 19.6% of the industries exhibited extensive establishment clustering ($k^t < .50$) while 44.7% were classified as moderately concentrated ($.50 < k^t < 1.50$) and 35.7% of the manufacturers had relatively weak agglomeration tendencies ($k^t > 1.50$).

A comparison of 1981 and 1992 k^t estimates indicates that the clustering of industry establishments in nonmetro areas has become less prevalent over time (Figure 3). From 1981 to 1992, the mean dispersion parameter increased from 1.70 to 2.51 and the median k^t increased from .95 to 1.08. In addition, among the 104 industries with computable k exponents for 1981 and 1992, 80 industries had higher dispersion parameters in 1992 than in 1981, indicating an increase in spatial dispersion. And more manufacturing industries were highly concentrated ($k^t < .50$) in 1981 (28.7%) than in 1992 (19.6%). These findings of a decline in establishment clustering over time do not reflect a widespread movement to the spatial concentration of industry establishments in nonmetro areas.

Industries experiencing an increase in nonmetro establishment clustering from 1981 to 1992 include “high technology” manufacturers that have been the focus of much of the research on external economies and industry clustering (e.g., electrical industrial apparatus, 362; communications equipment, 366; aircraft and parts, 372; and measuring and controlling devices, 382). Other industries with significant increased spatial concentration include fat and oils (207), beverages (208), paper mills (262), paperboard mills 9263), plastics materials (282), asphalt paving and roofing (295), and plumbing and heating (343). These manufacturers do not appear to fit the classic examples of increased spatial concentration resulting from rapid technological change, shorter product life cycles, and enhanced need for inter-firm information flows.

A recent study by Dumais, Ellison, and Glaeser suggests that industry expansion or contraction may influence geographic concentration as well as the rate of technological change and industrial restructuring. Specifically, the authors find that the births of new firms tend to reduce agglomeration while plant closures reinforce clustering. The 1981-1992 growth experiences of the seven low tech industries with significant increased clustering generally fit the findings of Dumais, Ellison, and Glaeser that declining industries become more spatially concentrated. Five of these seven industries had fewer nonmetro establishments in 1992 than in 1981. A thorough analysis of the relationship between industry growth (decline) and nonmetro spatial concentration is beyond the scope of this paper; however, our preliminary evidence indicates that further study of this issue is warranted.

Spatially Concentrated Industries. As noted earlier, establishments in an industry may concentrate spatially to take advantage of “natural advantages” and/or “inter-industry spillovers” provided by select locations. This typology of industry concentrations (natural advantages and inter-industry spillovers) provides a useful framework for analyzing the types of manufacturing industries that exhibit high versus low concentrations in nonmetro areas. Our data set does not permit a detailed analysis of the specific determinants of nonmetro concentrations. Nevertheless, interesting insights into nonmetro agglomerations are provided through a comparison of industry types.

Table 2 lists the 30 industries with the greatest concentrations in nonmetro areas based on the dispersion parameter k^t. The most striking observation is the prevalence of textile and apparel manufacturers among the most concentrated. The six most concentrated industries (SICs 228, 222, 235, 224, 221, and 226) are textile and apparel manufacturers and 11 of the top 30 industries are from SIC 22 or 23. Nonmetro textile and apparel manufacturers historically have been characterized by routinized production processes relying on low-skill, low-wage labor (Perloff, et al.). As such, Enright suggests that nonmetro textile/apparel concentrations may be attributable to the incidental agglomerating of establishments in areas with low labor costs. Rosenfeld documents that concentrations of manufacturers with routinized production processes may lead to the development of localization economies in the form of labor pooling, specialized service providers and accommodating institutions. Thus, as noted by Ellison and Glaeser, regions with high concentrations of textile and apparel plants may provide both natural advantages (e.g., access to low labor costs) and spillover economies.

Three leather products manufacturers also were present among the 13 most spatially concentrated industries (SICs 311, 314, and 319). These industries also appear to fit the pattern of incidental concentration resulting from selecting locations with availability of specific inputs (e.g., low-cost labor and/or animal hides).

A relatively large number of the most concentrated industries have significant dependence on natural resources or agricultural products, inputs that are geographically concentrated. For example, paper mills (262), petroleum refining (291), miscellaneous primary metal products (339), logging (241), petroleum and coal products (299), structural clay products (325), and dairy products (202) all have dispersion parameters less than .60. The location of establishments in these industries appears to be sensitive to location-specific inputs or transport costs for such inputs.

Finally, among the most spatially concentrated are industries where production processes may require special labor skills or adaptability to changes in technology (jewelry and silverware, 396; ordnance and accessories, 348; glass and glasswares, 322; communications equipment, 366; and computer and office equipment, 357). These industries appear, more so than the others, to be likely candidates for the dynamic and static localization economies that have received much attention in the recent literature.[12]

The manufacturing industries with relatively little spatial concentration are a diverse group, but some commonalities among the industries are evident (table 3).[13] Many of the less concentrated industries are market oriented (e.g., commercial printing, 275; bakery products, 205; newspapers, 271; periodicals, 272; miscellaneous publishing, 274; and beverages, 208), or manufacture products related to the packaging and shipping of market oriented goods (e.g., metal cans and shipping containers, 341; paperboard mills, 263; and wood containers, 244). The distribution of establishments for these manufacturers more closely follows the distribution of total employment and population. Other less concentrated industries are also local market oriented because they have high transportation costs relative to the value of the product (concrete, gypsum, and plaster, 327; cement, hydraulic, 324; and agricultural chemicals, 287). Finally, many of the low concentration 3-digit SICs are diverse industries with relatively large numbers of varied products (e.g., paints and allied products, 285; soaps, cleaners, and toilet goods; meat products, 201; toys and sporting goods, 394; cutlery, handtools, and hardware; and motor vehicles and equipment, 371). A large number of product lines in a 3-digit SIC may result in less spatial concentration of establishments if the individual products have different input and product markets or if locations near other industry members provide few spillover benefits.

Conclusions and Implications

The findings of this study indicate that nonmetropolitan manufacturing establishments are more concentrated spatially than would be expected to arise from a random distribution of establishments. Of the 120 industries with sufficient numbers of establishments for statistical analysis, 119 industries exhibited non-random location patterns for nonmetro plants. And approximately two-thirds of these industries had estimated dispersion parameters indicating a high or moderate level of spatial concentration. This propensity to cluster plants in nonmetro CEAs was evident for both 1981 and 1992, though weaker in 1992.

Analysis of manufacturing industries with highly concentrated distributions of nonmetro establishments provides insights into factors influencing geographic concentration and trends in the spatial evolution of the sector. Among rural manufacturers, spatial concentration appears to be most prevalent among industries characterized by routinized production processes using low-skilled labor and industries relatively dependent on natural resources or agriculture. A relatively small number of the more spatial concentrated manufacturers fit the characteristics generally associated with industries generating and benefitting from localization economies (high technology, skilled labor dependent, specialized production, short product cycles). Thus, only limited examples are available of industry establishment clusters in nonmetro areas primarily attributable to the presence of inter-industry spillovers.

Differences among industries in establishment clustering tendencies (and reasons for concentrating) have implications for industry targeting programs. The targeting of industrialization programs at specific industries is a popular local economic development strategy because it is perceived to be a means for promoting industry clusters and the resulting localization economies. The findings of this study generally support this strategy. Nonmetro areas with an existing industry cluster probably offer natural advantages for the industry and/or the potential for or availability of external economies. Thus, the targeting of establishments in, or related to, the existing industry cluster should provide a greater likelihood of success (attraction or development of new establishments) than a less focused industrial development strategy. In addition, nonmetro areas with good access to input and product markets or specialized local inputs appear more likely to develop the extensive establishment concentrations necessary to stimulate external economies.

Alternatively, we also found evidence of many manufacturing industries whose establishment location patterns were not strongly influenced by natural advantages or the availability of localization economies. These industries with low clustering propensities will be more realistic targets for rural areas not already blessed with industry-specific natural advantages or existing industry clusters. However, competition among communities for manufacturers with low clustering tendencies may be intense since many communities will perceive themselves as viable establishment locations. Thus, all communities targeting establishments in the low clustering industries are not likely to be successful. But this targeting approach remains more cost effective than the 'shoot anything that flies" industrialization strategy of the past.

Endnotes

1. See, for example, Glaeser, et al.; Rauch; Henderson, Kunkoro, and Turner; Soroko; O'hUallacháin and Satterthwaite; Partridge and Rickman; Henderson; Palivos and Wang; and Ciccone and Hall.

2. For example, assume the nation is divided into 10 equal sized regions ($x_t = .10$), and assume an industry with only three establishments. The spatial Hirschman-Herfindahl index for this industry has a minimum value of .233, a maximum value of .900, and a mean value of .354. Alternatively, for 10 equal sized regions and an industry with four establishments, the index has a minimum value of .150, a maximum value of .900, and a mean value of .286. Thus, the index provides a higher mean value for the three establishment industry than for the four establishment industry even if establishments in both industries are randomly distributed among the 10 regions.

3. According to occupancy theory, there are $(n + r - 1)!/(n-1)!r!$ number of ways in which r indistinguishable plants can be distributed among n regions, with no restrictions as to the number of plants permitted in any one region (Freund). The 2002 number of ways for distributing 5 plants among 10 regions include: 10 ways where all 5 plants are in one region, 180 ways where 5 plants are divided among 2 regions (4, 1 or 3, 2); 720 ways where 5 plants are divided among three regions (3, 1, 1 or 2, 2, 1); 840 ways where 5 plants are distributed among 4 regions (2, 1, 1, 1) and 252 ways where a region has at most one plant (1, 1, 1, 1, 1,). The Hirschman-Herfindahl index (g) for the various combinations of 5 plants are: 5 in one region ($g = .90$); 4 and 1 ($g = .58$); 3 and 2 ($g = .42$); 3, 1, and 1 ($g = .34$); 2, 2, and 1 ($g = .27$), 2, 1, 1, 1 ($g = .18$); and 1, 1, 1, 1, 1 ($g = .10$). Thus the expected value of g =

(10/2002) (.90) + (90/2002) (.58) + (90/2002) (.42) + (360/2002) (.34) + (360/2002) (.27) + 840/2002 (.18) + 252/2002 (.10) = .247.

4. The Poisson distribution is selected as the probabilistic model for many random distributions of events because the Poisson distribution approximates the binomial distribution for independent random variables when the number of trials (*n*) is large and the probability of success (*p*) is small.

5. Most research applying the proposed statistical methodology uses regions of equal size (e.g., field plots). However, statistical procedures are available for applying the methodology to regions of different sizes (e.g., counties and states), and these procedures are summarized later in the paper.

6. Component Economic Areas (CEAs) are multi-county-regions developed by the Bureau of Economic Analysis, U.S. Department of Commerce. Each area consists of one or more economic nodes (metropolitan areas or similar areas that serve as centers of economic activity) and the surrounding counties that are economically related to the nodes (Johnson). The main factor used in determining the economic relationships among counties in a CEA is commuting patterns, so each component economic area includes, as far as possible, the place of work and the place of residence of its labor force. The 3,141 counties in the U.S. are divided into 348 CEAs. Of the 348 CEAs, 38 CEAs are constituted by only nonmetropolitan counties, 30 CEAs are constituted by only metropolitan counties, and 280 CEAs have both metro and nonmetro counties. Our analysis was restricted to the nonmetro counties of the 280 CEAs with both metro core counties.

7. In retrospect, one might skip step one of this analysis and proceed directly to measuring the extent of contagious behavior by estimating a negative binomial distribution. An advantage of this approach would be the possibility that some of the industries with too few observations for the non-randomness test might have sufficient observations for the negative binomial test. A disadvantage of skipping step one would be that we would have less information on the spatial distribution of industries that did not "fit" the negative binomial distribution.

8. The observed industry establishments' distribution for SIC 382 fit a negative binomial with an unweighted $k\ (k^*) = .500$.

9. For example, among the 280 nonmetro CEAs, land area ranged from 235 to 541,186 square miles and 1992 manufacturing employment ranged from 3 to 144,601 employees.

10. Bissell noted that an important condition for the use of the weighed model is that the region sizes and local event rates should be conceptually independent. There is one situation in which the violation of this condition will invalidate either the model or the above methods of estimating its parameters. That is, the likelihood function may become $L\ (W_n \backslash k, m, X_n)$ rather than $L\ (X_n \backslash k, m, W_n)$ because of dependency between region size and local event rate (X_n represents a set of establishment counts from n number of nonmetro CEAs and W_n represents the relative region sizes for nonmetro CEAs). If the above situation occurs, the likelihood function leads to entirely different estimators. Bissell suggests a simple means of monitoring the validity of the present model, which is to estimate crude local event rates $8_i = x_i / w_i$ and to calculate the correlation between 8_i and w_i. The results of the correlation test between 8_i and w_i. indicate that there is no serious violation of the independence criterion for this study.

11. The use of alternative measures of concentration $(k^{*}, k^{a}, k^{e}, k^{t})$ resulted in different rankings of industries from most to least concentrated. However, in general, industries with low (high) values for the unweighted measure k^{*} also had low (high) values for the weighted measures k^{a}, k^{e}, and k^{t}.

12. An analysis of the location of nonmetro CEAs with establishment clusters was undertaken for a limited number of industries. Our findings indicate that CEAs with industry clusters also tend to be concentrated regionally. For example, nonmetro CEAs with establishment clusters in SIC 395 (Pens, Pencils, and Office Supplies) are located in the Southwest, upper Midwest, and east Texas. Nonmetro CEAs with clusters in SIC 282 (Plastics Materials and Synthetics) are located near Atlanta, along the Mississippi River Valley, and throughout the Mid-Atlantic.

13. Table 3 does not include miscellaneous manufacturers such as miscellaneous wood products (SIC 249).

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Table 1. Observed and Expected Distributions of Establishments, SIC 382, 1992.

Part A. Poisson Distribution

No. Est. in CEA (x)	No. of Observed CEAs (O_x)	No. of Expected CEAs (E_x)	$\frac{(O_x - E_x)^2}{E_x}$
0	142	71.05	70.85
1	61	97.44	13.63
2	27	66.81	23.73
3	17	30.54	6.01
4+	33	14.16	25.07
Total	280	280.00	139.29[a]

[a]Critical Value (Chi square) = 11.30.

Part B. Negative Binomial Distribution

No. Est. in CEA (x)	No. of Observed CEAs (O_x)	No. of Expected CEAs (E_x)	$\frac{(O_x - E_x)^2}{E_x}$
0	142	144.70	.05
1	61	53.05	1.19
2	27	29.16	.16
3	17	17.81	.04
4	10	11.42	.18
5	6	7.53	.31
6	3	5.06	.84
7	4	3.44	.09
8+	10	7.83	.60
Total	280	280.00	3.44[b]

[b]Critical Value (Chi square) = 12.6.

Table 2. Manufacturing Industries with Greatest Nonmetro Concentrations, $k = k^t$, 1992

SIC	Industry	k^t
228	Yarn and Thread Mills	.103
222	Broadwoven Fabric Mills, Manmade	.129
235	Hats, Caps, and Millinery	.136
224	Narrow Fabric Mills	.157
221	Broadwoven Fabric Mills, Cotton	.164
226	Dyeing & Finishing Textiles	.188
311	Leather Tanning & Finishing	.217
262	Paper Mills	.245
278	Blankbooks & Bookbinding	.252
291	Petroleum Refining	.271
314	Footwear	.277
234	Women's Undergarments	.306
319	Leather Goods, NEC	.332
339	Misc. Primary Metal Products	.333
236	Girls' and Children's Outerwear	.381
391	Jewelry, Silverware, & Plated Ware	.405
252	Office Furniture	.441
373	Ship & Boat Building	.447
241	Logging	.457
396	Costume Jewelry	.486
299	Misc. Petroleum & Coal Products	.498
325	Structural Clay Products	.506
202	Dairy Products	.550
348	Ordnance & Accessories, NEC	.561
322	Glass and Glassware	.562
345	Screw Machine Products	.576
232	Men's & Boys' Furnishings	.629
366	Communications Equipment	.677
233	Women's Outerwear	.679
357	Computer & Office Equipment	.704

Table 3. Manufacturing Industries with Least Concentration in Nonmetro CEAs, $k = k^t$, 1992

SIC	Industry	k^t
341	Metal Cans & Shipping Containers	45.227
275	Commercial Printing	26.618
327	Concrete, Gypsum, & Plaster	16.797
344	Fabricated Structural Metal Products	7.349
205	Bakery Products	6.353
271	Newspapers	5.413
285	Paints & Allied Products	4.405
386	Photographic Equipment	4.351
243	Millwork, Plywood	3.822
254	Wood Partitions & Fixtures	3.314
284	Soaps, Cleansers, & Toilet Goods	3.091
201	Meat Products	2.910
272	Periodicals	2.910
324	Cement, Hydraulic	2.614
394	Toys and Sporting Goods	2.552
356	General Industrial Machinery	2.461
274	Miscellaneous Publishing	2.368
342	Cutlery, Handtools, & Hardware	2.363
371	Motor Vehicles & Equipment	2.359
358	Refrigeration & Industrial Machinery Service	2.322
355	Special Industrial Machinery	2.289
361	Electrical Transmission Equipment	2.254
287	Agricultural Chemicals	2.212
263	Paperboard Mills	2.188
244	Wood Containers	1.989
267	Converted Paper Products	1.923
353	Construction & Related Machinery	1.772
208	Beverages	1.755
204	Grain Mill Products	1.742
364	Electric Lighting & Wiring Equipment	1.703

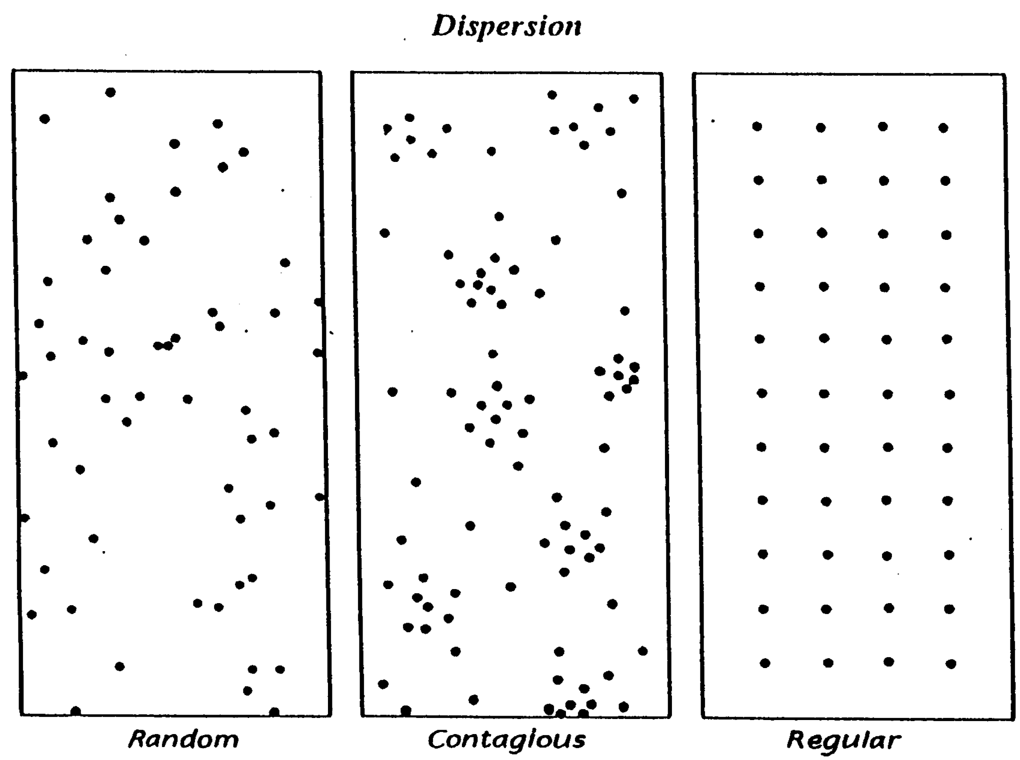

Figure 1. Alternative Types of Distributions

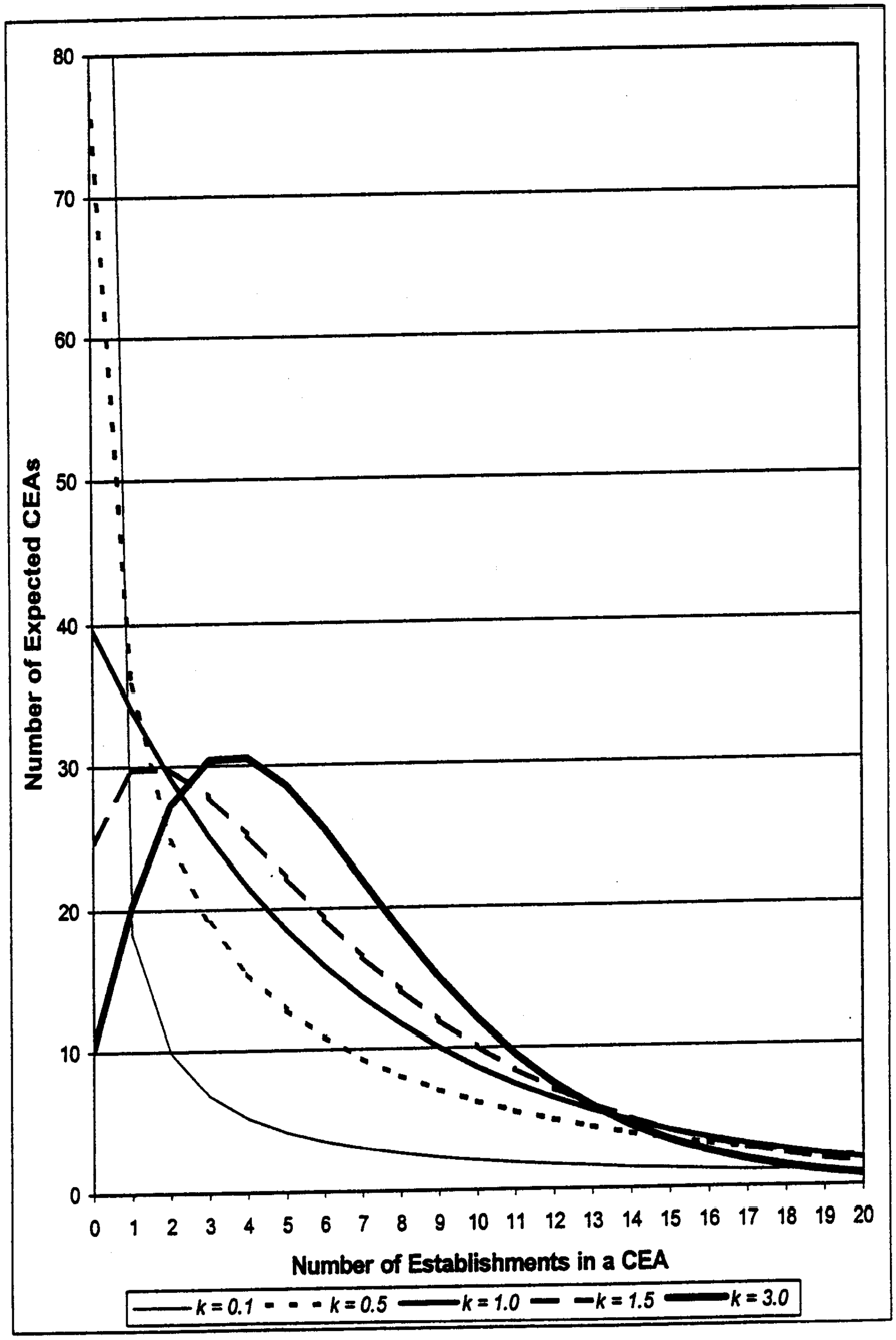

Figure 2. Hypothetical Distributions of the Number of Expected CEAs with Different *k*

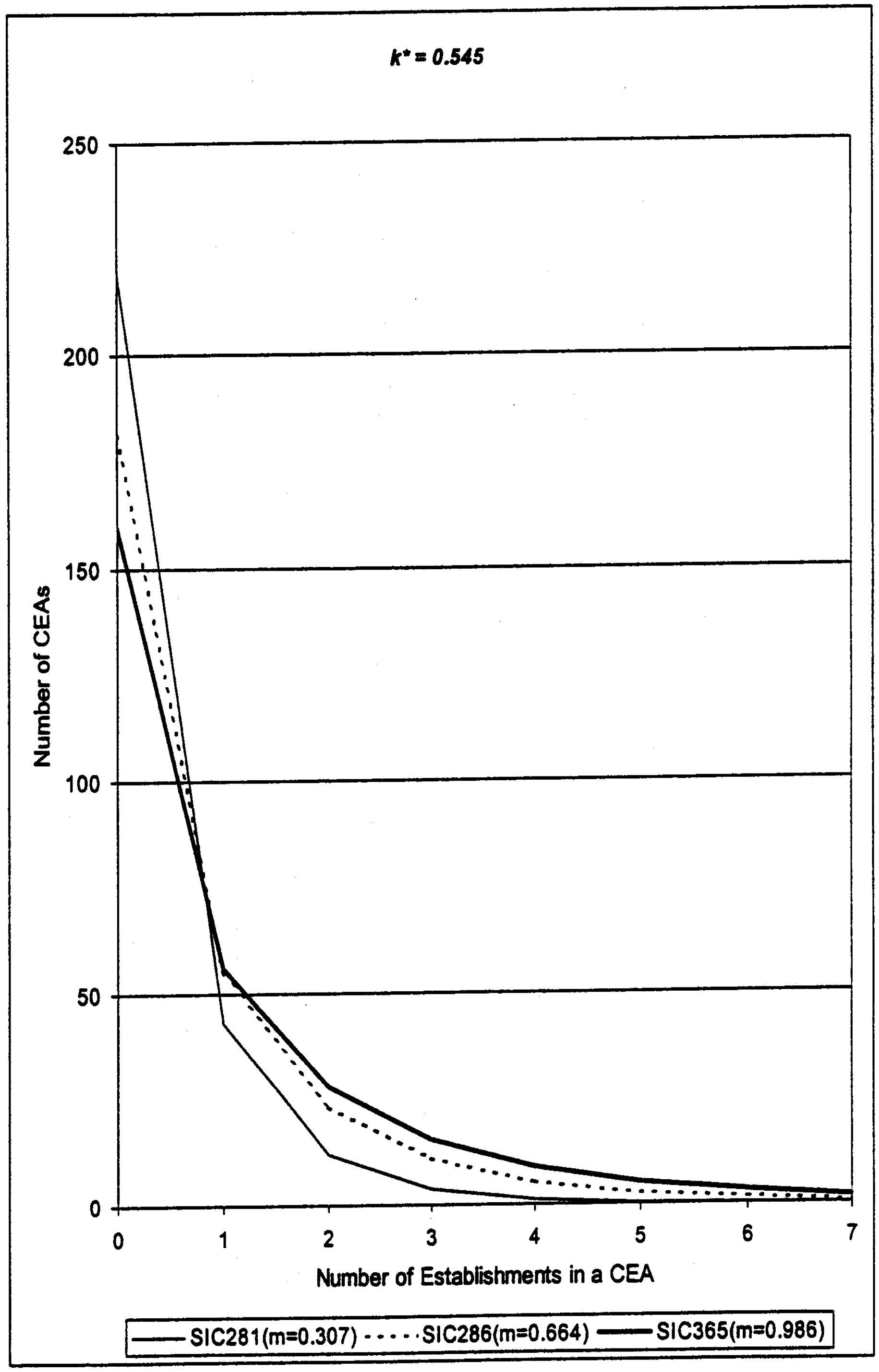

Figure 3. Hypothetical Distributions of the Number of Expected CEAs with Different *m*

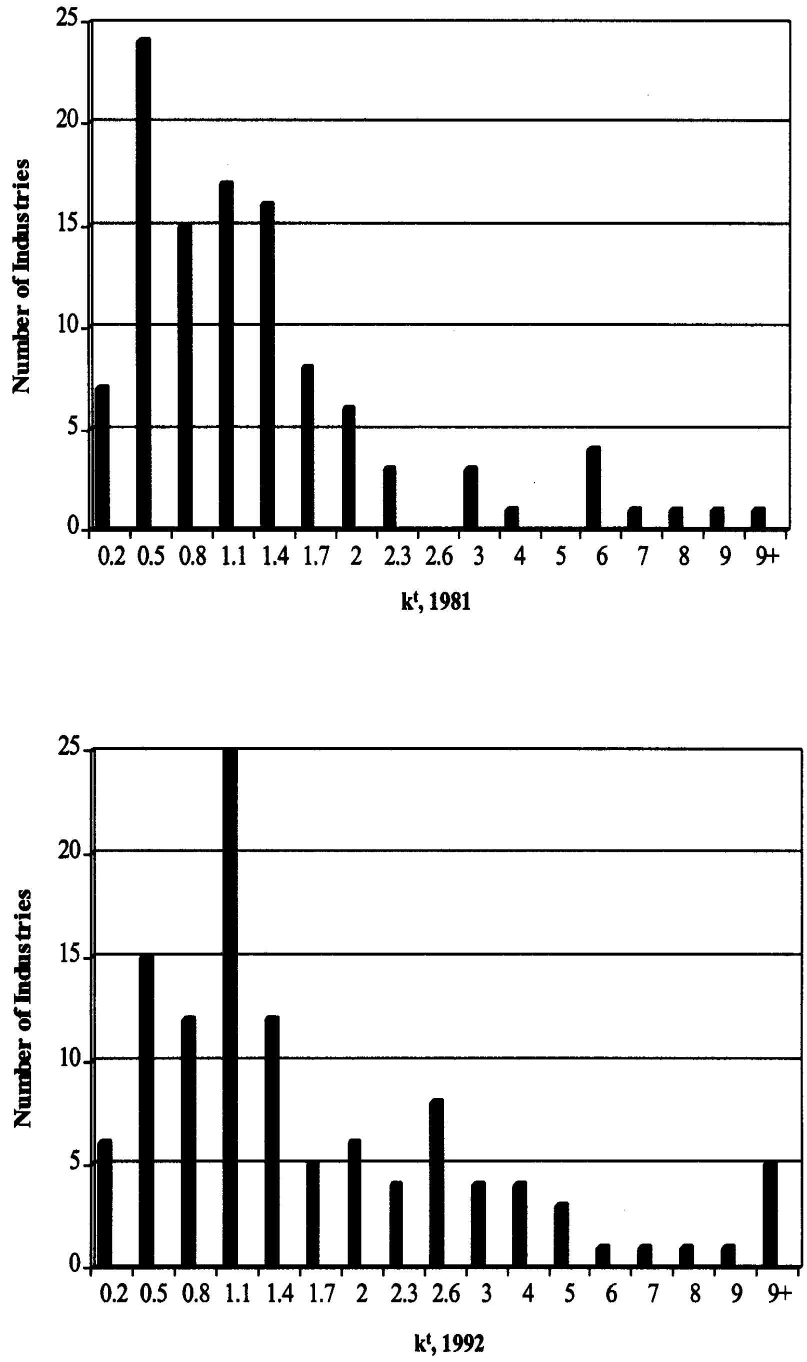

Figure 4. Estimated Dispersion Parameter (k^t) Values, Three-digit Manufacturing Industries, 1981 and 1992.

Appendix Table 1. Estimated Dispersion Parameters (k), Weighted and Unweighted, 1981 and 1992

SIC	1981				1992			
	k*	k^a	k^e	k^t	k*	k^a	k^e	k^t
201	0.86272	0.76504	2.04893	2.89944	0.90292	0.83154	2.07092	2.90998
202	0.38138	0.38540	0.51832	0.58515	0.36958	0.37547	0.49410	0.55055
203	0.37829	0.36910	0.45633	0.49091	0.52082	0.52464	0.68698	0.83222
204	0.67034	0.63288	1.28430	1.63092	0.71444	0.65846	1.53126	1.74177
205	0.82774	0.71224	1.53471	2.99386	0.96578	0.87083	1.89205	6.35250
206	0.34587	0.33973	0.37602	0.42014	0.66829	0.66836	0.76071	1.00171
207	0.68636	0.74856	1.25041	1.73073	0.49703	0.52223	1.08540	1.08922
208	0.93873	0.89779	3.41419	8.42460	0.71735	0.76807	1.21577	1.75488
221	0.07268	0.07059	0.10129	0.08420	0.12775	0.12239	0.20942	0.16360
222	0.08387	0.08181	0.11702	0.09787	0.10704	0.10415	0.15575	0.12923
224	0.22123	0.18482	0.28929	0.25898	0.12596	0.11726	0.17534	0.15749
225	0.12563	0.11548	0.18565	0.15253	N/A	N/A	N/A	N/A
226	0.09996	0.09428	0.15048	0.09428	0.14160	0.13492	0.24426	0.18796
228	0.08984	0.08387	0.12727	0.10459	0.08837	0.08369	0.12193	0.10352
229	0.23765	0.21551	0.49215	0.33341	N/A	N/A	N/A	N/A
231	0.25514	0.25163	0.67086	0.46206	0.33254	0.33240	1.44540	0.74211
232	0.31856	0.27955	0.75732	0.53298	0.34439	0.31499	0.91776	0.62901
233	0.34348	0.28077	0.70359	0.52517	0.40627	0.34292	0.93605	0.67892
234	0.22631	0.20084	0.38832	0.30719	0.22120	0.20052	0.34620	0.30590
235	N/A	N/A	N/A	N/A	0.10842	0.11833	0.13091	0.13632
236	0.22213	0.18862	0.33429	0.26471	0.28643	0.24648	0.47415	0.38103
238	0.34346	0.33086	1.26634	0.77352	0.44385	0.42960	1.50094	1.02341
239	0.76478	0.62859	3.37131	2.79323	0.86107	0.73324	3.12154	4.68235
241	N/A	N/A	N/A	N/A	0.28581	0.28800	0.48650	0.45674
242	0.48877	0.40663	1.22023	1.00921	0.48955	0.41052	1.19109	1.07126
243	0.83564	0.70934	1.90324	1.98951	0.97872	0.75001	2.63911	3.82185
244	0.51775	0.42211	1.50180	1.28710	0.64272	0.47621	2.99146	1.98861
245	0.57042	0.54685	1.24155	1.15749	0.65292	0.58016	1.23013	1.19101
249	0.65218	0.53709	1.20976	1.18769	0.72202	0.57558	2.02809	2.32304
251	0.45595	0.39992	1.31254	0.91456	N/A	N/A	NIA	N/A
252	0.15812	0.15732	0.20511	0.20172	0.28108	0.27830	0.51119	0.44085
253	0.54658	0.52008	1.99935	1.33964	0.42290	0.40570	1.59558	0.99471
254	0.61429	0.56498	1.72990	1.99885	0.81849	0.68563	3.10780	3.31433
259	N/A	N/A	N/A	N/A	0.41740	0.41417	1.44639	0.97171
262	0.30160	0.40826	0.31144	0.41318	0.20005	0.20028	0.22957	0.24492
263	1.53091	0.95790	1180	5.68640	0.71055	0.56083	3.88510	2.18766
265	0.57245	0.43655	2.90268	1.39939	0.48342	0.38591	2.80188	1.25093
267	0.42359	1.27354	0.42359	1.07238	0.54119	0.45912	2.93339	1.92293
271	1.12968	1.05091	1.91949	5.10940	1.18577	1.17003	2.16219	5.41255
272	0.51356	0.49505	0.86191	1.04940	0.80600	0.74437	1.30356	2.90994

Appendix Table 1: Estimated Dispersion Parameters (k), Weighted and Unweighted, 1981 and 1992

SIC	1981				1992			
	k^*	k^a	k^e	k^t	k^*	k^a	k^e	k^t
273	0.62575	0.61705	1.10980	1.57145	0.65601	0.63005	1.01404	1.57486
274	0.51998	0.50973	0.83082	0.96010	0.84353	0.77026	1.32432	2.36821
275	1.15149	0.78248	4.19386	31.59880	1.06348	0.77075	3.56038	26.61840
276	0.38240	0.36765	1.05096	0.92073	0.44809	0.40555	1.03201	0.95283
278	0.14027	0.14092	0.24321	0.21039	0.16958	0.17422	0.27708	0.25213
279	0.34207	0.33059	0.44813	0.48907	0.56059	0.46954	0.94596	1.31526
281	0.57348	0.61211	0.98454	1.21189	0.54453	0.58061	0.90382	1.05624
282	1.17850	0.77763	7.32040	5.49383	0.68741	0.53065	1.50553	1.17415
283	0.51080	0.49371	0.92261	1.09990	0.53561	0.57931	0.96319	1.21986
284	0.47354	0.42524	1.08764	1.06168	0.56776	0.50256	2.96973	3.09128
285	0.47540	0.42909	1.599515	1.32821	0.57377	0.55552	530	4.40515
286	0.66519	0.64897	1.05534	1.03483	0.54467	0.50464	0.85138	0.86704
287	0.65601	0.59042	1.22196	1.36177	0.75289	0.81110	1.69581	2.21217
289	0.63455	0.65778	1.07941	1.62355	0.88764	0.91460	2.15313	3.75439
291	0.26356	0.37943	0.29467	0.38340	0.21604	0.38470	0.24541	0.27128
295	0.57613	0.51024	1.44728	1.62686	0.44899	0.39590	1.00290	1.08713
299	N/A	N/A	N/A	N/A	0.38716	0.41171	0.45017	0.49823
305	N/A	N/A	N/A	N/A	0.45869	0.47606	1.16140	1.46894
306	0.35563	0.77206	0.35952	0.59252	0.47370	0.39340	1.36671	0.90986
308	0.63476	2.49590	0.68209	2.20934	0.72429	0.52269	3.41742	2.58931
311	N/A	N/A	N/A	N/A	0.18321	0.19033	0.22071	0.21688
314	0.18409	0.17805	0.29526	0.26280	0.19595	0.18936	0.31306	0.27717
315	0.11060	0.10952	0.12523	0.12311	N/A	N/A	N/A	N/A
317	0.42264	0.29480	0.45008	0.42166	0.42264	0.49650	0.65896	0.77203
319	0.24365	0.28206	0.29316	0.30897	0.27905	0.33418	0.32286	0.33181
322	0.18090	0.16391	0.22916	0.23402	0.36144	0.31597	0.51917	0.56251
323	0.56607	0.49907	1.32462	1.20097	0.50136	0.45094	1.33645	1.25338
324	0.33910	0.38270	0.48402	0.56158	0.69095	0.98120	1.41891	2.61390
325	0.29931	0.28750	0.48276	0.46299	0.31068	0.29699	0.55414	0.50632
326	0.41549	0.38420	0.69370	0.73308	0.56956	0.56044.	0.80577	1.04216
327	1.28484	0.94719	2.74108	10.84285	1.26620	0.96503	3.51455	16.79739
329	0.89105	0.77958	2.19653	3.67217	0.89975	0.84.422	11.07520	19.01590
331	0.45713	0.39781	0.87976	0.91935	0.51199	0.40312	1.17191	1.01872
332	0.41450	0.34261	0.79249	0.71252	0.46829	0.39512	1.00731	0.86122
333	0.15393	0.18133	0.17771	0.18652	N/A	N/A	N/A	N/A
335	0.45480	0.37229	1.35660	0.93553	0.51165	0.40804	1.63769	1.19461
336	0.46330	0.43010	0.88810	0.91117	0.43964	0.41542	0.94059	0.91484
339	0.23760	0.22204	0.30643	0.30371	0.25029	0.22742	0.37332	0.33332
341	0.60843	0.56596	2.08061 -	1.71549	0.9-1868	0.76858	1721	45.22700
342	0.53839	0.45187	1.24430	1.20530	0.77816	0.61087	2.61344	2.36327

Appendix Table 1. Estimated Dispersion Parameters (k), Weighted and Unweighted, 1981 and 1992

SIC	1981				1992			
	k*	k^{a}	k^{e}	k^{t}	k*	k^{a}	k^{e}	k^{t}
343	0.68967	0.74815	1.38003	1.89122	0.65126	0.60478	1.23496	1.39609
344	0.89636	0.67609	4.25657	7.45890	1.07761	0.72322	4.52373	7.34876
345	0.32563	0.28471	0.49143	0.46116	0.35792	0.32077	0.63137	0.57648
346	0.36585	0.28748	0.61265	0.53842	0.44728	0.36970	0.95899	0.82789
347	0.48356	0.39191	0.94463	0.82366	0.49831	0.42156	1.39916	1.18782
348	N/A	N/A	N/A	N/A	0.35545	0.46599	0.45706	0.56129
349	0.68577	0.51607	1.80637	1.72175	0.91091	0.63728	2.99426	2.86302
351	N/A	N/A	N/A	N/A	0.63281	0.51437	1.64647	1.18398
352	0.43568	0.48775	0.63287	0.75253	0.49900	0.54566	0.71605	0.84989
353	0.58324	0.57599	0.90563	1.38200	0.69487	0.64780	1.25064	1.77243
354	0.37955	0.30899	0.76211	0.67034	0.43163	0.32876	0.95904	0.84471
355	0.53164	0.46268.	2.10648	1.52461	0.61841	0.52815	3.08733	2.28856
356	0.58467	0.47718	1.58940	1.64394	0.76500	0.57248	2.55394	2.46093
357	0.27929	0.28031	0.46542	0.46988	0.37392	0.44048	0.60719	0.70371
358	0.53746	0.45573	1.47672	1.29391	0.61478	0.58108	2.73654	2.32162
359	1.12080	0.74590	3.19313	6.86191	1.00826	0.70995	3.80575	8.39189
361	0.44878	0.37009	0.86949	0.88458	0.75757	0.58142	1.88122	2.25424
362	0.60273	0.49157	2.07868	2.04435	0.55176	0.47215	1.33351	1.27943
363	0.31728	0.27865	0.63256	0.54072	0.40990	0.37979	1.35077	1.04235
364	0.53697	0.44806	1.48715	1.21448	0.75683	0.58135	1.81489	1.70291
365	0.47696	0.36096	0.81209	0.68984	0.54457	0.41033	0.83611	0.84309
366	0.48535	0.52235	0.82679	1.10365	0.44368	0.44468	0.61860	0.67669
367	0.53536	0.46629	0.96245	1.05024	0.56259	0.52426	0.95627	1.22405
369	0.44682	0.39726	1.06652	0.92633	0.50146	0.47698	1.14303	1.04776
371	0.66494	0.51948	1.63507	1.61837	0.69218	0.54964	3.22671	2.35877
372	0.53289	0.63060	0.83140	1.15462	0.47111	0.59340	0.67094	0.85519
373	0.25246	0.24014	0.32261	0.32884	0.30734	0.31117	0.41232	0.44696
379	0.44338	0.46138	0.72908	0.72914	0.49830	0.55445	1.00692	1.02387
381	0.32246	0.32462	0.59363	0.57544	0.73161	0.66598	1.17038	1.67188
382	0.58218	1.06697	0.58472	1.51649	0.50040	0.53213	0.80526	1.04082
384	0.46199	0.47510	1.14702	1.22507	0.54991	0.55637	1.13671	1.45981
386	N/A	N/A	N/A	N/A	1.40377	0.88141	3.19710	4.35148
391	0.34491	0.38752	0.32551	0.37394	0.32461	0.44581	0.33499	0.40535
393	0.42080	0.42325	0.85536	0.94950	0.39024	0.42793	0.61672	0.72885
394	0.69762	0.74168	1.88825	2.29165	0.77770	0.83056	1.67784	2.55189
395	0.23109	0.23653	0.41705	0.35610	0.54821	0.52572	2.33996	1.44526
396	0.32543	0.31628	0.47606	0.49432	0.38015	0.34897	0.44268	0.48583
399	0.94409	0.80891	3.44683	5.20185	0.95824	0.83590	3.50082	10.18744

k' Unweighted

k^{a} Weighted by CEA Geographic Area

k^{e} Weighted by CEA Manufacturing Employment

k^{t} Weighted by CEA Total Employment

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