Antitrust Issues in International Comparisons of Market Structure[1]

Joseph G. Hirschberg

Department of Economics
University of Melbourne

Esfandiar Maasoumi and Daniel Slottje
Department of Economics
Southern Methodist University,

And

Augustine C. Arize
Texas A&M University
Commerce, Texas

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Abstract

The analysis and definition of markets, their structure, and concentration, especially for international comparisons, are complicated by a lack of adequate and comparable data. This is particularly so for multi-product and multinational firms. For instance, the U.S. Department of Commerce reports measures of industry concentration which do not embody either the control of subsidiary firms or the possible multinational nature of their ownership. Nor are these reported measures consistently based on sales data. Other countries produce similar reports, but these studies are generally not comparable to U.S. due, in part, to incompatible sector definitions. Few government- sponsored studies provide firm-level detail or timely information. Also, given the widespread multinational nature of many larger firms, an international analysis of ownership and operations is necessary. This paper addresses the issues encountered in the construction of international market data from the existing financial reports, and provides methods for the comparison of measures of market concentration and industry diversity across countries.

Using 1991 financial data, a firm level data set is constructed and used to compute comparable measures of market concentration and industry diversity in the food industries for the U.S. and European Community (EC). One innovation is to impute the distribution of sales of sub-code products by a firm based on simulations as well as nonparametric estimates of an existing data set.

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Introduction

With the increasing globalization of the world's economies, antitrust concerns for industries within a given country become increasingly complex. Traditional analysis of antitrust, market definition, and market power is focused on the "structure" of industries under scrutiny. One important component of the market power puzzle is the degree of concentration within an industry.

Applied economists have understood for some time that measuring market power is not a one dimensional issue. Even before the advent of the so-called "New Empirical Industrial Organization" (henceforth NEIO) in the early 1980s, economists working on these matters understood well that one could not simply look at any one aspect of industrial behavior in a given industry, and draw meaningful conclusions about the level of competitiveness therein. Bresnahan (1989,1997) refers to the traditional empirical approach to analyzing competitiveness in a given market as the Structure, Conduct and Performance Paradigm (or the SCPP). That is, the traditional approach has been to define the relevant product and geographic markets, and then to examine structure by looking at the degree of concentration in the market and to look at pricing behavior to see if the firm(s) is (are) indeed pricing their outputs close to marginal cost. The implicit assumption in this body of work is that marginal cost is observable and measurable and that a reduced form analysis of structure and performance on cross-section data is sufficient, cf. Church and Ware (1997) for an initial critique of this approach. Church and Ware (1999, p. 239) note that under the SCP strategy, knowledge of market share is an important element in ascertaining the degree of market power within a given market.

The NEIO approach emphasizes the fact that in general, economic marginal cost is not observable. In addition, each industry has its own nuances which distinguish it from others and a "conduct parameter" is an unknown to be estimated, not assumed in a cross-section model, cf. Bresnahan (1989, pp. 952-953). Bresnahan further notes that the NEIO approach focuses on the use of an econometric model for an individual industry, NOT on its reduced form and using data over time.

The NEIO approach has been applied in practice in several applications. Ellison (1994) builds on work by Porter (1983) to show that demand for a given product (they focus on railroads) can be assumed to be log-linear in price and takes the form,

$$\log(Q) = \alpha_0 + \alpha_1 \log(P) + \alpha_2 \log(L)$$

in this model α_1 is the elasticity of own price demand. The supply relationship can take the form,

$$P\left(1 + S_i\ w_i / \alpha_1\right) = MC$$

Where S_i is the market share of the ith firm and w_i is a "conduct" parameter. As in Church and Ware (2000, p. 441), let $\theta = S_i w_i$ in the expression above. Then,

$$P\left(1 + \theta / \alpha_1\right) = MC$$

Thus, within the NEIO framework, the elasticity of demand for the product and a firm's market share are important determinants of conduct and, ultimately, of a given firm's market power within that industry. It should be clear that regardless of one's beliefs about how to econometrically ascertain market power, a firm's market share, and ultimately the degree of concentration in an industry, are important considerations in the determination of market power in that industry.

Unfortunately, the paradigm of a firm controlled locally producing one product in a single market is rarely found and would most likely never be the case for all the firms in a market in a country that is integrated into the World Economy. In addition, even if the level of concentration is determined for the market of a particular product within a country, this would only result in a particular value for the concentration statistic. The important question for that market is: How does this compare to equivalent markets in other countries where the same technology and multinational firms compete? Thus, an important aspect of any analysis of the concentration of a particular market is the ability to make international comparisons so that the local conditions for competition can be put in a relative position.

The purpose of this paper is to make international comparisons of market concentration and diversity from multi-product firm data. Thus we examine the measurement of concentration and diversity in a set of multinational multiproduct firms and demonstrate the comparisons that can be made between markets in different countries. In particular, we study firms in the food processing industry in the U.S. and the EC. Due to problems of data compatibility, cross-country comparisons of industrial structure are far less common (Yamawaki, Sleuwaegen and Weiss 1989). Furthermore, the majority of market structure studies used in antitrust analysis and elsewhere, employ "establishment-level" data that do not reveal the possibility of interrelated and multinational ownership that characterizes many of the larger firms. This paper presents a strategy for using firm-level data to estimate market structure variables that can be compared across countries. Our method provides not only point estimate comparisons of various market structure measures, but also probability statements on the computed differences.

One method for avoiding potential data incompatibilities is to use firm-level data, such as that collected by private investment information services, or from direct contact with the firms. This is the approach taken in Sutton (1991) for the *four* largest food-producing firms in France, West Germany, Italy, Japan, the United Kingdom and the U.S. In contrast, the present work examines many of the larger firms, in all countries, and attempts to trace the impact of multinational ownership. Furthermore, because this is a larger group of firms, it relies exclusively on the information available from private investor data.

An innovation of the present study is to employ a Monte Carlo method to simulate a firm's distribution of sales and employment over sub-product categories (SIC codes). Several statistical distributions were studied for the generation of "imputed sales/employment distributions". These were chosen either on the basis of stylized empirical facts (e.g., log normal and Pareto), or to examine bounds and sensitivities (various normal distributions). A particularly more detailed data set (Trinet) was also employed to verify and calibrate. Log Normal and Pareto receive further support from this latter exercise. The imputed shares and characteristics are then used to compute measures of industrial concentration and diversity that are subsequently compared across industry and country.

Given the global nature of the data it is also possible to define markets among groups of countries, allowing comparisons between trade groups and specific nations. Due to data limitations, we examine only major firms (with total sales in all lines of production over $150 million), with at least one product in the food processing industry (SIC 20) as reported in the Dunn & Bradstreet computer data base. These data limitations also restrict the concentration indices reported here to a class of Herfindahl-Hirschman measures as opposed to measures based on shares of the total market.

It should be noted that the definition of the market (i.e. the assumption of a 4 digit SIC and the entire EC as a single market) may be flawed for the direct application of the conclusions from this work into a particular legal proceeding. However, we present this method of analysis for consideration as a tool for acquiring sufficient information for the allocation of resources for a more complete investigation by authorities in a particular jurisdiction.

The paper is outlined as follows. In Section 1, the steps in constructing the data set are outlined. A description of the simulation analysis is given in Section 2, along with a comparison to results obtained from a similar source of these data for the U.S. alone. Then sample-size independent (weighted) measures of industrial concentration and diversity are developed and computed using the imputed shares. The concluding sections discuss the results of the comparisons of these measures both across sectors and across countries or country groups.

1. Firm Data

A firm's sales and employment data by SIC are often difficult to obtain. The most readily available source for this information is a firm's annual report. However, there are at least three reasons why annual reports are frequently inadequate for this purpose:

> 1. Private firms and producer cooperatives often issue no report and a significant segment of many industries may be composed of these types of organizations.
>
> 2. Very rarely do annual reports provide a decomposition of sales or employment by product or country.
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> 3. Annual reports often fail to identify the full set of subsidiary firms they hold, or if they are subsidiaries they may not identify any other similar subsidiaries or the parent firm.

Commercial investment data base vendors such as Dunn & Bradstreet, Ward's Business Directory (Gale Research), and Trinet are examples of readily accessible sources that include information for both *public and private* firms; see Hirschberg, Dayton and Voros, (1992) for more details concerning these and other data sources. Some of the data series also identify firms that are subsidiaries to other firms and the level of investment involved. Furthermore, these data sets list a standardized set of *product line classifications* as well as sales and employment information.

The information from the Dunn & Bradstreet's interactive computer data base service provides the most complete source for the U.S. and foreign firms. However, these data do not indicate the *intensity or level of production in any particular product line*. The Trinet and Ward's data do, however, for the U.S. firms. In the *Who Owns Whom* published data source, Dunn & Bradstreet provide a means for identifying both the U.S. and foreign parent firms for each data entry. Unfortunately the only market-specific information available is a ranking of up to six 4-digit SIC product codes. An example of the entries for the Dunn & Bradstreet data is given in the Appendix. The information extracted from these data is:

> Name of the firm, address of the firm, country where the firm is located, up to 6 4-digit SICs in order of importance, total annual sales (as of 9/91), the total number of employees (as of 9/91), whether the firm imports and/or exports, the name of the parent firm if the firm is a subsidiary.

An important element in the construction of our data set is the identification of the subsidiaries. Because of the incomplete nature of ownership correspondences in the electronic data sets, it was necessary to verify this information with two other sources: *Who Owns Whom* that contains the parent firm for subsidiaries located in North America, the United Kingdom, Ireland, and continental Europe, and the available annual reports that contain information on subsidiary. The data set contains information for 1,695 firms and subsidiaries which have total sales of over $150 million or more, and that sell at least one product in a SIC 20 market. In addition, because the entry for a parent firm may include the sales and employment from its subsidiaries (which also appear in the data set) it was necessary to subtract the sales of these subsidiaries from the parent firm to avoid possible double counting.

Table 1 shows the number of firms that are included from each country with combined sales of $150 million that do business in at least one industry in the SIC=20 (food) group. Thus, a firm may only do some business in a food category and have the majority of its sales in a sector other than food processing. **Table 2** provides an alternate view of the same data where the sales and employment are allocated by the country of the parent firms. Note that the ranking of the countries changes when "total sales by ultimate ownership" is used. In **Table 2** Switzerland moves to the 5^{th} position (from 9^{th} in **Table 1)**. This shift is due mainly to the influence of the Nestle Company. The net differences in the sales totals reflect the net balance of foreign ownership in each country for firms in this size group. In the U.S. American-held firms account for 89 percent of domestic sales. For Switzerland, almost 2.5 times the domestic market sales are sold by Swiss held firms world-wide. The Netherlands is another net owner nation with a relative world market of almost 1.7 times domestic sales. Note that these are sales by firms owned in the parent country and do not reflect the export sales. The sales are allocated to the country in which the firm is headquartered, not by country in which the goods are sold. Thus, some small countries may have totals that are larger than their domestic markets. Also, these sales are for the firms in the data set, thus they include sales in industries other than SIC=20. In the next section, the method for imputing an allocation of these sales by SIC will be described.

2. Simulated Diversity of Sales and Employment.

A model of firm diversity may rely on the ordering of the SICs given for each firm or subsidiary, along with a distribution for the shares of the sales and/or employment over these SICs.[2] Lacking detailed technological data, it is assumed that the types of distributions for firms' sales over SICs is the same as those for employment. Although technical factors may differ by industry, scale and country, this procedure assumes that firms that produce similar products employ roughly similar technologies. Let the number of SICs be denoted by *k*. In order to generate a distribution of the sales or employment, *k* random draws are made from a particular statistical distribution (the choice of distribution is discussed below) so that they form non-negative ordered weights that sum to one. The total sales and employment of the firm is then distributed over its SICs using these weights.

The statistical distribution chosen to generate the random values will determine the form of the weights chosen. Five distributions were employed. Three widely employed

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[2] Here we will use the definition of 4 digit SIC for the market although we recognize that in some cases this is

statistical distributions were used for sales by SIC; the uniform, the lognormal, and the Pareto. For verification and calibration purposes, two additional distributions were derived from a particular data set (Trinet) describing the distribution of sales by SIC for particular US firms. One of these two is a nonparametric multivariate kernel density function. The other is based on a shuffling technique based on the empirical distribution of the Trinet data.

2.1 Distributions of Firms Sales.

If it is assumed that each firm's product is produced by an independent subsidiary then the size distribution of subsidiaries within firms may be regarded as similar to distribution of firms without regard to ownership. While the reality may differ within a given firm, it is virtually impossible to test or analyze this assumption due to insufficient data. The assumption is quite innocuous, however, since relative ordering is the crucial factor, not the absolute size distribution. Our paper does, in fact, discuss firm specific diversity when ownership is explicitly accounted for. For example, a number of firms have purchased existing companies that produce a product that they had not previously sold in any corresponding market. Thus the size distribution of the firms that are owned by other firms is considered to be the same as the distribution of the firms without regard to ownership.

Drawing from a uniform or rectangular distribution is here similar to a non-informative prior. It results in the least difference between the weights as it represents the situation where a firm in an industry has an equal probability of having any size between the limits of the distribution (a = lower bound and b = upper bound). The weights from this distribution are generated by

$$r_{ik} = u_i \Big/ \sum_{i=1}^{k} u_i \quad \text{, where } u_i \sim \mathrm{U}(a,b) \text{ for all } i \leq k \text{ .}$$

The limits of the distribution (a,b) do not affect the weights computed so they where set to 0 and 1 respectively. These values are then sorted in descending order. The number of sectors

not completely accurate in every case. Unfortunately, this the only level of detail that may be available.

in which the firms sell is given as k. Thus if 4 SICs are given in the data entry, four values are drawn from the random number generator[3]. They are then sorted by size and divided by their total. The average value taken over the simulated runs from the uniform distribution are given in **Table 3**. From this table it can be seen that the average weights decline according to a linear relationship.

Weights were also drawn from the lognormal distribution. This choice reflects a long standing stylized empirical fact that the lognormal often well represents the size distribution of firms (e.g., Quandt, 1966, and Silberman, 1967). The values are drawn in the same manner as for the uniform, then sorted and weighted to form the sample weights by using $u_i \sim \mathrm{e}^{\mathrm{N}(0,1)}$.[4] The average weights from the lognormal distribution are listed in **Table 4.**

Another distribution that is suggested by stylized empirical evidence is the Pareto of the first kind (see Quandt, 1966). The cumulative distribution function of the Pareto is given by

$$\mathrm{F}(x) = 1 - x^{-c}, \text{where } 1 \le x \le \infty \text{ and } c > 0.$$

The weights generated by this distribution will depend on the shape parameter *c*. To calibrate to available data, this parameter was estimated as .9124 using the data described below. A Pareto distributed pseudo-random value is then generated by the following well known inversion process:

$$x_{ik} = (1/u_i)^{1/c}, \text{ where } u_i \sim \mathrm{U}(0,1).$$

The resulting average values of the weights are given in **Table 5**.

An alternative to the previous parametric, simulated weight distributions, is to use a nonparametric density estimation. In order to use a nonparametric method, it is necessary to

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3 All the uniform random numbers were generated by the SAS routine RANUNI.

4 The lognormal was generated by using the SAS RANNOR routine by raising e to the power of the pseudo-random value generated.

have observations on the proportion of sales in various markets. The advantage of nonparametric method is that it is based on some observed data; the disadvantage is that these distributions will always reflect the data that were used to create them, thus anomalies in the data will be treated as information, and generalized to yet unobserved markets.

The data used in this estimation are from a market-oriented data base that lists the sales of the 50 largest firms by four digit SIC in the U.S. These data are for 1991 and are compiled by the Trinet Corporation (1991). To combine the sales of one firm across markets, a new dataset was created where all the listings for a particular firm are combined with sales in each four digit SIC (using only SIC=20). To compute the weights implied by these values for firms that sell in two markets, all those firms that sell in at least two markets are used to estimate the weights; the same for those that sell in at least three, on up to six markets. In this way, the largest sample of firms in each category is used.

The first nonparametric technique employed is a multivariate kernel density estimate. This technique uses a weighing scheme (the kernel) to compute a continuous function as an estimate of the density function. This type of estimate may be viewed as a smoothed histogram with the possibility of tails that extend beyond the range of the data. In particular a modified multivariate Epanechnikov kernel estimator (see Silverman 1986) was used to generate a set of r_{ik}s, for values of k between 2 and 6. The modification was based on the two properties of the proportions that helps to simplify estimation: $\sum_{i=1}^{k} r_{ik} = 1$,

and $r_{ik} < r_{jk}$, when $i < j$. Using these distributions a series of random numbers was generated using a look-up table of the cumulative density distribution and a uniform random number generator. The average weights are given in **Table 6**.

The second nonparametric method used for generating weights was an empirical random number generator based on the Trinet data. This is equivalent to randomly selecting the weights from the data. To construct this type of random number generator it was first necessary to replicate the weights from the data a number of times (the number depends on how many weights need to be generated). To assure that the weights are independent from each, a random shuffle is implemented. **Table 7** reports the average values obtained from the Trinet data generated by this procedure.

2.2 An Evaluation of the Statistical Distributions of Sales.

In order to evaluate these and other possible distributions from which the weights could be drawn, the average weights computed from various distributions were compared to weights computed from the Trinet data set that estimates the largest (in sales) fifty U.S. firms by four digit SIC[5]. A modified goodness-of-fit statistic or distance measure (*D*) for discrete multivariate distributions (see Read and Cressie 1988), based on Kullback's (1958) concept of directed diversity, was calculated as follows:

$$D = \sum_{k=2}^{6} w_k \left(\sum_{i=1}^{k} \hat{r}_{ik} \ln(\hat{r}_{ik} / r_{ik}) + r_{ik} \ln(r_{ik} / \hat{r}_{ik}) \right)$$

where w_k is the proportion of the firms in the Dunn & Bradstreet data that report selling in k markets (SICs) ($w_1 = .266$, $w_2 = .231$, $w_3 = .167$, $w_4 = .130$, $w_5 = .107$, $w_6 = .099$), $\hat{r}_{ik}$ is the average prediction of the proportion of sales in the ith largest market for a firm selling in k markets (as given in **Tables 3**, **4**, **5** and **6**), and r_{ik} is the average observed value from the Trinet data set (as given in **Table 7**). Note that where k=1, $r_{11} \equiv \hat{r}_{11} \equiv 1$, the predicted and actual values of proportions are equal to one by definition, thus they are excluded from the computation of *D*. The smaller the value of *D*, the smaller the distance, and the greater the similarity between the distributions that generated the weights. Comparing samples of size 1000, the following results were obtained from the mean and the median of the generated

[5] The Trinet data were created by a combination of market research and an economic model of firm diversity applied to aggregate firm data. Thus in using these distributions in this study it important to qualify the inferences drawn from these data. Note that because the Trinet data do not provide empolyment we use only the sales values.

weights[6].

Distribution	D (Median)	D (Mean)
Uniform	.07649	.07906
Lognormal	.00664	.00659
Pareto (c = .9124)	.00497	.00756
Half-Normal	.03340	.03372
Normal^2	.04637	.05702
Normal^4	.22945	.31512
Multivariate Kernel Estimate	.00669	.00727

These values show that the kernel estimate and the lognormal distributions are very close, while the uniform distribution produces values that are an order of magnitude further away. The furthest distribution investigated was a normal raised to the fourth power; this is a highly skewed distribution. Note that all the candidate distributions were chosen so that they generate positive sales values and thus the normal was not used because it would require the assumption of a mean and a standard deviation that affects the distribution of the resulting weights. The lognormal, half-normal, and the normal distributions raised to even powers were functions of standard normals. As mentioned above, the Pareto was located with a shape parameter that minimized the value of D by estimating D under a series of values for c, thus, this value depends on the sample and is dependent to a small degree on the quality of the data.

The comparisons with and the calibration to the Trinet data are not meant to be necessarily definitive, nor is the use of a distribution based on the Trinet data necessarily the best alternative. The uniform appears to make the least informative assumption about sales distributions and may be considered a benchmark. The lognormal and Pareto, besides appearing to fit the Trinet data the best, are generally regarded as suitable size distributions in a variety of contexts. The multivariate kernel estimate is intended to be more general than the

[6] The choice of seed for the random number generator and the size of the sample drawn for the simulation will result in slight variations in the orders listed here. Those values that are close to each other in magnitude may change order in a different experiment.

empirical distribution because it allows for values that never occurred in the Trinet data while retaining the shape of the empirical distribution. However, as noted above, the empirical distribution may be too closely based on the Trinet sample. Yet, unlike any of the other distributions, it only reflects observed distributions (see Dagpunar, 1988). All the analysis that follows was performed with each of these five distributions to offer a degree of robustness.

The coverage of the Dunn & Bradstreet International data allows the computation of comparable measures of firm concentration by SIC and by country or group of countries. In the remainder of this paper the combination of SIC and region will be used to define a market. Because the sample of firms chosen in this study is determined by a size factor and the allocation of sales is done via a random selection criteria, the analysis that follows concentrates on the differences between the parameters computed for various regions and SICs. First we define measures of concentration which are independent of sample size, then comparisons are made between international regions.

3. Sample Size Independent Measures of Concentration.

A widely used index of market concentration is the Herfindahl-Hirschman index (H_{ij}) (Hirschman, 1945 and Herfindahl, 1950) for SIC j and region i:

$$H_{ij} = \sum_{k=1}^{n_{ij}} P_{ijk}^2$$

Where P_{ijk} is the proportion of total sales (or employment) in SIC *i* and region *j* for firm *k*, and n_{ij} is the number of firms in the *i-th SIC* and region *j* (market *ij*). As the value of H_{ij} increases the level of concentration increases.

In order to make international comparisons of market concentration, it is necessary to construct H_{ij}s which are based on a comparable number of firms. Here n_{ij} varies by market, thus direct cross-market comparisons of H_{ij} will be contaminated by differences in sample size.

H_{ij} can be written as:

$$H_{ij} = \sum_{k=1}^{n_{ij}} X_{ijk}^2 \left(\sum_{k=1}^{n_{ij}} X_{ijk} \right)^{-2},$$

where X_{ijk} are the level of sales or employment and H_{ij} can be rewritten as

$$H_{ij} = \frac{A_{ij}}{A_{ij} + 2B_{ij}}, \text{ where } A_{ij} = \sum_{k=1}^{n_{ij}} X_{ijk}^2 \text{ and } B_{ij} = \sum_{k=1}^{n_{ij}} \sum_{q=k+1}^{n_{ij}} X_{ijk} X_{ijq}.$$

Thus if H_{ij} is computed from data with the same distribution but from a different size sample (n_{ij}), H_{ij} will fall with increasing values of n_{ij} because, all else being equal, B_{ij} will be larger for larger n_{ij}. In order to compute a comparable H_{ij} it is necessary to define a sample size independent H_{ij}. One way of doing this is by weighing the average of A_{ij} and B_{ij} by sample size. Thus, one can compute:

$$\overline{A}_{ij} = \frac{A_{ij}}{n_{ij}}, \text{ and } \overline{B}_{ij} = \frac{B_{ij}}{(n_{ij}^2 - n_{ij})/2}, \text{ where } (n_{ij}^2 - n_{ij})/2 \text{ is the number of terms in } B_{ij}.$$

These averages can then be weighted to compute an equivalent A_{ij} and B_{ij} for a hypothetical sample size using the formulae given below

$$A_{ij}^* = \left(\frac{n_{ij}^*}{n_{ij}} \right) A_{ij}, \text{ and } B_{ij}^* = \left(\frac{(n_{ij}^{*2} - n_{ij}^*)}{(n_{ij}^2 - n_{ij})} \right) B_{ij}.$$

From these values we can compute a new H_{ij} based on these modified values of A_{ij} and B_{ij}. This index will be referred to as the means equivalent (*me*) value of H_{ij}.

$$H_{ij}^{me} = \frac{(n_{ij} - 1) H_{ij}}{(n_{ij} - n_{ij}^*) H_{ij} + n_{ij}^* - 1}.$$

For example, if $n = 25$, $n^* = 50$, and $H = .2000$ then $H^{me} = .1091$, the sample-size-compensated H is almost half the computed value.

An alternative method for creating a sample size compensated value of H_{ij} is to use the numbers equivalent (ne_{ij}) interpretation of the Herfindahl-Hirschman Index. For any H_{ij} it is possible to determine the number of equal size firms (ne_{ij}) that would have resulted in the same H_{ij},

$$H_{ij} = \sum_{k=1}^{ne_{ij}} \left(\frac{1}{ne_{ij}} \right)^2, \text{ or } H_{ij} = \frac{1}{ne_{ij}}.$$

This number of firms can be compared to the sample size used to construct the H_{ij}. A relative equivalent number of firms can be defined as

$$\alpha_{ij} = \frac{ne_{ij}}{n_{ij}}, \text{ or } = \frac{1}{H_{ij}\, n_{ij}}, \text{ where } 0 < \alpha_{ij} < 1.$$

H_{ij} written as a function of α_{ij} is $H_{ij} = 1 / n_{ij}\, \alpha_{ij}$. Under the assumption that α_{ij} is constant across sample size, a sample-size-equivalent H_{ij} can be defined that will be referred to as the numbers equivalent (ne) H_{ij}

$$H_{ij}^{ne} = \frac{1}{n_{ij}^{*}\, \alpha_{ij}}, \text{ or } H_{ij}^{ne} = \left(\frac{n_{ij}}{n_{ij}^{*}} \right) H_{ij}.$$

Using the same example as above where $n = 25$, $n^* = 50$, and $H = .2000$ then $H^{ne} = .1000$.

Both transformations of H_{ij} result in smaller values for H_{ij} when the hypothetical sample is larger than the actual sample. Because the values of H_{ij} are often based on samples sizes of 50 (c.f. U. S. Census Bureau 1992) $n^* = 50$ was used in this paper to construct the sample-size-equivalent H_{ij}. In all but one SIC, the sample size observed was smaller than 50.

It must be cautioned that both of these methods attempt to capture the shape of a distribution based on either one parameter (α_{ij}), or two (A_{ij},B_{ij}). While the means equivalent transformation is based on more information, the numbers equivalent transformation has a more intuitive form. The numbers equivalent transformation will weight both H with the same values if both samples are of the equal size, while the means equivalent transformation for the same case would use weights that depend on the H as well. In most cases $H^{me} > H^{ne}$. This can be seen in **Figure 1** which is a contour plot of the percent difference (PDIFF, where

PDIFF = 100 (H^{me} - H^{ne}) / H^{ne}) between the two sample-size-equivalent methods when n^* = 50. The percent increase of H^{me} to H^{ne} is at most 30 percent for a case in the lower right-hand corner where n = 10 and H = .3, but the percentage difference diminishes as H falls and n approaches 50. In the results discussed below both the *me* and the *ne* measures are reported.

4. A Comparison of Market Concentration in the U.S. and the EC.

For each SIC a set of H_{ij} were computed and weighted using both the means and numbers equivalent methods. These values were then used to form the differences between the H_{ij} for the EC and the H_{ij} for the U.S. The differences are defined as

$$DH_i^{me} = H_{i\,\mathrm{EC}}^{me} - H_{i\,US}^{me} \text{ and } DH_i^{ne} = H_{i\,\mathrm{EC}}^{ne} - H_{i\,US}^{ne}.$$

These differences were computed using the five distributions of the weights (uniform, lognormal, Pareto, multivariate kernel, and empirical) in a series of five hundred experiments each[7]. Five hundred values of the *DH*s were computed by SIC, distribution and equivalence method (*ne* or *me*). Those SICs in which 90 percent or more of all the *DH*s are either greater than or less than zero were are reported below. This amounts to a test under the assumption that the total sales or employment is correctly given but uncertainty existed as to the distribution of the weights for each firm's sales by SIC.

Table 8 reports a number of cases where a smaller number of firms in a market sample result in a lower market concentration than the market in the other region which has a larger sample size. This can be seen in SICs 2015, 2037, 2038, 2051, 2052, 2085, 2087. Obviously these results would not have been obtained without the application of an equivalence method.

The SICs which consistently indicate a higher concentration in the U.S. are 2024 (ice cream and frozen deserts), 2038 (frozen specialties), 2042 (cereal breakfast foods), 2045 (prepared flour mixes and doughs), 2052 (cookies and crackers), 2086 (bottled and caned soft

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[7] In comparisons with experiments of differing size, little variation in the results were observed except for the experiments drawing from the empirical based distributions.

drinks), 2087 (flavoring extracts and syrups), and 2095 (roasted coffee). The industries with less uniform results which indicate higher U.S. concentration are 2011 (meat packing plants), 2015 (poultry slaughtering), 2046 (wet corn milling), 2051 (bread cake and related products), and 2075 (soybean oil mills).

The EC only showed consistency higher concentration in the industries 2026 (fluid milk), 2062 (cane sugar refining), and 2064 (candy and other confection products). Less conclusive indications of higher EC concentration were found for 2063 (beet sugar) 2077 (animal and marine fats and oils), and 2085 (distilled and blended liquors).

For a number of SICs, sales and employment data imply contrary results. The most dramatic of these cases is SIC 2013 (sausages and other prepared meats) where the sales data infer higher concentration in the U.S. and the employment data infers a higher concentration for the EC. In both 2079 (edible fats and oils) and 2084 (wines brandy and brandy spirits) these results are reversed. Although these differences may indicate a technological differences, it is more probable, given the inconsistency of the reporting for employment data, that these conflicts are data artifacts.

Of further interest are those markets where in both the EC and the U.S. the number of firms is about equal, and under no distribution or equivalence method are there significant differences between concentration measures. This observation appears to confirm the assumption of a common distribution for the same industry no matter where it is located. The industry with the greatest number of firms where this occurs is 2041 (flour and other grain mill products) followed by 2047 (dog and cat food), 2034 (dehydrated fruits, vegetables, soups), and 2098 (macaroni and spaghetti). In a number of markets only one analysis method led to significant differences, for example, 2024 (creamery butter), 2022 (cheese; natural and processed), 2023 (Dry, condensed evaporated products), 2032 (canned specialties), 2033 (canned fruits and specialties), 2035 (pickles, sauces, and salad dressing) and 2066 (chocolate and cocoa products).

The table listed below summarizes the number of cases in which 90 percent or more of the DH_i are the same sign. The counts are based on cases were both the differences in employee and sales based concentration measures indicate significantly higher concentration in the U.S. or the EC. The uniform distribution resulted in the largest number of significant differences and the empirical had the fewest. This dichotomy was especially pronounced for the DH^{ne} although overall the *ne* sample-size-equivalent methods appear to result in more SIC's with significant results than the *me* method.

Distribution	$H_{US} > H_{EC}$ (*me*)	$H_{EC} > H_{US}$ (*me*)	$H_{US} > H_{EC}$ (*ne*)	$H_{EC} > H_{US}$ (*ne*)
lognormal	13	5	14	9
Pareto	9	6	14	9
uniform	13	7	15	10
empirical	14	8	16	10
multi kernel	13	9	15	11
All	7	5	13	5

This table shows that the different distributions did not introduce any obvious pattern, except that the Pareto is a bit lower in the determination of higher U.S. concentration under the means equivalent method of comparison. However, the means equivalent method results in a lower proportion of SIC's in which the EC has a higher concentration than the U.S. than is revealed by the numbers equivalent method. The row labeled "All" indicates the number of industries where over 90 percent of the cases generated by all the distributions share the same sign. Thus for the "$H_{US} > H_{EC}$ (*me)*" column over 90 percent of the differences calculated with any of the distributions share the same sign for seven industries. These results indicate that U.S. markets are more concentrated than the EC market.

Table 8 provides a summary of these results by SIC, of the count of cases in which 90 percent or more of the differences have the same sign. If $DH_{ij} < 0$ then the U.S. market is more concentrated than the EC and conversely if $DH_{ij} > 0$ the EC market has the higher concentration. Of the forty-nine 4-digit SICs in SIC=20, six had data for either only the EC or the U.S. and another five had no case in which 90 percent of the concentration indices were different between the U.S. and the EC. For the remaining thirty-seven SICs in at least one case (combination of distribution and method for equivalence), over 90 percent of the EC/U.S. differences were of the same sign for either sales or employment. In a number of cases the signs were reversed for the differences computed from employment and those computed from sales. This table provides the count of cases in which there is a significant difference. Because there were no cases in which a significant result was observed for one sign of DH_{ij} under one measure of firm size and another measure of firm size resulted in an opposite sign, only the counts for one sign are reported.

In cases when the sample sizes are very disparate between the U.S. and the EC (especially when the number in one market is small, i.e., less than four) there is a marked difference between the results obtained from the two equivalency methods. This occurred for SIC 2076 (vegetable oil mills), 2083 (malt) and 2091 (canned and cured fish). For this reason these cases are not referred to in the discussion of the SIC specific results that follows.

Twenty tables of concentration measures were computed - five distributions times two methods of equivalence, times two indicators of firm size (employment and sales). **Table 9** is a representative sample from this set of tables using the lognormal distribution, the means equivalent method of comparison and sales as the indicator of firm size. The lognormal is chosen because it fits the Trinet data well, while not being a function of that data. The means equivalent method is used because it incorporates more information in its value. Sales are used as the firm-size indicator because, although a subset of firms has no employment data, they all have sales data.

Table 9 provides the mean transformed concentration indices (times 10,000) and a column that indicates a level of significance that is the percentage of the five hundred experiments in which the difference between the U.S. and the EC is the same sign. Also given are the equivalent numbers of firms as well as the total sales for each market. In particular, the total sales for the smaller sectors appear to be a bit high; and this is due to the model employed here which does not weight sales by SIC but by order in a firm's portfolio of SICs. Furthermore, the sales totals reflect the sample that is drawn. Thus, if an industry is made up of firms that will not be represented in this sample due to size, the total will grossly underestimate the total market sales. An interesting result from this table is the high proportion (thirty-nine of forty-two) of industries where over 90 percent of the differences between concentration indices are in the same direction. Also listed in this table is the equivalent number of firms computed as the average of the actual non-transformed reciprocal of H_{ij}. This means that they may not be made into an equivalent value and thus can not be compared between samples.

A correlation analysis was performed for the H_{ij} between the U.S. and the EC markets. A number of researchers (c.f. Bain 1966 and Sutton 1991) have noted the cross-economy relationship of industry concentration. The rationale for this phenomena is that the similarity of technology and tastes determines that a certain level of concentration will hold across countries. A test was performed to determine if this was true using the lognormal *me* transformed indices. The correlation between the concentration indices was computed for each experiment using both the Pearson correlation coefficient and the Spearman rank correlation coefficient. With both measures a positive correlation was found. For the Pearson correlation coefficient of the sales based concentration measure they ranged between .42 and .02 with a mean of .19 and a median of .18. The rank based Spearman coefficient ranged between .22 and -.06 (a lower 25 percent value at .0) with a mean of .05 and a median of .04. Both correlation analyses when applied to the employment based concentration measures did not result in statistically significant correlation coefficients. This was probably due to the poorer quality of the employment data. Thus, this statistical relationship between the concentration indices, at least in sales, is confirmed in these data.

5. Diversity Comparisons Between the U.S. and EC.

The level of diversity of the firms selling in each market (SIC-region combination) is determined by the measure proposed by Berry (1971) for the study of diversity of production by a conglomerate firm. This value is defined as B_{ij};

$$B_{ij} = 1 - \sum_{k=1}^{m_{ij}} Q_{ijk}^{2}$$

where Q_{ijk} is the proportion of total sales of all the firms in region j and SIC i that are in k industry SICs and m_{ij} is the number of these other markets where they operate; markets are defined both as different SICs and different regions of the world (U.S., EC, rest of Europe, Mexico and Canada, the Far East, and the rest of the world). If all the firms in this market sold only in this market, B_{ij} would be equal to zero. As the firm sells an equal amount in a large number of other markets, this value would approach one. Thus, the greater the value of B_{ij}, the greater the diversity of the average firm in market ij.

Not all the SICs for each firm are SIC=20; they are all the other product markets in which the parent firm has an interest. This implies that B_{ij} will measure both the degree of vertical and horizontal integration. No classification of the SIC's was performed to differentiate these forms of diversity.

B_{ij} can be interpreted as 1 minus an appropriately defined Herfindahl- Hirschman index, thus the definitions of the sample size compensated versions (*me* and *ne*) of B_{ij} are identical to those defined for H_{ij} given above. In the present case the ideal sample size of 250 other market/firm combinations is used to compare to m_{ij}. These measures are similar to the industry diversity measures proposed by Clarke and Davies (1983); however, in the present case, the individual diversity computations are not computed because in most cases they will be solely a function of the distribution assumed to compute them.

The statistical distributions described in **Section 4** are used to allocate each firm's sales and employment by SIC. Then the sales and employee values of firms that are subsidiaries to the same parent are aggregated into one large firm by SIC and country and/or region. Thus, via the activities of its subsidiary firms, an EC firm may sell in many different international regions and in more than 6 SICs. In this sample the largest number of SIC/region markets in which any firm sells is 46. However, more than 90 percent of the firms have 6 or fewer SIC/regions in which they sell; the average is 3.7 with a median of 3. Once this allocation has been made, sales and employment by SIC and region are summed to make an industry measure for comparison. As in the market concentration ratios compared above, the diversity indices are compared between the U.S. and the EC.

The table given below shows the count, by distribution and sample-size-equivalency,

Distribution	$B_{US} > B_{EC}$ (*me*)	$B_{EC} > B_{US}$ (*me*)	$B_{US} > B_{EC}$ (*ne*)	$B_{EC} > B_{US}$ (*ne*)
lognormal	8	2	10	8
Pareto	3	2	3	8
uniform	18	3	17	12
empirical	14	6	14	4
multi kernel	6	5	8	10
All	3	2	3	2

of the number of SICs for which over 90 percent of the 100 experiments[8] result in differences in market diversity of the same sign. This table shows that the number of SICs in which a significant number of differences in diversity are recorded is greater than those for which concentration was high. Again, as with the comparison of concentration, it is the uniform distribution that results in the highest level of significant results compared to the other distributions; the Pareto is the lowest. The EC markets appear to have firms that are less diverse than the comparable U.S. markets.

Table 10 gives the breakdown of the diversity results by SIC. This table corresponds

[8] Due to the larger scale of the diversity computations only 100 experiments could be performed without the need for a completely restructured method for their computation.

to **Table 8** for the concentration ratios in that it lists the counts of distributions in which 90 percent or more of the experiments lead to differences of the same sign. In this case a positive sign indicates that the EC market is more diverse than the U.S. market and a negative value indicates the opposite. Again, the first number is the comparison based on sales and the second is the number based on employment. The "number of firms" column lists the total number of other firms-markets that are sold to by the firms in the market over the number of firms in the market. Thus, for industry 2091 the 3 firms in this sample that sell in the EC have 45 other industries and regions in which they or their parent also sell.

From **Table 10** it can be seen that the U.S. markets are made up of more diverse firms than the corresponding EC markets, although there are only three industries in which the U.S. is more diverse under all comparisons; 2032 (canned specialties), 2038 (frozen specialties) and 2091 (canned and cured fish and seafoods). Definitive results were obtained for greater diversity in the EC in only 2037 (frozen fruits and vegetables) and 2046 (wet corn milling). A majority of the diversity differences are not significant and in general these results are not as strong as the concentration results; these results are based on only one hundred experiments versus the five hundred on concentration. Yet, the one hundred experiment results for the concentration values did not result in markedly fewer significant results.

Table 11 is the corresponding table to **Table 9**. These are the experimental results for the diversity computations using the lognormal firm diversity distribution, the mean equivalent comparison method and the sales as the indicator of size. The sales totals are for all the firms that sell in a particular market; this means that a firm's total sales may be included in both the EC and the U.S. total if it sells in both.

6. Conclusion

This research demonstrates the quality of the inferences available from a data set that is solely constructed from financial report data supplemented with a set of market participation ordered by importance. The concentration differences can be made a function of other variables that capture the taste and technological aspects of the SICs. The inclusion of all the countries in the EC in a single market may not be very reasonable for a number of industries - such as 2051 (bread, cakes and related products), 2082 (malt beverages) and 2084 (wines, brandy, and brandy spirits) - where individual EC countries have long histories of special tastes for these products. However, the EC is moving to develop true integration among these markets.

Furthermore, some of the EC/U.S. comparisons may not be very meaningful due to the limit of the size of the firm included in the sample. In a number of cases the $150 million limit mean that a large proportion of firms (especially for the EC) were excluded. This will result in an over-statement of the concentration. This may well be the reason for the high relative concentration of SIC=2082 (malt beverages) and SIC=2064 (candy and other confection products) of the EC over the equivalent U.S. data. The malt beverage concentration may reflect the presence of only the large UK brewers which dominate the market as constructed because the smaller firms in the German market are not included. Careful attention should be paid to many of the comparisons made here.

However, under the objective to study the potential for U.S. firms competing abroad and for EC firms competing in the U.S., the limitation to only large firms may prove to be very useful. If an argument can be made that scale economy is needed to consider competition in foreign markets, then limiting the analysis to large firms may be reasonable. However, the argument that concentration translates into potential ability to compete abroad may not be a viable argument, especially in light of the highly concentrated U.S. car market and the relatively low propensity for U.S. food producers to export (see Handy and Henderson(1992)).

Future directions for this research include the verification of these results using simulated data for smaller firms that would be sampled under the $150 million sales level.

Another future topic would be to differentiate the diversity measures to account for upward and downward vertical integration as well as other horizontal integration by region. Furthermore, the simulations used here could be extended to include simulations of data used in a second level econometric analysis. This could involve the use of the simulated data along with other information in regression analysis. A first step in this direction was the interregional correlation of the concentration measures.

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Appendix

The following are fabricated examples of the data Collected from the Dun & Bradstreet computer data base. A U.S. firm would appear as:

```
BIG FOOD COMPANY
ONE E DESOTO STREET
CHICAGO, UNITED STATES

TELEPHONE: 3125554000
STATE/PROVINCE: IL

BUSINESS:  CANNED FRTS,VGTBLS

PRIMARY SIC:   2033  CANNED FRUITS AND SPECIALTIES
SECONDARY SIC: 2079  EDIBLE FATS AND OILS
SECONDARY SIC: 2015  POULTRY SLAUGHTERING AND PROCESSING
SECONDARY SIC: 2013  SAUSAGES AND OTHER PREPARED MEATS
SECONDARY SIC: 2022  CHEESE; NATURAL AND PROCESSED
SECONDARY SIC: 2099  FOOD PREPARATIONS, NEC

YEAR STARTED:                1990

EMPLOYEES TOTAL:              16,900
SALES (LOCAL CURRENCY):       4,560,000,000
SALES (U.S. CURRENCY):        4,560,000,000
THIS IS:
    A SUBSIDIARY

DUNS NUMBER:           14-468-2555

PARENT NAME:           BIGGER INC
PARENT DUNS:           00-527-9000
PARENT CITY:           LOS ANGELES
PARENT STATE/PROVINCE: CA
PARENT COUNTRY:        UNITED STATES

        Copyright 1991 Dun & Bradstreet, Inc.
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A firm in the European Community might appear as:

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GROSSE-BRAUEREI
JOSEFSBERGSTR 25
XBURG, GERMANY FED REP OF

TELEPHONE: 5555 1111
TELEX: 4444444
STATE/PROVINCE: SAARLAND

BUSINESS:  MALT BEVERAGES

PRIMARY SIC:   2082  MALT BEVERAGES
SECONDARY SIC: 2086  BOTTLED AND CANNED SOFT DRINKS
SECONDARY SIC: 2024  ICE CREAM AND FROZEN DESERTS
SECONDARY SIC: 5181  BEER AND ALE

EMPLOYEES TOTAL:              1,855
SALES (LOCAL CURRENCY):       604,800,000
SALES (U.S. CURRENCY):        345,000,000

THIS IS:
    IN THE EUROPEAN ECONOMIC COMMUNITY (EEC)
DUNS NUMBER:           31-555-5555

CHIEF EXECUTIVE:       KARL SCMIDT,KOMPLEMENTAR

        Copyright 1991 Dun & Bradstreet, Inc.
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Table 1. Firms by country of sales.

Country	Number of firms	Sales in Millions of $ US	Number of Employees
UNITED STATES	600	617004	3323686
UK	136	173853	1424119
JAPAN	111	100645	203048
NETHERLANDS	76	76354	111972
AUSTRALIA	53	49243	107359
FRANCE	94	45020	218136
WEST GERMANY	104	43456	121434
NEW ZEALAND	17	26637	42984
SWITZERLAND	6	22376	87010
SWEDEN	7	19533	104486
ITALY	54	18378	42516
CANADA	11	11322	71333
SPAIN	37	11095	48677
DENMARK	17	7429	34283
IRELAND	15	6316	21352
HONG KONG	2	5870	27500
BELGIUM	18	5430	16011
FINLAND	11	5113	19590
AUSTRIA	4	5111	19492
KOREA, REP OF	13	4459	38325
ISRAEL	6	4384	4110
MEXICO	5	1052	13057
SINGAPORE	2	492	4270
PORTUGAL	2	357	4740
NORWAY	1	208	1890
GREECE	1	170	2250
TOTAL	1403	1261307	6113630

Table 2. Parent firms by country.

Parent Country	Number of Parent Firms	Sales in Millions of $ US	Number of Employees
UNITED STATES	357	549410	2977714
UK	78	178298	1249673
NETHERLANDS	42	129125	449981
JAPAN	100	97497	213698
SWITZERLAND	6	55779	252519
AUSTRALIA	29	54069	102803
FRANCE	58	42124	214208
WEST GERMANY	82	36308	113090
SWEDEN	6	19533	104486
ITALY	39	16165	30729
CANADA	13	15919	147517
NEW ZEALAND	13	15464	35644
DENMARK	14	7683	36239
SPAIN	25	7134	32110
IRELAND	9	6539	16392
HONG KONG	2	6070	28600
FINLAND	11	5379	22790
AUSTRIA	4	5111	19492
ISRAEL	6	4384	4110
KOREA, REP OF	11	3981	29705
BELGIUM	10	3293	9383
MEXICO	4	815	9597
SINGAPORE	2	492	4270
PORTUGAL	2	357	4740
NORWAY	1	208	1890
GREECE	1	170	2250
TOTAL	925	1261307	6113630

Table 3. The Average weights from a Uniform distribution.

Number of SICs (k)	r_1	r_2	r_3	r_4	r_5	r_6
2	.697	.303				
3	.522	.321	.157			
4	.418	.300	.190	.092		
5	.348	.270	.194	.126	.062	
6	.296	.239	.188	.139	.092	.045

Table 4. The Average weights from a Lognormal Distribution.

Number of SICs (k)	r_1	r_2	r_3	r_4	r_5	r_6
2	.719	.281				
3	.596	.273	.131			
4	.520	.256	.147	.078		
5	.461	.239	.150	.096	.053	
6	.424	.225	.145	.100	.067	.039

Table 5. The Average weights from a Pareto Distribution (c = .9124).

Number of SICs (k)	r_1	r_2	r_3	r_4	r_5	r_6
2	.704	.296				
3	.614	.237	.149			
4	.564	.213	.129	.094		
5	.506	.201	.127	.094	.072	
6	.509	.183	.113	.081	.063	.051

Table 6. The Average weights from a Multivariate Estimated Kernel Distribution.

Number of SICs (k)	r_1	r_2	r_3	r_4	r_5	r_6
2	.665	.335				
3	.571	.281	.148			
4	.549	.252	.131	.068		
5	.533	.235	.125	.070	.038	
6	.517	.235	.127	.067	.035	.018

Table 7. The Average weights as Estimated from the Trinet data for U.S. Food Processing Firms.

Number of SICs (k)	r_1	r_2	r_3	r_4	r_5	r_6
2	.706	.294				
3	.592	.267	.141			
4	.540	.245	.136	.079		
5	.510	.228	.130	.079	.053	
6	.478	.222	.127	.081	.055	.038

Table 8. The Counts of cases where 90 percent or more of the experiments result in interregional differences of market concentration (DH_i) of the same sign.

SIC	Description	me*	ne	# of US firms	# of EC firms
2011	Meat Packing Plants	-3, -3	-4, +1	42	47
2013	Sausages And Other Prepared Meats	-5, +5	-4, +3	30	40
2015	Poultry Slaughtering And Processing	-3, -3	-4, +1	37	14
2021	Creamery Butter	+1, -1	+2, -1	19	44
2022	Cheese; Natural And Processed	+1, +1	+1, +1	34	41
2023	Dry, Condensed, Evaporated Products	+1, +1	+1, +1	24	32
2024	Ice Cream And Frozen Deserts	-5, -5	-4, +1	38	10
2026	Fluid Milk	+5, +5	+5, +5	59	63
2032	Canned Specialties	+1, +1	+1, +1	15	12
2033	Canned Fruits And Specialties	----	+1, +1	42	19
2034	Dehydrated Fruits, Vegetables, Soup	----	----	15	9
2035	Pickles, Sauces, And Salad Dressing	+1, -1	----	20	11
2037	Frozen Fruits And Vegetables	-2, -2	-5, +1	35	6
2038	Frozen Specialties, Nec	-5, -5	-5, -5	25	16
2041	Flour And Other Grain Mill Products	----	----	22	22
2043	Cereal Breakfast Foods	-4, -4	-3, -3	10	7
2044	Rice Milling	-1, +1	-3, +3	6	2
2045	Prepared Flour Mixes And Doughs	-5, -5	-5, -5	9	8
2046	Wet Corn Milling	-3, -3	-4, -4	10	5
2047	Dog And Cat Food	----	----	15	15
2048	Prepared Feeds, Nec	+1, +1	+1, +1	40	50
2051	Bread, Cake, And Related Products	-4, -4	-5, +1	23	12
2052	Cookies And Crackers	-5, -5	-5, -5	19	13
2053	Frozen Bakery Products, Expt Bread	----	----	6	0
2061	Raw Cane Sugar	----	----	1	5
2062	Cane Sugar Refining	+5, +5	+5, +5	7	8
2063	Beet Sugar	+5, +5	+5, -1	7	18
2064	Candy And Other Confection Product	+5, +5	+5, +5	21	23
2066	Chocolate And Cocoa Products	----	+1, -1	8	15
2067	Chewing Gum	----	----	5	0
2068	Salted And Roasted Nuts And Seeds	----	----	2	0
2074	Cottonseed Oil Mills	----	----	2	0
2075	Soybean Oil Mills	-4, -4	-5, -5	13	7
2076	Vegetable Oil Mills, Nec	----	+5, -1	3	9
2077	Animal And Marine Fats And Oils	+5, +5	+4, +4	5	10
2079	Edible Fats And Oils	+5, -5	+3, -3	17	13
2082	Malt Beverages	+1, -1	+5, -1	6	33
2083	Malt	----	+4, -1	2	8
2084	Wines, Brandy, And Brandy Spirits	+4, -4	+4, -3	7	21
2085	Distilled And Blended Liquors	+3, +3	+2, +2	12	18
2086	Bottled And Canned Soft Drinks	-5, -5	-5, -5	31	27
2087	Flavoring Extracts And Syrups, Nec	-5, -5	-5, -5	22	14
2091	Canned And Cured Fish And Seafoods	-1, -1	-5, -4	10	3
2092	Fresh Or Frozen Packaged Fish	----	----	15	5
2095	Roasted Coffee	-5, -5	-5, -5	10	9
2096	Potato Chips And Similar Snacks	----	----	10	0
2097	Manufactured Ice	----	----	0	2
2098	Macaroni And Spaghetti	----	----	4	8
2099	Food Preparations, Nec	-3, +3	-1, +1	42	53

*The first number is the number of indices based on sales and the second number is the index based on employment. A plus sign indicates that the EC industry is more concentrated than the U.S. industry and a minus sign indicates that the U.S. industry is more concentrated than the EC industry.

Table 9. Concentration experiment results for the lognormal distribution using the means equivalence.

SIC	Description	HHI (sales) $(\times 10{,}000)$		Level of Signif	Est N of Firms		Num of Firms		Sales (Mill$)	
		US	EC		US	EC	US	EC	US	EC
2011	Meat Packing Plants	1186.42	390.44	0.99	7.2343	24.1289	42	47	41,693.60	12,926.61
2013	Sausages And Other Prepared Meats	791.98	2917.34	0.99	8.1662	2.9399	30	40	12,561.57	17,806.62
2015	Poultry Slaughtering And Processing	668.22	375.93	0.99	11.3023	7.8348	37	14	13,550.15	1,325.30
2021	Creamery Butter	743.30	643.14	.	5.9162	13.9374	19	44	2,576.94	10,734.47
2022	Cheese; Natural And Processed	647.07	588.04	.	11.0147	14.0830	34	41	10,849.12	6,320.68
2023	Dry, Condensed, Evaporated Products	1254.43	1455.70	.	4.4552	4.7981	24	32	9,607.94	8,420.56
2024	Ice Cream And Frozen Deserts	875.92	392.14	0.99	9.1891	5.5220	38	10	11,125.91	3,047.41
2026	Fluid Milk	441.08	625.37	0.99	26.8407	19.9964	59	63	18,263.70	22,372.91
2032	Canned Specialties	521.83	613.93	.	6.2749	4.5356	15	12	7,705.43	3,571.79
2033	Canned Fruits And Specialties	1081.28	1205.17	.	8.3159	3.7159	42	19	24,057.54	8,185.58
2034	Dehydrated Fruits, Vegetables, Soup	595.02	582.24	.	5.7837	3.6482	15	9	5,396.37	5,445.94
2035	Pickles, Sauces, And Salad Dressing	818.19	496.18	0.95	5.5681	5.1235	20	11	6,524.89	2,616.08
2037	Frozen Fruits And Vegetables	535.40	410.58	0.95	13.3282	3.4188	35	6	7,069.89	1,620.73
2038	Frozen Specialties, Nec	979.38	347.76	0.99	5.6226	9.5636	25	16	8,857.75	2,134.62
2041	Flour And Other Grain Mill Products	813.26	498.53	0.95	6.1657	9.1765	22	22	8,819.09	6,826.99
2043	Cereal Breakfast Foods	406.08	329.83	0.90	5.4109	4.6225	10	7	8,739.95	2,406.52
2044	Rice Milling	245.58	718.86	0.99	5.0512	1.3102	6	2	1,733.76	194.47
2045	Prepared Flour Mixes And Doughs	963.73	513.35	0.95	2.6064	3.8148	9	8	2,475.82	2,072.20
2046	Wet Corn Milling	756.82	334.12	0.99	3.3887	3.3877	10	5	8,675.49	1,091.39
2047	Dog And Cat Food	480.65	502.40	.	6.6977	6.4911	15	15	4,079.42	3,358.53
2048	Prepared Feeds, Nec	1187.94	1898.13	.	7.2563	6.6083	40	50	10,246.06	19,147.64
2051	Bread, Cake, And Related Products	697.29	497.71	0.95	7.0831	5.3732	23	12	11,092.42	5,220.11
2052	Cookies And Crackers	1075.70	335.90	0.99	4.1847	8.1429	19	13	8,896.47	3,773.94
2053	Frozen Bakery Products, Expt Bread	558.81	.	0.99	2.7901	.	6	.	2,292.32	.
2061	Raw Cane Sugar	.	631.95	0.99	.	2.2668	.	5	.	2,281.49
2062	Cane Sugar Refining	311.33	689.27	0.99	4.8480	2.9828	7	8	2,390.55	4,792.99
2063	Beet Sugar	229.28	363.65	0.99	6.2179	10.1968	7	18	3,121.63	6,921.76
2064	Candy And Other Confection Product	481.34	1078.66	0.99	9.2914	4.7389	21	23	3,845.64	9,330.75
2066	Chocolate And Cocoa Products	700.57	565.27	0.90	2.9322	5.8016	8	15	3,423.92	6,044.02
2067	Chewing Gum	246.89	.	0.99	4.2598	.	5	.	1,960.71	.
2068	Salted And Roasted Nuts And Seeds	1988.53	.	0.99	1.0986	.	2	.	1,494.87	.
2074	Cottonseed Oil Mills	10000.00	.	0.99	1.0000	.	2	.	1,718.13	.
2075	Soybean Oil Mills	1053.04	220.53	0.99	3.1818	6.4284	13	7	12,983.43	1,216.09
2076	Vegetable Oil Mills, Nec	381.38	425.66	.	2.1461	4.7018	3	9	785.39	2,991.78
2077	Animal And Marine Fats And Oils	302.62	507.22	0.99	3.6512	4.5838	5	10	358.96	2,023.55
2079	Edible Fats And Oils	840.39	630.02	0.95	4.6186	4.6640	17	13	9,026.01	3,914.05
2082	Malt Beverages	518.54	488.52	.	2.8669	13.7398	6	33	14,911.26	20,786.31
2083	Malt	499.95	502.35	.	1.4638	3.8909	2	8	948.75	1,586.93
2084	Wines, Brandy, And Brandy Spirits	592.16	372.59	0.98	3.0299	11.7079	7	21	1,181.02	5,933.45
2085	Distilled And Blended Liquors	451.65	572.43	.	5.9189	6.7713	12	18	4,681.99	9,809.87
2086	Bottled And Canned Soft Drinks	1014.35	370.58	0.99	6.4484	14.8173	31	27	16,030.70	6,275.97
2087	Flavoring Extracts And Syrups, Nec	1816.46	527.31	0.99	3.0032	5.8548	22	14	11,230.86	2,134.34
2091	Canned And Cured Fish And Seafoods	558.61	358.87	0.90	4.1843	2.2118	10	3	2,414.52	842.61
2092	Fresh Or Frozen Packaged Fish	411.36	430.47	.	7.8982	2.8792	15	5	2,004.35	585.40
2095	Roasted Coffee	1446.44	458.02	0.98	2.3106	4.4443	10	9	4,099.67	5,913.36
2096	Potato Chips And Similar Snacks	554.68	.	0.99	4.2229	.	10	.	5,654.24	.
2097	Manufactured Ice	.	362.52	0.99	.	1.7263	.	2	.	400.74
2098	Macaroni And Spaghetti	394.29	560.84	.	2.5880	3.4789	4	8	757.81	706.45
2099	Food Preparations, Nec	1204.60	1490.59	0.90	7.2935	7.0699	42	53	18,760.52	23,626.78

Table 10. The Counts of cases where 90 percent or more of the experiments result in interregional differences of market diversity (DB_i) of the same sign.

SIC	Description	me*	ne	# of US firms	# of EC firms
2011	Meat Packing Plants	-1, +1	-1, +1	208/42	198/47
2013	Sausages And Other Prepared Meats	-2, -2	-3, -3	224/30	285/40
2015	Poultry Slaughtering And Processing	-1, +1	-4, +1	228/37	134/14
2021	Creamery Butter	-2, -2	-4, -4	88/19	339/44
2022	Cheese; Natural And Processed	-1, -1	-1, -1	209/34	294/41
2023	Dry, Condensed, Evaporated Products	----	----	160/24	217/32
2024	Ice Cream And Frozen Deserts	-2, -2	-1, -1	294/38	100/10
2026	Fluid Milk	----	----	307/59	301/63
2032	Canned Specialties	-5, -5	-5, -5	173/15	116/12
2033	Canned Fruits And Specialties	-3, -3	-3, -3	355/42	131/19
2034	Dehydrated Fruits, Vegetables, Soup	+2, +2	+2, +2	105/15	103/9
2035	Pickles, Sauces, And Salad Dressing	-4, +4	-4, +4	200/20	135/11
2037	Frozen Fruits And Vegetables	+5, +5	+5, +5	256/35	35/6
2038	Frozen Specialties, Nec	-5, -5	-5, -5	257/25	104/16
2041	Flour And Other Grain Mill Products	----	----	213/22	228/22
2043	Cereal Breakfast Foods	+1, -1	+1, -1	145/10	114/7
2044	Rice Milling	+1, +1	+1, +1	39/6	27/2
2045	Prepared Flour Mixes And Doughs	----	----	80/9	58/8
2046	Wet Corn Milling	+5, +5	+5, +5	104/10	15/5
2047	Dog And Cat Food	-3, -3	-3, -3	120/15	76/15
2048	Prepared Feeds, Nec	-4, -4	-4, -4	238/40	240/50
2051	Bread, Cake, And Related Products	+2, +2	----	159/23	109/12
2052	Cookies And Crackers	+2, +2	+2, +2	125/19	112/13
2053	Frozen Bakery Products, Expt Bread	----	----	62/6	0
2061	Raw Cane Sugar	-2, -2	-3, -3	6/1	33/5
2062	Cane Sugar Refining	-2, +2	-2, +2	26/7	35/8
2063	Beet Sugar	-1, +1	-1, +1	38/7	66/18
2064	Candy And Other Confection Product	-1, -1	-2, -2	168/21	181/23
2066	Chocolate And Cocoa Products	-2, -2	-2, -2	91/8	139/15
2067	Chewing Gum	----	----	26/5	0
2068	Salted And Roasted Nuts And Seeds	----	----	15/2	0
2074	Cottonseed Oil Mills	----	----	11/2	0
2075	Soybean Oil Mills	-2, -2	-2, -2	113/13	48/7
2076	Vegetable Oil Mills, Nec	-2, -2	-3, -3	34/3	76/9
2077	Animal And Marine Fats And Oils	-1, +1	-1, +3	24/5	122/10
2079	Edible Fats And Oils	-2, -2	-1, -1	155/17	116/13
2082	Malt Beverages	----	-1, +1	63/6	164/33
2083	Malt	----	-3, +3	21/2	82/8
2084	Wines, Brandy, And Brandy Spirits	-2, -2	-2, -2	30/7	95/21
2085	Distilled And Blended Liquors	-1, +1	----	89/12	107/18
2086	Bottled And Canned Soft Drinks	+1, +1	+1, +1	150/31	184/27
2087	Flavoring Extracts And Syrups, Nec	----	----	212/22	151/14
2091	Canned And Cured Fish And Seafoods	-5, -5	-5, -5	45/10	45/3
2092	Fresh Or Frozen Packaged Fish	----	----	61/15	17/5
2095	Roasted Coffee	----	----	84/10	69/9
2096	Potato Chips And Similar Snacks	----	----	72/10	0
2097	Manufactured Ice	----	----	0	6/2
2098	Macaroni And Spaghetti	-1, -1	-1, -1	46/4	124/8
2099	Food Preparations, Nec	-2, -2	-2, -2	380/42	446/53

*The first number is the number of indices based on sales and the second number is the index based on employment. A plus sign indicates that the EC industry is has a higher degree of diversity than the U.S. industry and a minus sign that the U.S. industry is the more diverse than the EC industry.

Table 11. Diversity experiment results for the lognormal distribution using the means equivalence.

SIC	Description	B(sales) US	B(sales) EC	Level of Signif.	N of Inds US	N of Inds EC	Num of Firms US	Num of Firms EC	Sales (Mill $) US	Sales (Mill $) EC
2011	Meat Packing Plants	0.97433	0.97580	.	208	212	42	47	146,167.73	102,061.22
2013	Sausages And Other Prepared Meats	0.98162	0.97944	0.99	236	309	30	40	133,262.59	169,969.76
2015	Poultry Slaughtering And Processing	0.97821	0.97953	.	238	148	37	14	129,895.84	138,194.32
2021	Creamery Butter	0.98738	0.97936	0.99	88	363	19	44	18,304.63	191,194.86
2022	Cheese; Natural And Processed	0.97834	0.97761	.	219	318	34	41	110,265.13	164,137.75
2023	Dry, Condensed, Evaporated Products	0.98442	0.98528	.	170	227	24	32	73,962.19	89,108.43
2024	Ice Cream And Frozen Deserts	0.98106	0.97845	0.90	317	104	38	10	174,156.07	68,102.97
2026	Fluid Milk	0.98434	0.98440	.	320	311	59	63	114,280.33	105,292.19
2032	Canned Specialties	0.98586	0.98055	0.99	190	130	15	12	79,779.14	89,284.60
2033	Canned Fruits And Specialties	0.97873	0.97344	0.95	385	135	42	19	222,763.12	70,207.77
2034	Dehydrated Fruits, Vegetables, Soup	0.97753	0.97932	0.99	109	107	15	9	71,547.62	72,340.73
2035	Pickles, Sauces, And Salad Dressing	0.98015	0.98149	0.95	220	149	20	11	116,744.11	113,344.94
2037	Frozen Fruits And Vegetables	0.98023	0.99185	0.99	280	35	35	6	117,867.32	9,902.77
2038	Frozen Specialties, Nec	0.98311	0.96547	0.99	289	108	25	16	158,979.62	52,558.93
2041	Flour And Other Grain Mill Products	0.97590	0.97932	0.99	216	252	22	22	136,534.49	163,335.12
2043	Cereal Breakfast Foods	0.98614	0.98518	0.95	172	138	10	7	123,004.53	95,437.36
2044	Rice Milling	0.95728	0.98412	0.98	43	27	6	2	18,936.41	5,560.31
2045	Prepared Flour Mixes And Doughs	0.96740	0.97440	.	80	58	9	8	50,993.34	53,428.26
2046	Wet Corn Milling	0.97785	0.99344	0.99	108	15	10	5	101,729.96	3,085.00
2047	Dog And Cat Food	0.98813	0.98199	0.99	127	80	15	15	67,273.75	17,920.47
2048	Prepared Feeds, Nec	0.96600	0.93033	0.99	243	244	40	50	105,069.02	140,999.97
2051	Bread, Cake, And Related Products	0.98133	0.98248	.	184	119	23	12	105,644.51	66,613.60
2052	Cookies And Crackers	0.98471	0.98626	.	146	122	19	13	95,830.20	58,240.31
2053	Frozen Bakery Products, Expt Bread	0.98702	.	0.99	66	.	6	.	29,044.68	.
2061	Raw Cane Sugar	0.99208	0.98765	.	6	33	1	5	665.83	10,254.02
2062	Cane Sugar Refining	0.98677	0.98758	.	26	35	7	8	9,214.22	12,956.08
2063	Beet Sugar	0.98891	0.98935	.	38	66	7	18	13,527.87	19,499.83
2064	Candy And Other Confection Product	0.98396	0.98329	0.90	195	207	21	23	119,650.87	115,194.01
2066	Chocolate And Cocoa Products	0.98575	0.98373	0.90	105	165	8	15	55,823.01	102,113.75
2067	Chewing Gum	0.98912	.	0.99	29	.	5	.	22,027.04	.
2068	Salted And Roasted Nuts And Seeds	0.98834	.	0.99	18	.	2	.	16,012.81	.
2074	Cottonseed Oil Mills	0.98334	.	0.99	11	.	2	.	8,420.34	.
2075	Soybean Oil Mills	0.97883	0.97419	0.99	113	48	13	7	96,874.10	48,490.32
2076	Vegetable Oil Mills, Nec	0.97977	0.97790	.	34	80	3	9	28,045.22	85,936.34
2077	Animal And Marine Fats And Oils	0.97134	0.98005	0.98	24	136	5	10	4,838.48	133,838.13
2079	Edible Fats And Oils	0.98085	0.97920	.	168	130	17	13	130,876.79	96,956.69
2082	Malt Beverages	0.98283	0.98782	0.99	73	164	6	33	62,819.74	63,687.71
2083	Malt	0.97710	0.98793	0.99	21	82	2	8	19,116.42	33,096.47
2084	Wines, Brandy, And Brandy Spirits	0.98692	0.98551	.	39	107	7	21	11,669.66	29,205.85
2085	Distilled And Blended Liquors	0.98374	0.98472	.	94	112	12	18	46,167.18	52,359.48
2086	Bottled And Canned Soft Drinks	0.98237	0.98359	.	172	202	31	27	74,427.33	108,959.82
2087	Flavoring Extracts And Syrups, Nec	0.98349	0.98300	.	240	175	22	14	145,062.67	144,941.01
2091	Canned And Cured Fish And Seafoods	0.98931	0.97551	0.99	53	49	10	3	15,073.40	42,467.67
2092	Fresh Or Frozen Packaged Fish	0.98520	0.98745	.	75	17	15	5	20,125.72	1,880.79
2095	Roasted Coffee	0.98015	0.98679	0.98	94	79	10	9	77,390.68	68,326.71
2096	Potato Chips And Similar Snacks	0.98593	.	0.99	75	.	10	.	54,573.22	.
2097	Manufactured Ice	.	0.99271	0.99	.	6	.	2	.	2,900.00
2098	Macaroni And Spaghetti	0.98517	0.98407	.	46	144	4	8	11,759.47	94,539.56
2099	Food Preparations, Nec	0.98005	0.97780	.	407	479	42	53	263,343.59	266,320.52

Figure 1 The % difference between H^{me} and H^{ne} ($n^* = 50$).