FIRM DATA AND INDUSTRY AGGREGATES IN THE ANALYSIS OF DIVERSIFICATION AND INTEGRATION*

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Using the Dun and Bradstreet sample of diversified manufacturing firms, the authors explore whether valid conclusions can be drawn from industry aggregates about decisions of firms to diversify or to integrate their output. They conclude that even with highly conglomerate two-digit categories, average diversification for industries is a meaningful concept. Through another test, involving data on the input-output structure of the United States, they conclude that the principal secondary activities of the diversified firms do not appear to have been undertaken for the purpose of serving the input requirements or marketing needs of the primary activities.

The task of identifying aggregation errors is a common one in empirical research in economics, but the form that these errors take varies with the problem. In this paper, we are concerned mainly with the extent to which inferences can be drawn about certain aspects of market behavior from data for industry aggregates. More specifically, can valid conclusions be drawn from industry aggregates about decisions of firms to diversify or to integrate their output?

Let us measure firm diversification by the proportion of the firm's output that is outside the industry in which the firm is primarily based.[1] Let us, further, measure average industry diversification by the proportion of the aggregate output of all firms, classified in a given industry, that is outside that industry. Equation (1) below is a general form of a model designed to explain differences in diversification.

$$D_{ij} = f(x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in}) + D'_j + U_{ij} \tag{1}$$

where the x's refer to variables that measure the relevant firm characteristics and

D_{ij} = the measure of diversification for the ith firm in industry j.
D'_j = average diversification for industry j.
U_{ij} = random variance.

Equation (1) hinges on the assumption that there are industry peculiarities that explain differences in diversification among companies.[2] These peculiarities provide greater incentives for firms based in some industries to diversify. For example, firms based in declining industries may wish to escape from a declining market, or firms based in industries with technologies resembling those of newly developed products may have an absolute advantage over other firms in entering the markets for new products. Equation (1) envisages an additive relation with respect to industry influences and individual firm variables. That is, the individual

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[1] The firm will be deemed primarily based in that industry which accounts for more of the firm's output than any other.

[2] Empirical support for this assumption may be found in M. Gort, *Diversification and Integration in American Industry*, Princeton University Press, 1962.

firm's decisions to diversify are a function of a set of variables that relate to the characteristics of firms as distinct from their primary industries, and these variables explain the deviations in the measure of diversification for the firm from the industry average.

All the above assumes that there are relevant industry characteristics—in short, that differences among industry means are not simply chance variations. Empirically, one can examine the question in two ways. First, one can ask if industry means for the entire population of firms differ significantly. Second, one can ask the same question with the population of firms limited to those that are diversified. It appeared to us that the second was the more appropriate question since industry averages for the entire population of firms are heavily influenced by the number of small, single-establishment firms with homogeneous product structures. These small firms are often characterized by quite different technologies from the larger ones in their industries and, frequently, even the products they produce differ from those of the larger firms.

To test the hypothesis that differences in industry means were not chance variations, we resorted to a sample of 156 multi-industry firms in manufacturing.[3] The size of our sample restricted analysis to the two-digit industry level. This provides a severe test of the hypothesis that industry means vary significantly since two-digit categories are fairly conglomerate in terms of the products and technologies they encompass. The primary industry of each company, however, was defined at the four-digit level and, hence, non-primary activities were defined as all those outside the primary four-digit industry. The measure of diversification was based on the statistic, number of employees, since data on output were not available.

Table 1 shows that when a Chi-square test was applied to the above-mentioned measure of diversification, for only three out of eighteen[4] industries (industry codes 23, 27 and 32) was the value of Chi-square consistent (at the 0.05 level of significance) with the hypothesis that the deviations from industry means were attributable to chance. Turning now to analysis of variance to see if differences among industry means for the previously noted measure of diversification are significant, a test was carried out for twenty two-digit industries with the help of our sample of 156 firms. We derive a value of $F_{19,136} = 1.12$. Thus, at the 0.05 level of significance, we must accept the null hypothesis that variations among industry means are not statistically significant. If we change the measure of diversification to a simple count of the number of separate four-digit industries in which the companies had one or more plants,[5] we find that the variance within industry cells exceeds that between industry means ($F_{136,19} = 1.51$).

A closer examination, however, reveals that the conclusions are less drastic than they at first appear. For almost all industries, a very large proportion of the variance was attributable to one or two observations. We therefore proceeded to delete one extreme observation if there were at least five firms in the sample for a

[3] These 156 firms comprised all the diversified manufacturing firms for which we had adequate data from the Dun and Bradstreet establishment record.

[4] For two industries of the twenty two-digit categories there was only one observation and hence they are excluded from Table 1.

[5] Plants were classified by industry on the basis of which industry accounted for more of the plant's sales than any other.

TABLE 1

CHI-SQUARE VALUES FOR 18 INDUSTRIES FOR DEVIATION OF OBSERVED DIVERSIFICATION FROM AVERAGE DIVERSIFICATION FOR INDUSTRY

Industry SIC Code	χ^2	Number of Firms
20	70.03	11
21	21.42	2
22	41.36	8
23	6.43	4
24	26.26	4
26	46.01	7
27	2.77	3
28	66.72	10
29	35.15	2
30	33.56	7
32	10.17	6
33	81.78	18
34	84.06	13
35	66.05	18
36	89.26	15
37	92.01	11
38	62.06	11
39	21.04	4

Source: Based on individual company data compiled by Dun and Bradstreet.

given industry, and two observations if there were at least fifteen.[6] Once again using analysis of variance we derive $F_{19,121} = 1.82$ for the measure of diversification based on the relative magnitude of non-primary employment, and $F_{19,121} = 10.29$ for diversification measured by a count of industries. For both measures the differences between industry means become statistically significant, and the use of a model such as that in Equation (1) now seems appropriate.

From the foregoing, we draw two conclusions. First, even with the highly conglomerate two-digit categories, average diversification for industries is a meaningful concept. Homogeneity in diversification patterns for firms classified within three- and four-digit industry categories can, of course, be expected to be considerably greater. Second, a considerable proportion of the differences among industry averages for measures of diversification are attributable to a few extreme observations. This, in turn, suggests that there is an important random component in the differences among industry averages.

Thus far we have examined the possible use of diversification data for industries at a point in time. Still other problems arise when one attempts to draw inferences from measures of changes in diversification over time based on such data. Consider the problem raised by Equation (2).

$$\frac{E_j}{R_j} = f(I_{j1}, I_{j2}, I_{j3}, \ldots, I_{jn}) \tag{2}$$

[6] This procedure assured that the within sample variance was roughly equal among samples—a theoretically necessary condition for the test. All the deleted observations were at one (upper) end of the distribution of diversification measures.

where the I's refer to the variables that measure the relevant industry characteristics and E_j = the output of firms classified in industry j that is outside j. R_j = the output of industry j contributed by firms classified in other industries on the basis of their primary activity.

Equation (2) is derived from the assumption that there are distinctive industry characteristics that explain why some industries attract entry by firms based elsewhere in the industrial spectrum, while other industries tend to be a primary base for diversifying firms.[7] But suppose that at some point in time there were several large diversified firms based in j that had a substantial output also in industry k. If their output in k subsequently grew faster than their output in j, they may at some later time be reclassified in industry k on the basis of their primary activity. This would have the effect of reducing E_j/R_j while increasing E_k/R_k. The usual inference from such a change would, however, be misleading. For the reason for the change will have been that j was apparently a good base out of which to diversify in the relevant period, while k was attractive to entrants based elsewhere. In contrast, the movement of the above ratios suggests an opposite inference. Clearly what is needed for correct inference is a transition matrix.

Let us turn now to the problem of measuring vertical integration with the help of input–output data for industry aggregates. The direct measurement of vertical integration has in the past proved very difficult because of the large amount of information about the internal structure of firms that it requires. Attempts, therefore, have also been made to use indirect measures such as the ratios of value added to sales, or ratios of inventories to sales, as indexes of integration. These indirect measures lead to serious problems in interpreting results. Consequently, alternative approaches are most welcome.

Suppose that an input–output matrix shows that a large proportion of the output of industry k is sold to industry j or, alternatively, that k is a principal supplier of intermediate products to j. Can one infer that a company with plants in both k and j combines the two sets of activities for purposes of vertical integration? Perhaps, but not without significant risk of error. Consider, for example, petroleum refiners in the United States. Most of the larger ones have crude oil producing properties. But because of locational constraints and the consequent transportation costs for domestic crude oil within the United States, and import quotas for foreign crude oil, refiners sell to others most of the oil they extract themselves and purchase the supplies for their own refineries. Aggregative input–output data would suggest the industry is highly integrated but, in fact, so-called "integrated refiners" are really engaged in two independent classes of business activity. Notwithstanding such difficulties in interpreting data, it is worth seeing to what extent the principal non-primary activities of companies are related to the primary ones as judged by an input–output matrix.

Table II presents such an analysis. It is based on data for the non-primary activities of companies grouped into 138 industries as shown in the U.S. Bureau of the Census, *Enterprise Statistics: 1963* (1968). The 138 industries comprised all those for which the industrial classification system used could be reconciled with

[7] Empirical support for this assumption may be found in M. Gort, *op. cit.*

TABLE 2

IMPORTANCE OF DIVERSIFYING ACTIVITIES AS SOURCES OF SUPPLY AND DEMAND FOR PRIMARY ACTIVITIES OF COMPANIES, 1963

Diversifying Activities in Order of Importance	Percent of Diversifying Activities Larger than Average as Source of Supply[1]	Percent of Diversifying Activities Larger than Average as Source of Demand[2]
First	53.6	42.9
Second	18.2	36.4
Third	31.1	31.1
Fourth	21.4	25.0
Fifth	28.6	28.6

Source: Based on U.S. Bureau of the Census, *Enterprise Statistics: 1963*, 1968, and U.S. Office of Business Economics, *Input–Output Structure of the U.S. Economy: 1963*, 1969.

* There were 47 primary industry categories in the sample. The table concerns the 138 "diversifying" activities of the companies in these primary industries. An additional 75 diversifying activities could not, for classification reasons, be identified in the input–output tables.

[1] Larger than average for all industries that were suppliers to a given industry.

[2] Larger than average for all industries that were purchasers of the output of a given primary industry.

that in the input–output tables.[8] Table 2 shows that the five principal non-primary (diversifying) activities of the companies in these 138 industries were not, on the average, strongly associated with the phenomenon of either backward or forward integration. Most of the industries in which the principal five secondary activities were classified contributed less as inputs to primary industries than average for all of the primary industries' suppliers.[9] Similarly, the industries of the five principal secondary activities were less important than average as sources of demand for the products of the primary industries.

To be sure, some of the non-primary activities could be classified as integration with respect to other *non-primary* activities. This raises questions as to how activities should be grouped and how diversification is most effectively measured. But it leaves unchallenged the proposition that the principal secondary activities do not generally appear to have been undertaken for the purpose of serving the input requirements or marketing needs of the primary ones.

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[8] U.S. Office of Business Economics, *Input–Output Structure of the U.S. Economy: 1963*, 1969. The 138 non-primary activities were associated with 47 primary industries identified in both sources.

[9] An exception was the most important secondary activity. Roughly half of the industries in this class were above and half below average in importance as suppliers to the primary industries.