WORKING PAPERS

DOES THE CHOICE OF CONCENTRATION RATIO REALLY MATTER?

John E. Kwoka, Jr.

WORKING PAPER NO. 17

October 1979

BUREAU OF ECONOMICS
FEDERAL TRADE COMMISSION
WASHINGTON, DC 20580

I. Introduction

A common observation in industrial organization literature is that the measure of "concentration" used to describe an industry or to relate its structure to performance is an issue of at most secondary importance. Since concentration ratios and other statistics of firm size distribution are highly correlated, it is argued, empirical investigations will show similar results regardless of the choice of index. This paper will demonstrate both theoretically and empirically why that conclusion is unfounded in the case where it is most likely to be valid, namely, in a comparison of different concentration ratios. In addition, we shall suggest some economic implications of the statistical results produced by concentration ratios consisting of different numbers of firms.

The belief that the choice of structural measure is unimportant stemmed originally from experience with structure-performance studies. In his pathbreaking article, Bain (1951) employed an industry's eight-firm concentration ratio to explain its leading firms' profitability. The relationship he found--a significant break at eight-firm concentration of 70 percent--has stimulated a great deal of analogous research. Occasionally the eight-firm, but more often the four-firm, ratio (both available in the Census of Manufactures) was used, since the latter offered somewhat more highly significant results.[1]

But since the difference in explanatory power among these alternatives was never overwhelming, the question of the appropriate concentration ratio was generally not even mentioned, or at most, quickly dismissed. Only Kilpatrick (1967) raised the issue directly by studying correlations between the four, eight, and twenty firm concentration ratios (plus some variants) and industry profit rates. The similarity of correlation coefficients, he concluded, "provide[s] much evidence that the particular choice is not crucial" and "that an economist can use an ordinary concentration ratio in a cross-sectional study without concern that a different choice would have altered his conclusions appreciably" (p. 260). Although Miller's nearly simultaneous study of marginal concentration ratios can be interpreted to mean that different concentration ratios do contain different information, that implication has not prevailed.[2] Indeed, the conventional conclusion that alternative measures are indistinguishable has generally been extended to other structural indices.[3]

Direct comparisons of these measures of concentration seemed to provide corroboration. Rosenbluth (1955), Scherer (1970), and Bailey and Boyle (1971) all calculated correlation coefficients between a variety of alternative indices, using different data and time periods. Almost all correlations were in excess of .90, and Scherer's conclusion reflected the consensus: "[I]t is senseless to spend sleepless nights worrying about choosing the right concentration measure" (Scherer, 1970,

p. 52).[4] Two reservations were voiced concerning this conclusion. Stigler (1968) cautioned that some such correlations were spurious, since, for example, the common elements of the three- and four-firm concentration ratios (namely the top three shares) insure a high correlation. A "proper" formulation (e.g., between the three-firm ratio and the fourth share), he predicted, would reveal a "vastly lower" correlation. Schmalensee (1976) devised twelve "more or less plausible" concentration indices by manipulating Census data and tested their correspondence to the Herfindahl. His conclusion that important differences exist, however, is tempered by his assumption that the Herfindahl is the "ideal" measure of industrial concentration.

In any event, none of these studies have explored the fundamental properties of correlation coefficients which determine why and when alternative concentration measures may make a difference. The next section of this paper develops these properties, thereby clarifying, modifying, or refuting some of the claims in the literature. Then detailed data by four-digit SIC industry are used to construct alternative concentration ratios and provide a specific example of these properties in structure-performance tests. We conclude with some implications of these findings for economic research and public policy.

II. Properties of Correlation Coefficients

Let us suppose we wish to explain some measure of performance (Y) by either of two indices of market structure, X_1 and X_2. Assume we calculate the correlation coefficient between Y and X_1 (denoted r_{Y1}), and know from previous work that between X_1 and X_2 (denoted r_{12}). What can we infer about r_{Y2}, the correlation between Y and X_2? In particular, if r_{12} is very large and highly significant, and r_{Y1} is also significant (if not nearly so large), can we conclude that r_{Y2} must also be significant?

The answer is most definitely in the negative. The necessary conditions on r_{Y2} yield very low lower bounds for typical values on r_{Y1} and r_{12}. To see this, consider the following matrix of correlation coefficients:

$$R = \begin{bmatrix} r_{11} & r_{12} & r_{1Y} \\ r_{21} & r_{22} & r_{2Y} \\ r_{Y1} & r_{Y2} & r_{YY} \end{bmatrix} \qquad (1)$$

The diagonal elements r_{ii} are of course unity, and the matrix is symmetric (i.e., $r_{ij} = r_{ji}$). In addition, R shares with the covariance matrix from which it is derived the property of being positive definite, that is, the determinants of its principal minors are all positive.[5] Within that constraint, however, a wide variety of values of r_{12}, r_{1Y}, and r_{2Y} is possible.

In order to focus on the present question, let us explore what values of r_{12} and r_{1Y} are consistent with $r_{2Y} = 0$, that is, when Y is wholly unrelated to X_2. Then the matrix R can be rewritten

$$R = \begin{bmatrix} 1 & r_{12} & r_{1Y} \\ r_{12} & 1 & 0 \\ r_{1Y} & 0 & 1 \end{bmatrix} \qquad (2)$$

Positive definiteness (see footnote 5) now requires only that

$$1 - (r_{12})^2 - (r_{1Y})^2 > 0 \qquad (3)$$

Possible solutions include $r_{12} = .7$, $r_{1Y} = .7$; also, $r_{12} = .9$, $r_{1Y} = .4$; or even $r_{12} = .95$, $r_{1Y} = .3$. Such values of r_{12} are consistent with the evidence cited in the previous section, and these r_{1y}'s are very much on the order of those found in structure-performance studies (see Weiss, 1974, and references therein).

Thus, one conclusion of this exercise is that a high correlation between two measures of market structure (r_{12}) and substantial correlation between one measure and industry performance (r_{1Y}) need not imply any relationship whatsoever between the other measure and performance (r_{2Y}). Certainly they do not imply a relationship of similar size and/or significance. Alternatively, these correlations can be interpreted to mean that the weakness or absence of one relationship (r_{2Y}) and a high correlation between two structural measures (r_{12}) does not preclude a relationship between the second structural statistic and performance (r_{1Y}). Inferences that alternative concentration ratios and/or other indices are indistinguishable are simply not justified by such correlations.

III. Properties of Concentration Ratios

In this section we shall describe alternative concentration ratios for U.S. manufacturing and explore their relationships to industry performance. There are, of course, as many concentration ratios as firms (i.e., market shares) in any industry. The data required for their calculation, however, have not generally been available, and this study will use estimates generated by a private marketing research firm. Their reliability has been checked and found satisfactory, and the data have performed well in previous uses.[6]

The top 10 market shares for each of 314 four-digit SIC industries in 1972 constitute the basic new data. These have been summed into the corresponding succession of concentration ratios, labeled C1,...,C10 and described in Table I. Thus C1 (the largest share itself) averages .175 for all industries, and ranges from a high of .686 to a low of .011. Since at least one industry has only seven firms identified in the data base, the maximum C7 = 1.000. The pattern of increasing means in these data is quite regular, though it obscures huge ranges.

The last two columns of Table I speak to Stigler's comment and the argument of the preceding section. Correlations among successive concentration ratios are extremely large, in part

TABLE I

Descriptive Statistics of Concentration Ratios

Concentration Ratio	Mean	Max.	Min.	Correlation With C(n+1)	Correlation With S(n+1)
C1	.175	.686	.011	.965	.702
C2	.275	.875	.019	.991	.708
C3	.345	.912	.026	.995	.614
C4	.398	.973	.032	.997	.540
C5	.440	.995	.037	.998	.464
C6	.474	.999	.041	.999	.299
C7	.502	1.000	.045	.999	.180
C8	.526	1.000	.049	.999	.087
C9	.546	1.000	.053	.999	.017
C10	.564	1.000	.057	--	--

because C(n) constitutes the largest component of C(n+1). The correlations between any C(n) and the next share S(n+1), however, are substantially different, ranging from somewhat less for S2 and S3 to the "vastly lower" Stigler predicted in the case of smaller shares.[7] Clearly succeeding shares are not "determined" by any given concentration ratio, and hence different ratios embody different information about industry structure.

In any event, the preceding section cautions against concluding too much about relationships to industry performance from such correlations. A crucial test of alternative concentration ratios lies in their relative ability to explain performance directly. Our procedure is to build on the well-established methodology of price-cost margin analysis (Weiss, 1974; Kwoka, 1979) by using different concentration ratios as alternative explanatory variables in the following relationship:

PCM = f(C; KO, GD, GR, MPT, DUM) (3)

Here PCM = price-cost margin, defined as industry value-added minus payroll, divided by value of shipments. It measures the elevation of price over direct cost and hence (with some control factors) the exercise of market power. Data are from the <u>1972 Census of Manufactures</u> (1975).

C = various concentration ratios.

KO = capital-output ratio, to correct PCM for inter-industry differences in capital intensity. Data are from <u>Census of Manufactures</u> (1975).

GD = geographical dispersion variable, to reflect local, regional, or national extent of market and thereby correct Census data for scope of true economic markets. Its definition implies a negative sign against PCM.[8]

GR = a growth variable defined as the percentage change in industry shipments between 1967 and 1972. Theory predicts more rapidly growing industries will have higher margins, *cet. par.*

MPT = the market share of the midpoint plant size in the industry, to capture scale economies which require different minimum market shares in different industries.[9]

DUM = zero for producer good industries, one for consumer goods industries. This variable reflects the greater importance of advertising outlays and product differentiation in the latter. Data are from FTC, *Industry Classification and Concentration* (1967).

Regressions of equation (3) were performed on all ten concentration ratios, as reported in Table II. Although C1, the leading firm share, has considerable strength and significance by itself in explaining industry price-cost margins, substantial improvement occurs from using the two-firm concentration ratio.[10] That statistic yields the highest $\bar{R}^2$ (.175) and t-value (2.43) of any of the alternatives. Furthermore, the

TABLE II

Multivariate Regressions of Industry Price-Cost Margins on Various Concentration Ratios

Concentration Ratio		KO	GD	GR	MPT	DUM	CONST	$\bar{R}^2$
1. .0906	C1	.0813	-.0425	.0530	.0652	.0394	.2128	.169
(1.93)		(4.45)	(3.06)	(2.75)	(2.91)	(3.74)		
2. .0853	C2	.0786	-.0423	.0515	.0541	.0391	.2088	.175
(2.43)		(4.30)	(3.06)	(2.68)	(2.30)	(3.72)		
3. .0647	C3	.0791	-.0420	.0529	.0568	.0389	.2088	.171
(2.09)		(4.30)	(3.02)	(2.76)	(2.35)	(3.70)		
4. .0515	C4	.0800	-.0419	.0538	.0603	.0388	.2094	.168
(1.76)		(4.32)	(3.01)	(2.80)	(2.42)	(3.68)		
5. .0445	C5	.0806	-.0420	.0543	.0625	.0338	.2095	.166
(1.57)		(4.34)	(3.02)	(2.82)	(2.48)	(3.68)		
6. .0411	C6	.0808	-.0420	.0547	.0637	.0389	.2092	.165
(1.49)		(4.34)	(3.02)	(2.84)	(2.51)	(3.68)		
7. .0374	C7	.0812	-.0420	.0550	.0655	.0389	.2093	.164
(1.37)		(4.35)	(3.01)	(2.86)	(2.51)	(3.68)		
8. .0348	C8	.0815	-.0420	.0552	.0670	.0389	.2093	.164
(1.27)		(4.36)	(3.01)	(2.87)	(2.62)	(3.68)		
9. .0315	C9	.0820	-0.0420	.0556	.0691	.0389	.2097	.163
(1.16)		(4.39)	(3.01)	(2.88)	(2.71)	(3.68)		
10. .0278	C10	.0827	-.0420	.0560	.0716	.0389	.2104	.162
(1.03)		(4.42)	(3.01)	(2.90)	(2.82)	(3.68)		

pattern of results with the more inclusive concentration ratios is perfectly regular, with $\bar{R}^2$ declining from .175 with C2 to .162 with C10. The performance of the readily available concentration ratios for four and eight firms is distinctly inferior to that using C2, with C8 the worst for being the largest aggregate. Indeed, while C2 is significant at over .99, C4 is significant at only .95 in a one-tail test, and C8 actually falls below .90. This occurs despite the fact that the partial correlation between C2 and C4 is .96, and that between C2 and C8 is .88.[11] It is also worth noting that all the control variables are stable, significant, and have the expected signs throughout. Industry margins are higher with larger capital-output ratios, less geographical dispersion, faster growth, larger scale economies, and a consumer goods orientation to the industry.

Thus, the fact that C2's relationship to price-cost margins is highly significant and all these concentration ratios are highly correlated does not insure the emergence of a clear relationship between these alternatives and margins. The more inclusive concentration ratios simply are too inclusive. Adding shares not causally related to performance adds random noise which in sufficient amounts can drive even a significant underlying variable (C2) to statistical insignificance (as in C8). Research confined to the more aggregated concentration ratios and mechanically applying conventional tests of significance would in this case even be led to reject the hypothesis that industry concentration affects performance.[12] The mere fact that the correlations between ratios were very high (as most would surely characterize those just mentioned) would be insufficient to draw the same conclusion regarding other--and more appropriate--measures of industry structure.

V. Conclusions

This study has demonstrated that the choice of concentration ratios can matter a great deal. The usual argument for dismissing the choice as unimportant has been demonstrated theoretically incorrect, or at least incomplete. Furthermore, in practice, the choice is shown potentially crucial to the strength of the relationship found and in some circumstances even to whether a relationship is uncovered at all. This is not a trivial, dismissable issue.

The economic significance of the superiority of the two-firm concentration ratio is intriguing. It suggests that an industry's ability to coordinate behavior and raise price-cost margins above competitive levels may be determined not by twenty, eight, or even four firms, but by the leading two. This could reflect the greater difficulty of securing and maintaining agreement among more numerous rivals, where even the third firm poses some problems. Such possibilities lie buried within conventional concentration ratios, but their importance for public policy demonstrates the value of more disaggregated data.

Footnotes

1. Weiss' review of 35 studies of U.S. manufacturing industries reveals an overwhelming number which focused on the four-firm concentration ratio (Weiss 1974, pp. 204-20). More recent research maintains that pattern.

2. Miller (1967) disaggregated the eight-firm concentration ratio and found that a large fifth-through-eighth firm group could exert a negative effect on industry performance. This result suggests that the four- and eight-firm ratios are fundamentally different constructs.

3. Two exceptions to this view are Miller (1972) and Kwoka (1977).

4. In fairness, Scherer's comment was partially intended to contrast the "more serious" problems of market definition and contaminated data due to diversified firms.

5. This implies the following conditions:

   (a) $r_{11} > 0$

   (b) $r_{11} r_{22} - r_{21} r_{12} > 0$

   (c) $r_{11} r_{22} r_{33} + r_{12} r_{2Y} r_{Y1} + r_{21} r_{Y2} r_{1Y}$

   $-(r_{1Y} r_{22} r_{Y1} + r_{2Y} r_{Y2} r_{11} + r_{12} r_{21} r_{YY}) > 0$

   For an elaboration, see Chiang (1972), pp. 338-40.

6. For a description of the nature and previous use of the data, see Kwoka (1979).

7. Also lower are correlations between nonsuccessive concentration ratios, e.g., the four, eight, and twenty firm versions.

8. It is defined as the sum of absolute values of the differences in percentages of all manufacturing value added and a particular industry's value added for all four Census regions of the country. Data are from the 1972 Census of Manufacturers (1975).

9. This variable is the market share of the plant producing the fiftieth percentile of output in each industry, as estimated from employment size classes of plants in the Census of Manufactures.

10. These results do not fully reflect the degree of added explanatory power due to C2 vs. C1. The $\bar{R}^2$ of the regression without either concentration ratio is .162. While the addition of C1 raises this by .007, C2 causes $\bar{R}^2$ to increase by .013, a near doubling of the importance of the concentration itself.

11. Although it is the partial correlations (holding the other independent variables constant) that are relevant to these multivariate relationships, another common error in the literature is to note only the simple correlation coefficients among structural measures. In the present example, they are larger yet. The simple correlation between C2 and C4 is .98; and between C2 and C8, .93.

12. Indeed, the use of inappropriate concentration ratios might be a factor contributing to some findings of no such relationship. See Weiss (1974), pp. 203 ff.

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