TESTING THE DIFFERENTIAL EFFICIENCY HYPOTHESIS

by

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ABSTRACT

The predictions of collusion- and efficiency-based static equilibrium explanations of inter-industry profitability differences are developed and tested using intra-industry data on 70 US Internal Revenue Service minor manufacturing industries in 1963 and 1972. The 1963 data favor collusion-based models, while the 1972 estimates are inconsistent with both paradigms. Patterns of profitability are radically different (in complex ways apparently unrelated to cyclical forces or the Phase II price controls) in these two years. These findings call into question the value of single-year inter-industry studies and suggest the potential importance of panel data and dynamic disequilibrium models in industrial economics.

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I. Introduction

Since the pioneering work of Joe Bain (1951), the existence of a positive, but typically weak correlation between concentration and accounting measures of profitability has been accepted as an important stylized fact of industrial economics. Until relatively recently, this fact was almost universally rationalized by means of the Differential Collusion Hypothesis (DCH):

> Industries differ in the effectiveness with which sellers are able to limit competition by tacit or explicit collusion. Collusion is more likely to be effective, and profitability is more likely to be above competitive levels, the higher are concentration and barriers to entry (as defined by Bain (1956)).

This hypothesis has inspired a multitude of cross-section studies relating industry-level measures of concentration, of conditions of entry, and of other factors thought likely to affect the effectiveness of collusion to various measures of industry profitability. (See Weiss (1974) and Scherer (1980, ch. 9) for overviews of this literature.) Most of these efforts have produced results broadly consistent with the DCH, with statstical weaknesses generally rationalized in terms of the difficulty of measuring key variables (especially conditions of entry) with great precision.

A decade ago, Harold Demsetz (1973, 1974) proposed an alternative explanation of the positive correlation between concentration and profitability, the Differential Efficiency Hypothesis (DEH):

> Effective collusion is rare; effective tacit collusion is virtually nonexistent. Industries differ in the importance of long-lived efficiency differences among sellers. Where these differences are unimportant, concentration and accounting profitability will be low. Where efficiency differences are important, the most efficient firms will grow large relative to their rivals and will earn Ricardian rents based on their lower costs. Both concentration and profitability will thus be high in such cases.

If this hypothesis is correct, seller behavior in the absence of explicit cartel arrangements can be analyzed using competitive or non-cooperative models, issues of entry barriers and entry deterrence do not arise, and elements of market structure central to DCH-based analysis can be ignored.[1] The DEH also implies that antitrust should abandon its historic, DCH-supported concern with market structure and limit itself to prosecution of collusive behavior.

The present study examines the consistency of these hypotheses with intra-industry profitability differences in US manufacturing. Demsetz (1973, 1974) conducted the first empirical examination of this sort. He has been followed by a host of subsequent authors, including Carter (1978), Caves and Pugel (1980), Clarke, Davies, and Waterson (1984), Daskin (1983), Long (1982), Porter (1979), Round (1975), Ravenscraft (1983), and Schmalensee (1985).[2] The strategy in much of this work, which is also employed here, has been to focus on the inter-industry relation between seller concentration and various parameters of industry-specific distributions of profitability and market share. (Scherer (1980, ch. 9), Brozen (1982), and Daskin (1983) provide contrasting summaries of this literature.)

Most previous empirical comparisons of the DEH and the DCH have not employed formal models of industry behavior under alternative hypotheses. As a consequence, it is often unclear whether the empirical results obtained are consistent with one, both, or neither of these hypotheses. Accordingly, I begin in Section II by analyzing simple equilibrium models that serve to clarify the intra-industry and inter-industry implications of the DEH, the DCH, and a hybrid hypothesis combining the key features of both. The goal of this analysis is <u>not</u> to develop a full-blown structural model of the determinants of accounting profitability. The aim is less ambitious (and, I would argue, more realistic): to use simple models to identify critical testable predictions of these alternative world-views. I am concerned here with empirical regularities and stylized facts, not structural coefficients.

Section III describes the data used in this study. The same industries are examined in 1963 and 1972, two cyclically comparable years. This design was chosen to permit both evaluation of the stability of key relationships and analysis of industry-level changes over time. Section IV presents the results of estimating intra-industry profitability relations, taking explicit account both of the aggregation of firms into size classes in the (U.S. Internal Revenue Service) data employed and of plausible patterns of heteroscedasticity.

Section V presents the results of inter-industry analyses for 1963 and 1972 of the levels of key industry-specific parameters, along with an evaluation of the consistency of the DEH and the DCH with the main features of these data. Intra-industry estimates are explicitly treated as measuring the unknown industry-level parameters of interest with error. Section VI employs the same estimation technique to describes the pattern of parameter changes between 1963 and 1972, and Section VII summarizes the main findings of this study and their implications for future research.

II. Implications of Alternative Hypotheses

Two central features of the DEH, which should be present in any formal model designed to reveal the implications of that hypothesis, are the dependence of market shares on efficiency differences and the independence of seller behavior and market concentration. In contrast, a central feature of the DCH is the dependence of seller behavior on market concentration. I also take as a central feature of what I term the "pure" DCH the lack of a general relation between market share and differential efficiency within industries. In at least some textbook versions of the DCH, mergers, historical accidents, and random shocks are stressed as sources of concentration, rather than differential efficiency or, except for very small firms, economies of scale. (See, for instance, the discussion in Scherer (1980, ch. 4).) I begin by deriving the implications of the DEH for the parameters of a simple intra-industry profitability equation. I then explore the implications of the pure DCH for that equation. The Section concludes with an analysis of the implications of a hybrid DEH/DCH model, in which shares reflect efficiency differences and concentration facilitates collusion.

A. The Pure DEH

This relation between market share and differential efficiency under the DEH is basically a long-run relation, since an efficiency-enhancing innovation's full impact on the innovator's market share is usually not felt until capacity has been expanded or modified. To explore the inter-industry implications of the DEH, it is thus natural to focus on long-run equilibria that reflect the presence of efficiency differences. Moreover, while one cannot expect all industries in any data set to be in long-run equilibrium, it seems reasonable in the absence of a suitable dynamic theory of disequilibrium to treat deviations from long-run equilibrium as random in cross-section data. This is, of course, the standard practice in the cross-section literature in industrial economics.

I thus consider an industry in long-run equilibrium in which N firms sell a homogeneous product. Suppose that all have attained minimum efficient scale and hence face constant long-run average costs. (Most studies of scale economies have concluded that firms generally need relatively small market shares to be in this position; see Scherer (1980, ch. 4) for a survey.) Let there be long-lived efficiency differences among these firms, so that $c_1 \leq c_2 \leq \ldots \leq c_N$, with at least one inequality strict, where c_i is firm i's unit cost.[3] Unit cost should not be interpreted in narrow process efficiency terms here. A firm with a superior product may simply be more efficient in the production of the Lancastrian characteristics it supplies to an existing market. While major product innovations that yield substantial differentiation and create something approaching a new market cannot be sensibly modeled as simply reducing costs, it seems reasonable to think of minor differences among products in cost/efficiency terms for purposes of formal analysis of profitability.

Adoption of the DEH as a working assumption rules out collusive behavior. But I do not think that as a logical matter it requires pure price-taking behavior. Firms with large shares of industry capacity or output should not simply be assumed to ignore the effects of their actions on market price. It seems much more plausible to begin with the basic assumption of non-cooperative behavior, under which each firm simply makes its best (most profitable) response to its rivals' actions. As we are concerned with long-run equilibria, investment in productive capacity becomes a central decision variable. This is in effect an output choice, which suggests that Cournot equilibria are the most relevant. More formally, Kreps and Scheinkman (1983) have recently shown that non-cooperative capacity decisions, followed by non-cooperative (Bertrand) price competition yield Cournot outcomes.

Accordingly, let us explore the implications of the DEH by examining Cournot equilibria with cost differences. (As is noted below, the fundamental behavioral assumption here is that all firms, in all industries, behave identically; that behavior need not be Cournot). The economic profit of a typical firm is given by

$$\pi_i = [P(q_i+\bar{q}_i) - c_i]q_i, \qquad (1)$$

where P is market price, P(Q) is the inverse demand function, and $\bar{q}_i \equiv Q - q_i$

is the total output of firm i's rivals. Firm i's first-order condition, with rivals' output treated as exogenous, can be written as follows:

$$(P - c_i) = ePq_i/Q, \tag{2}$$

where $e \equiv -1/[(\partial Q/\partial P)(P/Q)]$ is <u>the reciprocal of</u> the industry elasticity of demand. Multiplication of (2) by q_i yields firm i's <u>economic</u> profit in equilibrium. If firm i employs assets worth K_i, and if the normal, competitive rate of return on invested capital relevant to the industry is ρ, firm i's <u>accounting</u> profit is given by

$$\pi a_i = \rho K_i + e(q_i/Q)(Pq_i). \tag{3}$$

Finally, letting $s_i \equiv q_i/Q$ be firm i's market share and $v_i \equiv Pq_i/K_i$ be its revenue/capital ratio, one can divide (3) by K_i to obtain a simple equation involving the accounting rate of return on assets:

$$r_i = A + B(s_i v_i), \tag{4}$$

where, under the DEH, $A = \rho$, the competitive rate of return, and $B = e$, the reciprocal of the market elasticity of demand. One can think of A as the rate of return corresponding to a zero market share. The smallest firms actually operating in any industry will thus generally have rates of return in excess of A under the DEH. The size of this excess may even be positively related to concentration.[4] While equation (4) flows directly from the DEH, one need not accept that hypothesis to view (4) as a natural specification to employ in investigations of intra-industry profitability differences. (Note in particular that the presence of v_i gives the independent and dependent variables the same units.) It is employed as such in what follows.

Under DEH, as described above, both A and B should be positive for all industries. Further, neither parameter should be correlated (positively or negatively) with seller concentration across industries. Under the DEH, variations of A across industries ought mainly to reflect differences in risk and in accounting biases, while variations in B should mainly reflect differences in demand elasticities. To obtain an alternative measure of large-firm profitability advantage that should be correlated with concentration, define RA as the difference between an industry's average rate of return, R, and its intercept parameter, A. Then, using equation (4), the DEH implies

$$RA \equiv \left(\sum_{i=1}^{N} \pi a_i / \sum_{i=1}^{N} K_i\right) - A = veH, \tag{5}$$

where $v \equiv (PQ/\Sigma K_i)$ and $H \equiv \Sigma (s_i)^2$ is the Hirschman-Herfindahl index of seller concentration. RA should be positive for all industries under the DEH, and it should be positively correlated with most concentration measures, especially when differences in capital intensity are controlled for. Since e varies across industries, however, one cannot expect the correlation between RA and concentration to be particularly strong.

B. The Pure DCH

Under what I have called the pure DCH, market shares are not determined by differences in efficiency. Under this hypothesis, estimation of (4) should still yield positive values of A. But, since share and profitability are not systematically related, the distribution of B and RA across industries should have a mean of approximately zero. Inter-industry differences in these parameters would reflect accounting quirks and historical accidents.

There is no reason why B should be correlated with concentration under the DCH, but the implications regarding A and RA are less clear. On the one hand, if industries differ in the importance of barriers to entry, but barriers to mobility (Caves and Porter (1977)) are generally unimportant, collusive behavior will raise the profits of all firms together. With market shares and concentration unrelated to efficiency differences, A will be positively correlated with concentration in cross-section, but RA (which may be positive or negative in any particular industry) will not be. On the other hand, a positive correlation between RA and seller concentration is also consistent with the pure DCH. To see this, suppose (following Porter (1979)) that in industry has two strategic groups: one in which market shares are small and into which entry is free, and one in which established sellers are protected by barriers to entry and mobility. Sellers in the first group will earn only competitive returns, while the DCH implies that if (and only if) the second group is concentrated, its members will earn monopoly rents, and the industry average rate of return will be supracompetitive. If this two-group structure is typical, RA will be positively related to concentration in cross-section, while A will not be. To summarize, the pure DCH predicts that B will be uncorrelated with concentration, while either A, or RA, or possibly both will be positively correlated with concentration in cross-section.

C. A DEH/DCH Hybrid

Since both the DEH and the DCH seem rather special, it is important to investigate the implications of DEH/DCH models, in which shares are related to differential efficiency <u>and</u> seller concentration facilitates collusion. To do this, I generalize the Cournot model developed above, using the conjectural variation formalism to describe possible collusive equilibria. If λ_i is firm i's conjectural derivative, $\partial\bar{q}_i/\partial q_i$, equation (4) can written as

$$r_i = \rho + [(1+\lambda_i)e](s_i v_i). \tag{6}$$

It is easy to show that all else (including rivals' total output) equal, the higher is λ_i, the lower is firm i's output. In other words, the higher is λ_i, the more firm i restricts output in equilibrium. Under the DEH/DCH, one would expect the λ_i to be positive and to be generally larger the more concentrated is the industry considered.

If $\lambda_i = \lambda$ for all firms in some industry, equation (6) implies immediately that estimation of (4) should yield $A = \rho$, $B = e(1+\lambda)$, and $RA = evH(1+\lambda)$. If, in addition, λ is constant across industries, or at least uncorrelated with concentration, the implications of this model are indistinguishable from those of the pure DEH. Under the DEH/DCH, however, λ should be positively correlated with concentration across industries. Then A, B, and RA should be positive, A should be independent of concentration, and both B and RA should be positively correlated with concentration.

There is no strong theoretical or empirical support for the assumption that the λ_i are equal within industries, of course. Clarke and Davies (1982) have proposed the alternative assumption $\lambda_i = \alpha(1-s_i)/s_i$, with α positively correlated with concentration. (See also Long (1982) and Clarke, Davies, and Waterson (1984).) Under this assumption, equation (6) becomes

$$r_i = [\rho+\alpha e v_i] + [(1-\alpha)e](s_i v_i). \tag{7}$$

This version of the DEH/DCH thus implies that greater seller concentration should be associated with higher estimates of A and <u>lower</u> estimates of B. The main rationale for the Clarke-Davies assumption appears to be that as $\alpha \to 1$ (with rising marginal cost), the equilibrium described by (7) converges to the maximization of total industry profit.

While total industry profit may be a plausible cartel objective function when side payments are possible, however, it does not seem especially plausible when, as in the U.S., such payments are essentially impossible. Moreover, maximization of total industry profit requires small, inefficient firms to be the main restrictors of output, and the inverse relation between s_i and λ_i in the Clarke-Davies assumption imposes this pattern on all imperfectly collusive equilibria (i.e., those with $\alpha<1$). But this pattern seems inconsistent with most descriptions of the actual behavior of imperfect cartels. (See almost any recent discussion of behavioral differences within OPEC, for instance.[5]) The Clarke-Davies assumption also runs counter to relevant cooperative and non-cooperative theory. If, (loosely) following the widely-employed Nash model of bargaining as a cooperative game without side payments, one examines the conditions for maximizing the product of the firms' profits, it is easy to show that the optimium can be represented as a conjectural variation equilibrium in which firms with lower costs have higher λ's. On the non-cooperative side, it follows from Stigler's (1964) model of oligopoly that small firms run a lower risk of detection and punishment than large firms if they fail to do their "fair share" of output restriction. I thus conclude that a positive relation between s_i and λ_i is more plausible than a negative relation of the sort postulated by Clarke and Davies.

To explore the implications of such a relation, suppose that the DEH/DCH holds for some industry, so that equation (6), with the addition of a homoscedastic disturbance distributed independently of the λ_i and $(s_i v_i)$, is the correct specification. To focus on the influence of concentration, suppose that $v_i = v$ for all i. Finally, assume that the λ_i have mean λ and are linear in the s_i, so that $\lambda_i = \lambda + \gamma[s_i-(1/N)]$, where N is the number of firms in the industry, and γ is some constant. Then if least squares is employed to estimate equation (4), a bit of algebra yields the following expectations of the estimated parameters:

$$E(A) = \rho + ev\gamma[H^2 - \Sigma(s_i)^3]/[NH-1], \tag{8a}$$

$$E(B) = e(1+\lambda) + e\gamma[N^2\Sigma(s_i)^3 - 2NH+1]/[N(NH-1)], \tag{8b}$$

$$E(RA) = \rho + evH(1+\lambda) + ev\gamma[\Sigma(s_i)^3 - (H/N)] - E(A), \tag{8c}$$

where $H = \Sigma(s_i)^2$, as above.

If the distribution of the s_i can be adequately approximated by the lognormal, which is commonly treated as a workable approximation to firm size distributions, it is easy to show (using results from Aitcheson and Brown (1963), ch. 2) that the expected value of $\Sigma(s_i)^3$ is NH^3. Making this substitution in equations (8) yields

$$E(A) = \rho - ev\gamma H^2, \tag{9a}$$

$$E(B) = e(1+\lambda) + e\gamma[N^3H^3 - 2NH+1]/[N(NH-1)], \tag{9b}$$

$$E(RA) = evH(1+\lambda) + ev\gamma[NH^3 + H^2 - (H/N)]. \tag{9c}$$

As an empirical matter, N is at best weakly (negatively) correlated with concentration. (See, for instance, Schmalensee (1977), esp. footnote 1.) And it is easy to show that the second terms on the right of (9b) and (9c) are positive and increasing in H for $H > 1/N$, its lower bound.

Equations (9) thus imply that if γ is generally positive and independent of concentration, A should be <u>negatively</u> correlated with concentration in cross-section, though the correlation may be weak, while the positive correlation between concentration and both B and RA will be stronger than if $\gamma = 0$. If γ is large, A could be negative for highly concentrated industries, but B and RA should be positive in all cases. In what follows I treat these as the most likely outcomes under the DEH/DCH.

Equations (9) also show that negative values of γ, which I have argued are relatively implausible, will tend to induce a positive correlation between concentration and A and to weaken the positive correlations between concentration and B and between concentration and RA. If γ is generally negative and large, these latter correlations could become negative, producing results like those implied by equation (7). If $\gamma<0$ is the norm, A should be positive in all cases, but negative values of B and RA could be observed in highly concentrated industries. Since e may vary substantially among industries (along with v and γ), one cannot expect any of the correlations predicted by this hybrid DEH/DCH model to be particularly strong.

III. Data Employed

The data employed in this study cover U.S. Internal Revenue Service (IRS) minor manufacturing industries for 1963 and 1972. I chose to use years for which Census of Manufactures data could be used to measure seller concentration. These particular Census years were selected because data for them were readily available, they were far enough apart in time for changes in industry-level variables to reflect changes in their fundamental determinants, and because they were comparable in terms of the business cycle.[6] Both 1963 and 1972 were relatively prosperous years. The overall unemployment rate was 5.5% in both years, while the civilian unemployment rate was 5.7% in 1963 and 5.6% in 1972.[7] Real GNP grew 4.6% during 1963 and 5.7% during 1972. Inflation was somewhat higher in 1972 than in 1963: the GNP deflator rose only 1.5% during 1963 but rose 4.9% during 1972.

Focusing on the manufacturing sector, the two years studied again appear quite similar. The Federal Reserve Board's measure of capacity utilization was 83.5% in both periods. Real GNP originating in manufacturing rose 7.7% in 1963 and 10.4% in 1972. The corresponding implicit deflator *fell* 1.1% during

1963 and rose only 0.3% during 1972. Almost all the inflation that worried policy-makers during 1972 occurred outside the manufacturing sector.

Perhaps the most obvious difference between 1963 and 1972 is the operation of Phase II price controls during 1972. But there are at least three reasons for concluding that this is unimportant for the present study. First, the macroeconomic literature suggests that these controls did not have large effects on the economy as a whole; see, for instance, Dornbusch and Fischer (1981, pp. 566-67) and the references they cite. Second, Appendix A reports the results of a time-series analysis indicating that the Phase II controls had an insignificant effect on manufacturing profits. Third, Appendix A also reports the results of a small-scale study of the time-series behavior of the relation between firm size and profitability in US manufacturing. This study, undertaken to test for the possibility that the Phase II controls were enforced mainly against leading firms, giving their smaller rivals artificial competitive advantages, does not find 1972 to be an outlier in any relevant sense.

Data by industry and by industry-specific asset size-class for Internal Revenue Service minor industries for 1972 were mainly obtained from the Project on Industry and Company Analysis (PICA) at the Harvard Graduate School of Business Administration. In order to reduce well-known measurement problems associated with very small firms and to reduce the importance of scale-related cost differences (the presence of which would tend to bias our results in favor of the DEH) in the data, data on firms with assets below $500,000 were excluded. In order to have at least four usable size classes for each industry, five IRS industries (2380, 2398, 2899, 3860, and 3870) were then dropped from the sample. Many of the remaining industries are sufficiently broadly defined that they should be thought of as including several markets with at least some supply-side links. A final industry (3990, miscellaneous manufactured products, except ordinance, manufacturing not allocable) was dropped because the markets it included seemed unlikely to be at all closely linked. Our final sample consisted of 70 IRS minor industries, each with at least four usable size classes. The maximum number of usable classes was eight; the mean number was 6.8.

Data for 1963 IRS industries was provided by Allan J. Daskin, from the data set assembled for use in his dissertation (Daskin (1983)). These data were aggregated (size-class by size-class) to conform to the 1972 industry definitions, following the 1968 IRS Sourcebook of Statistics of Income. All 1963 industries had between five and nine usable size classes, with a mean of 8.3 classes per industry.

For each size-class for each industry, I compiled the number of firms, total assets, pre-tax profits plus interest payments, and business receipts. The ratio of total pre-tax returns (profits plus interest) to total assets employed was used as the accounting rate of return, r. This measure avoids the distorting effects of differences in leverage and effective income taxation. (Daskin (1983) reports that the effects in this context of the use of after-tax returns are negligible.) Like all accounting measures of profitability, r is inherently imprecise. The inter-industry equations discussed below include controls (crude ones, to be sure) for some frequently-discussed accounting biases. More importantly, however, it is not clear why one should expect the most obvious infirmities of accounting data to do anything more than add noise to our estimates. In particular, it is not obvious why accounting biases should be correlated with concentration in such a way as to produced biased estimates of key cross-section coefficients. Similarly, the conglomerate merger wave of the late 1960's undoubtedly serves to lower the quality of the 1972 data, but it is not clear why it should bias estimates of relations involving concentration.

The following variables were computed for each IRS minor manufacturing industry in 1963 and 1972:

R = Ratio of pre-tax profits plus interest payments to total assets for all firms with assets above $500,000

CONC = Weighted average, using value-added weights, of four-firm concentration ratios of constituent 4-digit Census industries.

AD/K = Ratio of advertising outlays to total assets.

PQ/K = Ratio of business receipts to total assets.

DDUR = 1 - DNDR = 1 for durable goods industries, zero otherwise.

DCON = 1 - DPRO = 1 for consumer goods industries, zero otherwise.

The means, standard deviations, and inter-year correlations of the first four of these variables are shown in Table 1. Those figures seem generally consistent with the presumption that 1963 and 1972 are comparable years. They also indicate that dramatic changes between these years were relatively rare.[8]

The correlations between R and the corresponding industry-wide rates of return were above .99 in both years. If one thinks of IRS minor industries as including multiple markets, observed rates of return must be thought of as asset-weighted averages of rates of return in those markets. Thus CONC should ideally also be computed using (net) asset weights; value-added weights seemed the closest readily available substitute. The advertising-sales ratio, AD/PQ, is often treated as a proxy for product differentiation under the DCH. The correlations between AD/K, which seems slightly preferable because it has the same units as the other variables, and AD/PQ exceeded .96 in both years. AD/K is also the more natural variable to use as a rough correction for advertising-related accounting biases; see Demsetz (1979). The variable PQ/K serves both to control for differences in capital intensity and as a rough correction for accounting biases in asset valuation during inflation. I do not attempt to provide structural interpretations of the coefficients of AD/K and PQ/K; these variables are included as controls and for descriptive purposes.

Similarly, in the interests of providing an adequate description of the data, it seemed desirable to examine differences between industries producing durable and nondurable goods and between industries producing consumer and producer goods. I used Ornstein's (1977, Appendix B) classification of four-digit Census industries in 1967, along with 1963 value-added weights and the correspondence between 1963 and 1972 IRS definitions to classify the sample industries along these lines. Seventeen of the 70 industries in the sample were found to produce mainly durable goods, and 22 were classified as consumer goods industries by this procedure.[9]

IV. Intra-Industry Estimation

In order to compare values of A, B, and RA across industries, equation (4) must be estimated for each industry in the sample. This is not a completely straightforward task, since (4) relates to individual firms, while the data are for groups of firms within asset-based size-classes. Only Daskin (1983) seems to have recognized that one cannot obtain unbiased or even consistent estimates by simply substituting size-class averages into equations like (4). He dealt with the problem by estimating an intra-industry equation linear in profits and assets, for which there is no problem of aggregation bias. Unfortunately, it is difficult to interpret the parameters of Daskin's equation in terms of the hypotheses of interest here.

The approach taken in this study is to aggregate (4) from firm to size-class data explicitly and to substitute consistent estimates of the unobservable quantities (defined below) that appear as a consequence of aggregation. Consider size class c in some industry. Suppose it has N_c firms, and let the subscript "ci" denote the i^{th} firm in class c. Multiplying equation (4) by the firm's total assets and adding a disturbance term yields

$$\pi a_{ci} = AK_{ci} + BP(q_{ci})^2 + \varepsilon_{ci}. \tag{10}$$

The basic equation for size-class average rates of return is then obtained by summing over the firms in class c and dividing by total assets in the class:

$$r_c \equiv \sum_{i=1}^{N_c} \pi a_{ci} / \sum_{i=1}^{N_c} K_{ci} \equiv \pi a_c/K_c = A + B(f_c \bar{s}_c v_c) + u_c. \tag{11}$$

The new variables in this equation are defined as follows:

$$f_c \equiv N_c \sum_{i=1}^{N_c} (q_{ci})^2 / (\sum_{i=1}^{N_c} q_{ci})^2 \equiv N_c \sum_{i=1}^{N_c} (q_{ci})^2/(q_c)^2 \tag{12a}$$

$$\bar{s}_c \equiv (q_c/N_c)/Q, \tag{12b}$$

$$v_c \equiv Pq_c/K_c, \tag{12c}$$

$$u_c \equiv \sum_{i=1}^{N_c} \varepsilon_{ci}/K_c. \tag{12d}$$

The unobservable quantity f_c equals one if and only if all firms in size class c have the same sales. In general f_c equals one plus the ratio of the sample variance of the q_{ci} to the square of their sample mean. It thus is an indicator of the importance of intra-class differences in market share.

In order to handle the unobservability of the f_c, I assume that intra-class differences in assets are as important as those in sales:

$$f_c = N_c \sum_{i=1}^{N_c} (K_{ci})^2/(K_c)^2. \tag{13}$$

This assumption is needed here because size-class boundaries relate to assets, not sales. A sufficient (but not necessary) condition for (13) to be satisfied is that within a given industry, all firms in each size class have the same revenue/capital ratio. Given (13), the f_c are estimated using N_c, K_c, and the values of size-class boundaries. The procedure employed is based on the assumption that assets of firms within each class are drawn from a class-specific density function linear in assets. Details are given (and an alternative approach based on the lognormal distribution is discussed) in Appendix B.

A second problem in estimating (11) with size-class data is that aggregation may produce differences in the variances of the u_c. To deal with possible heteroscedasticity among the u_c within industries, I employ two alternative, bounding assumptions about the distribution of the ε_{ci} in (10). Perhaps the most natural of these is that the standard deviation of ε_{ci} is equal to σK_{ci} for all i and c, where σ is an industry-specific constant. Under this assumption, the variance of u_c is given by

$$\sigma^2(u_c) = \sigma^2 \sum_{i=1}^{N_c} (K_{ci})^2/(K_c)^2 = \sigma^2(f_c/N_c). \tag{14}$$

Division of (11) by $(f_c/N_c)^{1/2}$ yields what is referred to below as the <u>CRS</u> estimating equation, because it embodies the assumption of stochastic constant returns to scale:

$$r_c(N_c/f_c)^{1/2} = A(N_c/f_c)^{1/2} + B[\bar{s}_c v_c(f_c N_c)^{1/2}] + \xi_c. \tag{15}$$

The variance of ξ_c is σ^2 for all classes in a given industry if (14) holds.

The literature on the effects of scale on the time-series and cross-section variability of firms' rates of return suggests an alternative to the CRS specification. These studies generally find that the standard deviation of rates of return declines with firm size, with the decline less rapid than that of $(K_i)^{-1/2}$. (See Prais (1976, pp. 92-98) and Daskin (1983) for overviews of this literature.) This suggests that the standard deviation of ε_{ci} is generally equal to $\sigma(K_{ci})^b$, where σ is as before and $1/2 < X < 1$. The CRS specification assumes $b = 1$. Since b is unknown and may vary from industry to industry and from year to year, I deal with the possibility that b is less than unity by exploring the implications of the alternative bounding assumption $b = 1/2$. Under this assumption the variance of u_c is simply

$$\sigma^2(u_c) = \sigma^2/K_c. \qquad (16)$$

Division of (11) by $(K_c)^{-1/2}$ yields the IRS estimating equation, which embodies the assumption of stochastic increasing returns to scale:

$$r_c(K_c)^{1/2} = A(K_c)^{1/2} + B[\bar{s}_c v_c f_c(K_c)^{1/2}] + \xi_c. \qquad (17)$$

The parameter estimates obtained by employing the CRS and IRS specifications with 1963 and 1972 data are summarized in Table 2. The statistics given under the heading "Sample Coefficients" are self-explanatory.[10] Those statistics indicate that essentially all estimates of A are positive in both years, while estimates of B and RA have both signs in both years. The majority of estimates of B (59%) and RA (56%) are positive in 1963, while negative values (66% of B's and 69% RA's) are the rule in 1972. Perhaps the most striking feature of this Table is the sharp difference between the 1963 and 1972 estimates. Table 1 shows that on average R (= RA + A) changed little between these years, but Table 2 reveals that A rose broadly and substantially, while B and RA generally fell.

The first two statistics given under the heading "Probability Levels" are the significance levels obtained in standard X^2 tests of the indicated null hypotheses. Except for estimates of B under the CRS specification, these indicate that the null hypotheses that the underlying parameters or their 1963-1972 changes are the same across industries can be confidently rejected. That is, the intra-industry estimates of the coefficients of equation (4) provide information on what seem to be real inter-industry differences.

The statistics under the heading "Population Estimates" in Table 2 provide summary information on the importance of those differences. Following, for instance, Swamy (1970, esp. Sect 5), if b_j is the estimate of some true parameter, β_j, for industry j, one can write

$$b_j = \beta_j + \eta_j = \mu + \nu_j + \eta_j. \tag{18}$$

Here η_j is the sampling error associated with b_j. It is unobservable, but it can be treated as having mean zero and standard deviation equal to the standard error of b_j, which we denote $\sigma(\eta_j)$. If μ is the mean of the population from which the β_j are drawn, so that the ν_j have mean zero, an unbiased estimator of the variance of the population distribution of the β_j is given by

$$\sigma^2(\nu) = \sum_{j=1}^{M} (b_j - \bar{b})^2/(M-1) - \sum_{j=1}^{M} \sigma^2(\eta_j)/M, \tag{19}$$

where $\bar{b}$ is the sample mean of the b_j, and M is the number of industries. Given $\sigma^2(\nu)$, the precision-weighted average of the b_j provides an efficient estimate of μ:

$$\mu = \sum_{j=1}^{M} \{b_j/[\sigma^2(\nu)+\sigma^2(\eta_j)]\}/ \sum_{j=1}^{M} \{1/[\sigma^2(\nu)+\sigma^2(\eta_j)]\}. \tag{20}$$

A comparison of μ with its large-sample variance, $1/\Sigma\{1/[\sigma^2(v)+\sigma^2(\eta_j)]\}$, yields a large-sample X^2 test of the null hypothesis that the population mean of the β_j is zero.

The statistics computed using equations (18) - (20) reinforce the impression of considerable inter-industry variation in underlying parameters. Population standard deviations appear large relative to population means, especially for RA and B. (Equation (19) yielded a negative estimate of $\sigma(v)$ for B under the CRS specification, reflecting the large standard errors of the corresponding parameter estimates.) Population means differ significantly from zero, and the changes in estimated values between 1963 and 1972 seem to reflect real changes in underlying population distributions.

I postpone discussion of the consistency of the results in Table 2 with the models of Section II until after an examination of the key inter-industry correlations identified by those models.

V. Inter-Industry Estimation: Levels

In order to estimate cross-section relations involving A, B, and RA efficiently, one must take explicit account of the fact that the estimates from intra-industry regressions measure the true underlying parameters with error. If β_j is the true value of some such parameter for industry j, and Z_j and δ are vectors of industry-specific explanatory variables and inter-industry coefficients, respectively, a typical inter-industry equation can be written as follows:

$$b_j = \beta_j + \eta_j = Z_j'\delta + (\xi_j + \eta_j). \tag{21}$$

The ξ_j and the η_j are assumed to be independent. If the ξ_j have common variance $\sigma^2(\xi)$,[11] the variance of the j^{th} error term in equation (21) is

$[\sigma^2(\xi)+\sigma^2(\eta_j)]$. Since the sampling variances of the b_j differ in general, application of ordinary least squares to (21) would yield inefficient estimates of δ.

This problem has been treated in general terms by Hanushek (1974) and Saxonhouse (1977); Long (1982) and Daskin (1983) have previously allowed for this source of heteroscedasticity in this context. In order to obtain efficient estimates of δ, one needs a consistent estimate of $\sigma^2(\xi)$. Since the standard errors of the b_j can be treated as known, such estimates can be obtained by applying least squares to (21), either as it stands or after division by the $\sigma(\eta_j)$. Because these two regressions often yield rather different estimates of $\sigma^2(\xi)$ and because estimates of δ are in many cases sensitive to the estimate of $\sigma^2(\xi)$ employed, I used an iterative fixed-point approach to the estimation of that variance, the details of which are presented in Appendix C. Weighted least squares estimation was then used to obtain efficient estimates of δ.

Table 3 presents weighted least squares estimates of the cross-section relation between concentration and A, B, and RA. For comparison purposes, estimates of the relation between between concentration and R are also presented. The statistics labeled "Basic Model" refer to a simple bivariate model in which CONC is the only independent variable, while in the "Full Model" the variables AD/K and PQ/K are added to control for advertising and capital intensity differences. All equations estimated included intercept terms, which are of little interest and hence are not reported. Equations labeled "Pooled" were estimated by simply stacking the weighted regressions corresponding to the CRS and IRS specification. (In no case could the null hypothesis of coefficient identity be rejected at any reasonable significance level.) Since the CRS and IRS parameter estimates cannot be considered independent, the "Pooled" estimates have no claim to optimality. They merely provide convenient summary information.

The first measure of goodness of fit presented in Table 3, R^2-Wtd., is the R^2 statistic of the weighted regression used to estimate δ. A second measure, R^2-Raw, is the square of the correlation between predicted and actual values of b_j. The second measure can be negative; the first must lie between zero and one. Chow tests for coefficient stability applied to equations involving A, B, or RA provided no evidence of significant coefficient differences between durable goods and nondurable goods industries or between consumer goods industries and producer goods industries.[12]

The "Prob. Level" statistics in Table 3 are the significance levels of F-tests of the null hypotheses of equal slope coefficients in 1963 and 1972, with intercepts allowed to differ in light of the results shown in Table 2. These statistics generally cast appreciable doubt on this null hypothesis. That is, not only do the average values of A, B, and RA differ between 1963 and 1972, but their correlations with concentration and other industry characteristics (themselves relatively stable, as Table 1 indicates) appear to differ as well. The instability detected in Table 2 is apparently quite fundamental.

Coefficient instability is most clearly present in Table 3 in the equations involving R, industry-level profitability. Estimates of both Models for 1963 yield the traditional weak positive relation between concentration and profitability; the estimated coefficients imply that an increase in CONC from .20 to .85 would raise R by only about one standard deviation. But in 1972 there is no visible relation at all between CONC and R. This is consistent with Weiss's (1974) observation (based on studies using pre-1970's data) that the concentration/profitability relation tends to weaken in inflationary periods, though (as was noted in Section III) the inflation rate in manufacturing was only 1.3 percentage points higher in 1972 than in 1963. The implications of the instability revealed in the first column of statistics in Table 3 for the reliability of conclusions drawn from single-year cross-section studies are obvious and depressing.

The remaining regressions in Table 3, none of which have much explanatory power, indicate that the relations between concentration and A, B, and RA are also likely to differ between the two years studied. On the other hand, the Basic and Full Models and the CRS and IRS specifications generally produce very similar estimates. Since the DEH and the DCH predict only the existence of statistically weak relations (because of inter-industry variation in E), it is appropriate to apply looser than usual standards for rejecting null hypotheses of no relation. With this in mind, A and RA appear to be positively correlated with concentration in 1963. In 1972, A appears to be negatively correlated with concentration, while the correlation between concentration and B appears to be positive. There is not a hint here of a non-zero correlation between B and concentration in 1963 or between RA and concentration in 1972.

Table 4 summarizes the implications of the DEH, the DCH, and the DEH/DCH developed in Section II, along with the corresponding statistical findings from Tables 2 and 3. Consider first the findings for 1963. The evidence for a positive relation between A and concentration, which is predicted only by the pure DCH, is as strong as that for a similar relation between RA and concentration, which is consistent with all three hypotheses and required by the DEH and the DEH/DCH. The DEH/DCH prediction of a positive relation between B and concentration receives absolutely no support. The correlations with concentration in 1963 thus tend to favor the DCH as against the other two hypotheses.

Similarly, the DEH and the DEH/DCH both predict positive values of B and RA in all industries, but the 1963 estimates imply that these parameters are nearly as likely to be negative as positive. While the estimates means of the population distributions of both parameters are significantly different from zero, they are small both absolutely and relative to the corresponding estimated population standard deviations. This pattern appears consistent only with the DCH. Results similar to these have been reported by a host of previous authors, including Caves and Pugel (1980), Clark, Davies, and Waterson (1984), Comanor and Wilson (1974), Daskin (1983), Long(1982), Marcus (1969), and Porter (1979), using a variety of specifications and data sets. It is clear from this literature as well as from Table 2 that one cannot treat the positive intra-industry relation between profitability and market share predicted by the DEH and the DEH/DCH as a stylized fact in US manufacturing.[13]

While the 1963 data thus favor the DCH over the DEH and the DEH/DCH, the results obtained for 1972 are basically inconsistent with all three hypotheses. Negative values of B and RA are the norm; the null hypotheses that the corresponding population means are zero are decisively rejected. The estimated population mean of B is small relative to the corresponding standard deviation, however, so that the estimated distribution of B could perhaps be described as approximately symmetric around zero and thus consistent with the DCH. But the statistics for RA describe a distribution with most of its mass below zero, and this is consistent with none of the three hypotheses.

Similarly, the clear lack of a positive correlation between RA and concentration in 1972 is inconsistent with both the DEH and the DEH/DCH. It would be consistent with the DCH if the correlation between A and concentration were positive, but it is negative. The correlations involving A and B are consistent with the DEH/DCH, but that hypothesis predicts a positive relation between concentration and RA, and no such relation is present. In short, the pattern of correlations observed for 1972 is consistent with none of the three static equilibrium hypotheses considered here.

Perhaps the most disturbing aspect of the findings summarized in Table 4 is the striking difference between the 1963 and 1972 estimates for identically defined industries. This difference casts doubt on the stability assumption implicit in single-year cross-section work in industrial economics. The results obtained here may well signal the presence of fundamental weaknesses in the static equilibrium approach on which standard versions of both the DEH and the DCH rest. Except in periods of unusual stability, it may be necessary to model deviations from long-run equilibrium explicitly in order to explain the main patterns of intra-industry and inter-industry profitability differences. Panel data seem necessary to provide tests of such models with adequate power.

VI. Inter-Industry Estimation: Changes

I had originally intended to estimate a variety of dynamic specifications using data from 1963 and 1972 to test some DEH-based hypotheses about relations between changes in concentration and the industry-specific parameters analyzed in Table 3. (For instance, industries with above-average B's in 1963 might be expected to have become more concentrated on average by 1972 as leading firms expanded to exploit cost advantages not yet fully reflected in market share.) The evidence of coefficient instability presented in Table 3, the dramatic changes in the distributions of industry-specific parameters shown in Table 2, and the results of a few attempts to estimate dynamic models indicate that the stationarity conditions necessary for such an exercise to be sensible are simply not satisfied here.

The pattern of changes in A, B, and RA across industries over the nine-year period between 1963 and 1972 is nonetheless of some interest. Tables 5 and 6 present simple descriptive estimates of the Basic and Full models using parameter changes as dependent variables and average values of CONC, AD/K, and PQ/K as independent variables. (As Table 1 indicates, these quantities generally change little between 1963 and 1972, and a number of experiments make clear the futility of trying to associate changes in A, B, or RA with changes in these three variables.) The presentation follows that in Table 3. All estimated relations were checked for stability across sub-sets of industries. No real evidence of differences between consumer goods industries and producer good industries was encountered. Surprisingly, however, Chow tests showed most versions of the Full Model (but not of the Basic Model) to be unstable between durable goods and nondurable goods industries. I have no supportable explanation for this basic finding or for the related details discussed below; I present these results in part in the hope that someone will be thereby stimulated to provide such an explanation.[13]

The estimates in Table 5 indicate that more concentrated industries experienced smaller than average increases in A and larger than average decreases in R. As the P-Levels reported at the bottom of the Table indicate, durable/nondurable instability in the Full Model for A seems to be confined to the intercept (CNST) and the coefficient of average PQ/K. (The Full Model for R shows no significant instability of this sort; it is estimated in the same version as the A equations entirely for purposes of comparability.) All else equal, durable goods industries experienced smaller increases in A than nondurable goods industries. Among durable goods industries, increases in A are smaller the higher is capital intensity, while there is some evidence of the opposite effect in the nondurables subsample. The Full Model also indicates that industries with higher than average advertising intensity experienced smaller than average increases in A, while advertising intensity was unrelated to changes in R.

Table 6 presents a similar analysis of changes in RA and B. The Basic Model indicates a weak tendancy for more concentrated industries to experience larger than average declines in RA and smaller than average declines in B. Instability in the Full Models for RA and B did not seem to be confined to a subset of the coefficients, so that separate estimates of the Full Model are presented in Table 6 for durable and nondurable good industries. (Recall that there are 17 durable good industries and 53 nondurable good industries in this sample.) All else equal, the intercept terms point to larger declines in both RA and B for industries producing nondurables. Among the durable good industries, higher concentration is associated with larger than average declines in RA but had no significant effect changes in B. Among industries producing nondurables the pattern is reversed: concentration has no effect on changes in RA, but higher concentration is associated with smaller declines in B among nondurables. Advertising intensity has a positive sign in all estimates, but coefficients and significance levels vary considerably. Higher capital intensity has a positive effect on changes in RA and B in the durables subsample but has a negative effect on both changes among industries producing nondurables.

There may be some simple explanation for the apparently complex pattern of changes shown in Tables 5 and 6. But static equilibrium versions of the DEH and the DCH do not seem likely to produce it, nor do plausible hypotheses regarding the incidence of the Phase II price controls.

VII. Conclusions and Implications

This essay has derived a set of testable implications of the DEH, the DCH, and a hybrid DEH/DCH model and employed new techniques for testing those

Appendix A

To explore the impact of the Phase II price controls on manufacturing profits, I estimated a variety of standard macroeconometric profit equations with data for the period 1955-1970. (I excluded 1971 because the Nixon price controls began with the imposition of the Phase I price freeze in August of that year. Estimates also employing post-controls (1975-1982) were less satisfactory, presumably at least in part because of the 1973-1974 oil shock and contemporaneous changes in the definitions of the manufacturing profit and sales series employed.) Both manufacturing sales and real GNP originating in manufacturing were used as measures of activity. Standard cyclical variables were employed in these experiments, along with trend terms and ΔHE, the rate of growth of average gross hourly earnings of production and non-supervisory manufacturing workers. (Unless otherwise specified, footnote 7 applies to all data series introduced in this Appendix.) Equations based on sales outperformed those based on GNP. Deletion of insignificant variables led to the following standard equation, which was then estimated using data for 1955-1970 and 1972:

$$\pi a/PQ = -.0320 - \underset{(2.34)}{.0011}\, T + \underset{(11.1)}{.1492}\, CU + \underset{(8.45)}{.0004}\, \Delta PQ - \underset{(2.69)}{.0031}\, D72 \quad (1.30) \qquad \text{(A1)}$$

$$R^2 = .973, \qquad DW = 2.33.$$

Here $\pi a/PQ$ is the ratio of pre-tax manufacturing profits to sales, T is a time trend (1954 = 1), CU is the Federal Reserve Board measure of capacity utilization in manufacturing (expressed as a fraction), ΔPQ is the percentage increase in manufacturing sales from the preceding year, and D72 is a dummy variable for 1972. Figures in parentheses are absolute values of t-statistics.

The coefficient of D72 in equation (A1) is insignificant at usual levels,

and its absolute value is only about a third of the standard deviation of the dependent variable. (In the best of the equations that also used 1975-1982 data, the coefficient of D72 had a t-statistic of -0.58.) This analysis suggests that the Phase II controls mainly affected the non-manufacturing sectors of the economy, where most of the inflation in 1972 occurred; the effects on total manufacturing profits were at any rate insignificant.

In order to see whether the Phase II controls produced a shift in the relative profitability of large and small manufacturing firms in 1972, I obtained the following variables from the IRS Statistics of Income and Sourcebook of Statistics of Income for the 20-year period 1958-1977, which is centered on the two years analyzed in the text:

RT = Pre-tax profits plus interest payments as a percentage of total assets for all manufacturing firms.

RS = Pre-tax profits plus interest payments as a percentage of total assets for manufacturing firms with assets between $500,000 and $1,000,000.[15]

dR = 100x(RT - RS).

RS gives the profitability of the smallest firms considered in our detailed analysis of 1963 and 1972. While most manufacturing firms in most years have asset values below $500,000, the aggregates used to compute RT mainly reflect the performance of firms with assets above $1,000,000. The variable dR thus gives a reasonable indicator of the average importance of large-firm profitability advantages, measured in basis points.

One might expect dR to be positive in most years, and it is in fact positive in 16 of the 20 years in the sample. It is negative in 1972, but it assumes much larger negative values in 1968, 1975, and 1977. (The values of dR in these years are as follows: 1968 = -26.7, 1972 = -4.2, 1975 = -80.1, and 1977 = -71.2.) Even if 1972 is something of an outlier, these findings do not point toward the Phase II price controls as the reason.

The behavior of dR over time is illustrated in Figure 1. In the first seven years of the sample, the mean of dR is 201.6. It is worth noting that a very large fraction of the published cross-section studies in industrial economics use data from this period. From 1965 through 1968, dR declines relatively steadily to -26.7. Thereafter its behavior is somewhat erratic. The mean of dR in the last seven years of the sample is 4.3, just over 2% of its mean in the first seven years of the sample.

In this sample, dR is negatively correlated with the rate of growth of the implicit deflator for GNP originating in manufacturing, a time trend, ΔHE, and RT. It is uncorrelated with CU and the rate of growth of real GNP originating in manufacturing, standard cyclical variables with which RT and other measures of aggregate profitability are positively correlated. (Simple correlations of these measures with RT are .62 and .27, respectively. See also equation (A1), above.) This suggests that the correlation with RT reflects accounting practice rather than economic reality.

The most satisfactory regression equation involving the variables discussed in the preceding paragraph and natural variants thereof is the following, where figures in parentheses are absolute values of t-statistics:

$$dR = \underset{(3.90)}{535.2} - \underset{(5.33)}{38.33}\,\Delta HE - \underset{(1.71)}{22.45}\,RT \qquad R^2 = .644 \quad DW = 2.26 \qquad (A2)$$

The residual for 1972 from equation (A2) is negative, but so is the residual for 1963. And 1961, 1967, and 1968 have larger negative residuals than 1972. The residual for 1971, the year in which price controls were first imposed, is also negative, but it is smaller in absolute value than the negative residuals for seven other years. When dummy variables for 1963 and 1972 are added to this equation, the coefficient of the former is a tenth of its standard error, and the coefficient of the latter is equal to 1.09 times its standard error. Once again, 1972 does not emerge as an outlier in any way that might be attributable to the operation of the Phase II price controls.

Appendix B

Consider a size class including N firms with assets between a and b, and let m be reported mean assets per firm. Let K be the assets of a typical firm in this class, assumed to be a draw from the density function g(K) with mean μ. Taking the expectation of the second-order Taylor series expansion of the right-hand side of equation (13) about the point at which all the $K_{ci} = \mu$, one obtains the asymptotic approximation employed to estimate the f_c:

$$f* = [1 + (N-1)R]/N, \quad (B1)$$

where the quantity R, which equals or exceeds unity and reflects the population dispersion in g(K), is given by

$$R = E(K^2)/\mu^2. \quad (B2)$$

Note that for N = 1, both the true f and the approximation f* equal one for any distribution, as there are no intra-class differences. As $N \to \infty$, both f and f* approach the population value R. The mechanics of estimating the population ratio R depend on whether b is known or unknown.

In the largest size class in each industry, the upper bound on firm size, b, is unknown. I deal with this by assuming that g(K) is a linear decreasing function of K and reaches zero at K = b. For such a triangular distribution it is easy to show that

$$\mu = (2a + b)/3, \quad (B3)$$

$$E(K^2) = (3a^2 + 2ab + b^2)/6. \tag{B4}$$

Setting $\mu = m$ in (B3) yields an estimate of b. Substitution into (B4) and division by m^2 then produces an estimate of R.

When b is known, I assume initially that $g(a) = \alpha$, $g(b) = \beta$, with $\alpha,\beta \geq 0$, and that g(K) is a linear function of K between these points. For such a trapezoidal distribution,

$$\mu = [\omega(2a+b) + (1-\omega)(a+2b)]/3, \tag{B5}$$

where $\omega = \alpha/(\alpha+\beta)$, and

$$E(K^2) = [6(a+b)\mu-(a^2+4ab+b^2)]/6. \tag{B6}$$

For $(2a+b)/3 \leq m \leq (a+2b)/3$, R is estimated by setting $\mu = m$ in (B6) and dividing by m^2. For $m < (2a+b)/3$, the triangular distribution of the preceding paragraph is employed. For $m > (a+2b)/3$, g(K) is assumed to be triangular with $g(b) > 0$ and $g(x) = 0$ for some $x > a$.

I experimented at some length with an alternative approach that involved assuming a lognormal distribution of firms' assets within each industry. This approach should be more efficient than that described above for industries with approximately lognormal size distributions. Parameter estimates were computed using variants of the basic maximum likelihood method for estimating the parameters of truncated lognormal distributions; see Aitcheson and Brown (1963, Sects. 9.2 and 9.6). Exact formulae for conditional expectations then produced class-specific estimates of R. For most industries this approach gave f^*'s and estimates of A and B that were very close to those produced by the method described above. In a few cases, however, involving industries with size distributions that seemed far from lognormality, this alternative approach yielded implausible estimates of the f_e. The technique described above was employed because of its apparently greater robustness to substantial departures from lognormality.

Appendix C

Consider estimating equation (21) in the text by weighted regression, dividing the j^{th} observation by $(w_j)^{1/2}$. For any set of positive w_j, a consistent estimate of $\sigma^2(\xi)$, the unknown variance of the ξ_j, is given by

$$v = [SSR - \sum_{j=1}^{M} (\sigma^2(\eta_j)/w_j)]/\sum_{j=1}^{M} (1/w_j), \qquad (C1)$$

where M is the number of industries, and SSR is the sum of squared residuals from the weighted regression. Interest attaches here to weights of the form

$$w_j = [v + \sigma^2(\eta_j)]. \qquad (C2)$$

Let D equal the coefficient of variation of the w_j, the ratio of the standard deviation of these weights to their mean. For weights given by (C2), D varies between 0 and s/m, where m is the mean of the $\sigma^2(h_j)$ and s is their standard deviation.

Now consider the function F, from [0,s/m] to the real line, defined constructively as follows. Pick a non-negative initial value of v, v^o. Use (C2) to compute the corresponding vector of weights, w^o, and directly calculate the initial value of D, D^o. Run a weighted regression with weight vector w^o and use (C1) to obtain a new value of v, which need not be non-negative. Finally, use (C2) to compute new weights and a new value of D, $D^1 \equiv F(D^o)$. Iterated weighted least squares is simply a search for a fixed point of F.

In this study it proved very efficient computationally to employ a linear approximation to the function F. OLS estimation of (21) yields F(0);

estimation with $w_j = \sigma^2(\eta_j)$ yields F(s/m). Let SSR_o be the sum of squared residuals from the first regression, and let SSR_w be the sum of squared residuals from the second. A bit of algebra establishes that if F is linear and has a fixed point, the corresponding value of v is given by

$$v* = (SSR_o/M)[(SSR_w/M)-1]/[(SSR_w/M)-1+\gamma], \text{ where} \qquad (C3)$$

$$\gamma \equiv [\sum_{j=1}^{M} \sigma^2(\eta_j)][\sum_{j=1}^{M} 1/\sigma^2(\eta_j)]/N^2. \qquad (C4)$$

Given an estimate of $\sigma^2(\xi)$ from (C3), one can use (C2) to compute weights for a third weighted regression. If a fixed point of F has been found, it follows from (C1) and (C2) that the sum of squared residuals from this regression will equal M.

This technique could not be applied to equations involving estimates of B computed using the CRS specification; because these estimates differed little relative to their standard errors, (C3) produced negative values of v*. (See the discussion of Table 2 in Section II of the text.) Instead, estimates of $\sigma^2(\xi)$ derived from the IRS specification were used for all equations involving estimates of B. (In equations involving estimates of A and RA, the CRS and IRS estimates of $\sigma^2(\xi)$ were generally nearly identical.) Otherwise, the approach described above either yielded an approximate fixed point directly or made it easy to obtain such a point with one additional iteration.

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Footnotes

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1. There is important common ground, however. Under the DEH, one should attempt to understand the obstacles to diffusion of knowledge that must be present if intra-industry efficiency differences are to persist. Under the DCH, obstacles of this sort are a subset of what Caves and Porter (1977) have termed "barriers to mobility".

2. The interesting work of Peltzman (1977, 1979) and Lustgarten (1979, 1984) on the relation between changes in concentration and improvements in productivity (see also Scherer (1979)) was designed to test the DEH in a rather different fashion. The main finding of these studies is that large increases or decreases in concentration are associated with above-average increases in productivity. While this is certainly consistent with the DEH, it is not inconsistent with the DCH. After all, one does not expect to see major changes in seller concentration under plausible variants of either hypothesis except in response to major alterations in competitive relationships. Major innovations, which are likely to be followed by an increase in the innovator's market share under almost any plausible hypothesis about market behavior, are an important source of such alterations. Innovations by market leaders should thus tend to be associated with increases in both concentration and industry productivity under either the DEH or the DCH. Innovations by new entrants or small firms should tend to lower concentration while raising average productivity. Industries in which little innovation occurs are likely to exhibit stable concentration along with below-average gains in productivity. (Note also that Peltzman (1977) finds evidence in support of the DCH assertion that increases in concentration lead to increases in price -- cost margins.)

3. This model has been used by Clarke and Davies (1982) to analyze the determinants of equilibrium concentration in the presence of efficiency differences; see also Long (1982) and Clarke, Davies, and Waterson (1984) for further development and empirical applications. The more complex DEH models of Jovanovic (1982), Lippman and Rumelt (1982), and Telser (1982) stress the dynamic mechanisms determining N and the c_i rather than equilibrium and do not lend themselves readily to use in empirical analysis. In the Cournot model in the text, the larger is N, the smaller the differences among the c_i that are consistent with non-negative market shares. If the market demand curve is $P = a - bQ$, for instance, non-negative shares require $c_i \leq [a + (N-1)\bar{c}_i]/N$ for all i, where $\bar{c}_i$ is the average of all c's except c_i.

4. To see this last point, suppose, in the spirit of the more complex DEH models cited in footnote 3, that in order to enter any particular

industry, firms must spend some industry-specific amount on research and development. This allows them in effect to draw a value of c from the industry-specific distribution of possible unit costs. Firms that draw a high c will elect not to start up production, while lucky firms with low c's will enter and earn positive rents on their luck. Depending on the pattern of differences in R&D costs and distributions of possible c's across industries, one might expect industries that attract relatively few firms to draw costs or to enter (and are thus concentrated ex post) to produce substantial rents to all those lucky enough to be able to operate profitably.

5. But see Spiller and Favaro (1984) for an apparent counterexample.

6. On the necessity of using substantial inter-period gaps in the analysis of structural change, see, for instance, the discussion of concentration changes by Caves and Porter (1980, esp. p. 9). It should be noted that Demsetz (1974) has argued that 1963 is an outlier that is somewhat less consistent with the DEH than surrounding years, though the statistical analysis that supports his argument is suspect because it is based on absolute firm size rather than market share. (See Daskin (1983) for a general discussion of this issue.)

7. All data used in this and the next paragraph come from the 1984 Economic Report of the President. Growth rates reported for any year T are are the annual rates of growth experienced between (T-1) and (T+1). This procedure better reflects growth during the second half of each year than the usual approach of reporting changes from the previous year.

8. To investigate the intertemporal stability of R and CONC, equations of the form $[X(1972)-X(1963)] = \gamma[\alpha - X(1963)]$ were estimated for each variable. (More complex specifications, in which γ, α, or both were functions of other variables, generally did not perform noticeably better.) Estimates of γ indicate a half-life of deviations of R from the mean (= $9.0 \times [\ln(0.5)/\ln(1-\gamma)]$, the equation's median lag in years) of 8.8 years, with an asymptotic standard error of 2.1 years. CONC also tends to regress toward the mean in these data, but the process seems much slower; the estimated half-life of deviations from the mean is 19.9 years, with an asymptotic standard error of 6.6 years. It is unclear exactly how to interpret this difference in adjustment speeds, especially in light of the differences in patterns of profitability between the 1963 and 1972 samples that are discussed in Sections IV - VI. The implications of this difference for choice between the DEH and the DCH are in any case not obvious.

9. Previous studies using IRS data from the early 1960's (e.g., Comanor and Wilson (1974) and Porter (1979)) typically have many more consumer goods industries. A good deal of the difference is accounted for by aggregation from 1963 to 1972 industries and the deletion of some of the latter. But a detailed comparison reveals that a number of industries generally classified as producing mainly consumer goods in earlier studies in fact generate the majority of their value-added in four-digit industries that Ornstein (1977, Appendix B) classifies as producer goods industries. Examples include IRS minor industries 2850 (Paints and allied products), 3010 (Rubber products), and 3420 (Cutlery, hand tools, and hardware).

10. Since R is known, the sampling variance of RA is equal to the square of the standard error of A. Similarly, since 1963 and 1972 can be treated as providing independent observations, sampling variances of changes in parameters between these two years are sums of the corresponding squared standard errors.

11. There is, of course, no guarantee that the ϵ_j are homoscedastic in fact. In particular, differences in the numbers and relative sizes of economic markets included in different IRS industries will induce heteroscedasticity, as will various differences among the basic markets themselves. As is usual in applied work, homoscedasticity is assumed here simply because it is unclear how to obtain plausible estimates of the pattern of heteroscedasticity.

12. The equations involving R (Table 3) and ΔR (Table 5) showed signs of coefficient instability between consumer and producer goods industries. But since these equations play no direct role in our comparisons of the DEH and the DCH, the sources of this instability were not explored.

13. A number of authors including Ravenscraft (1983) and Schmalensee (1985) have found highly significant relations between share and profitability in models in which the coefficient of share is constrained to be the same across industries. (See Scherer (1980, ch. 9) for a discussion of earlier work of this sort.) The tests of coefficient equality in Table 2 indicate that this constraint is highly suspect. Profitability is apparently strongly related to market share in _some_ industries, but not in all.

14. Aggregate time series for durable and nondurable goods industries do not reveal differences substantial enough to suggest obvious explanations based on either standard cyclical arguments or the findings reported in Appendix A. Real GNP growth (computed as per footnote 7) in 1963 was 8.6% for durables and 11.4% for nondurables. The 1972 figures were 6.4% and 9.0%. The corresponding figures for growth in the implicit GNP deflator were -1.2% and -0.6% for 1963 and 1.2% and -0.9% for 1972. Rates of growth of average hourly gross earnings per production or nonsupervisory worker (from _Business Statistics: 1982_) were 2.7% for both groups of industries in 1963, 7.0% for durables in 1972, and 6.4% for nondurables in 1972. (All these series are based on more precise divisions between durable and nondurable goods industries than could be employed with IRS data.) It has been suggested to me that an explanation of the durable/nondurable instability could be constructed out of cross-sectional differences in the incidence of unionization, coupled with changes in union behavior over time between 1963 and 1972. A serious attempt to construct such an explanation would carry me far beyond the bounds of the present study, however.

15. Interest payments by manufacturing firms in this size class were not published for 1962. A quadratic fit to the ratio of interest payments by these firms to interest payments by all manufacturing firms over the periods 1958-1961 and 1963-1970 had an R^2 of .975 and a Durbin-Watson of 1.76. This equation was used to estimate interest payments by manufacturing firms in this size class in 1962.

Table 1

Main Industry-Level Variables

Variable	1963 Mean	1963 Std. Dev.	1972 Mean	1972 Std. Dev.	1963-1972 Correlation
R	.1028	.0352	.0995	.0299	.5802
CONC	.3353	.1572	.3606	.1511	.7602
AD/K	.0270	.0326	.0197	.0226	.8302
PQ/K	1.5837	.6310	1.4086	.4502	.8764

Note. -- See text for sources and definitions.

Table 2

Summary Statistics from Intra-Industry Regressions

	Coefficient/Specification					
	A/CRS	A/IRS	RA/CRS	RA/IRS	B/CRS	B/IRS
Statistics for 1963						
Sample Coefficients						
Sample Mean	.0910	.0955	.0118	.0077	.4823	.1747
Standard Deviation	.0322	.0296	.0416	.0322	1.7599	.9397
Number Positive	69	70	39	40	42	40
Mean t-Statistic	11.2	7.27	1.27	0.64	0.31	0.89
Mean |t|-Statistic	11.2	7.27	3.35	1.68	0.76	2.29
Population Estimates						
Estimated Mean	.0919	.0929	.0114	.0077	*	.1359
Standard Deviation	.0275	.0220	.0381	.0254	*	.4391
Probability Levels						
Coefficients = 0	<.01	<.01	<.01	<.01	.18	<.01
Coefficients Equal	<.01	<.01	<.01	<.01	.29	<.01
Population Mean = 0	<.01	<.01	.02	.03	*	.03
Statistics for 1972						
Sample Coefficients						
Sample Mean	.1118	.1079	-.0123	-.0084	-.3554	-.3532
Standard Deviation	.0253	.0273	.0350	.0325	.8492	1.0839
Number Positive	70	70	19	24	23	24
Mean t-Statistic	18.0	12.8	-2.00	-0.99	-0.32	-1.18
Mean |t|-Statistic	18.0	12.8	4.31	2.83	0.83	3.45
Population Estimates						
Estimated Mean	.1121	.1077	-.1249	-.0079	*	-.2586
Standard Deviation	.0228	.0242	.0332	.0300	*	1.0119
Probability Levels						
Coefficients = 0	<.01	<.01	<.01	<.01	.08	<.01
Coefficients Equal	<.01	<.01	<.01	<.01	.08	<.01
Population Mean = 0	<.01	<.01	<.01	.04	*	.04
Changes, 1963 to 1972						
Sample Coefficients						
Sample Mean	.0208	.0128	-.0241	-.0162	-.8377	-.5279
Standard Deviation	.0323	.0336	.0372	.0330	1.8832	1.5400
Number Positive	53	49	15	20	18	19
Mean t-Statistic	1.86	0.87	-2.06	-1.09	-0.45	-1.44
Mean |t|-Statistic	2.34	1.50	2.04	1.69	0.67	2.29
Population Estimates						
Estimated Mean	.0211	.0135	-.0245	-.0170	*	-.3731
Standard Deviation	.0253	.0241	.0314	.0289	*	1.2373
Probability Levels						
Coefficients = 0	<.01	<.01	<.01	<.01	.97	<.01
Coefficients Equal	<.01	<.01	<.01	<.01	.99	<.01
Population Mean = 0	<.01	<.01	<.01	<.01	*	.02

*Could not be computed because estimated population variance was negative.

Table 3

Results of Inter-Industry Weighted Regressions

	Dependent Variable									
	R	A/Pooled	A/CRS	A/IRS	B/Pooled	B/CRS	B/IRS	RA/Pooled	RA/CRS	RA/IRS
Basic Model										
1963:										
CONC	.0631	.0344	.0360	.0326	-.1535	.1675	-.3425	.0367	.0316	.0399
	(2.42)	(2.23)	(1.72)	(1.42)	(0.44)	(0.34)	(0.68)	(1.94)	(1.05)	(1.61)
R^2-Wtd.	-	.035	.042	.029	.001	.002	.007	.026	.016	.037
-Raw	.079	.063	.082	.037	-.011	-.044	.006	-.011	.017	.007
1972:										
CONC	-.0131	-.0214	-.0165	-.0266	.7755	.5339	.9172	.0115	.0043	.0175
	(0.55)	(1.48)	(0.82)	(1.27)	(1.97)	(1.08)	(1.52)	(0.61)	(0.15)	(0.68)
R^2-Wtd.	-	.016	.010	.023	.027	.017	.033	.003	.0003	.007
-Raw	.044	.018	.017	.018	.024	-.007	.048	.002	.001	.001
Prob. Level: Slope Equal	.08	.01	.07	.06	.11	.83	.15	.34	.51	.53
Full Model										
1963:										
CONC	.0463	.0267	.0317	.0208	-.1865	.1948	-.3804	.0278	.0215	.0331
	(1.97)	(1.68)	(1.44)	(0.91)	(0.54)	(0.40)	(0.75)	(1.47)	(0.76)	(1.29)
AD/K	.5438	.1632	.0154	.3281	3.1304	5.3232	2.0313	.3579	.5267	.2178
	(4.85)	(2.15)	(0.15)	(2.90)	(2.06)	(2.52)	(0.93)	(3.99)	(4.03)	(1.75)
PQ/K	-.0094	-.0038	-.0036	-.0044	-.0183	-.0068	-.0191	-.0040	-.0055	-.0028
	(1.58)	(1.10)	(0.73)	(0.90)	(0.25)	(0.07)	(0.16)	(0.94)	(0.82)	(0.50)
R^2-Wtd.	-	.068	.049	.138	.032	.091	.020	.131	.214	.080
-Raw	.324	.089	.079	.154	-.103	-.055	.012	.097	.150	.059
1972:										
CONC	-.0211	-.0330	-.0325	-.0332	.7937	.7131	.8478	.0124	.0001	.0156
	(0.96)	(2.12)	(1.53)	(1.45)	(2.03)	(1.53)	(1.39)	(0.69)	(0.35)	(0.61)
AD/K	.7101	.0999	.0425	.1702	8.7236	8.4427	8.8881	.6039	.6657	.5445
	(5.05)	(1.04)	(0.32)	(1.19)	(3.74)	(3.16)	(2.40)	(5.35)	(4.14)	(3.39)
PQ/K	.0031	-.0099	-.0154	-.0035	.1673	.2966	.1011	.0111	.0165	.0062
	(0.42)	(1.87)	(2.14)	(0.45)	(1.27)	(1.85)	(0.50)	(1.80)	(1.89)	(0.70)
R^2-Wtd.	-	.043	.074	.044	.144	.215	.123	.222	.280	.180
-Raw	.303	.034	.055	.033	.112	.163	.097	.208	.253	.168
Prob. Level: Slopes Equal	<.01	.04	.17	.23	.03	.26	.19	.02	.11	.21

Note. -- Figures in parentheses are absolute values of associated t-statistics.

Table 4

Summary of Theoretical Predictions and Empirical Findings

Line		Parameter Value*			Correlation with CONC†		
		A	B	RA	A	B	RA
1.	Predictions: DEH	>0	>0	>0	0	0	>0
2.	Predictions: DCH	>0	Both noise, with $\mu \simeq 0$		≥0	0	≥0
3.	Predictions: DEH/DCH	>0	>0	>0	≤0	>0	>0
4.	Findings: 1963 (μ, σ)	>0	59% >0 (.14, .44)	56% >0 (.01, .03)	1.37	-0.17	1.18
5.	Findings: 1972 (μ, σ)	>0	66% <0 (-.26, 1.01)	69% <0 (-.07, .03)	-1.27	1.38	0.45

Note.-Predictions are from Section II; Findings summarize Tables 2 and 3. In Line 2, either A or RA or both should be positively correlated with CONC. Line 3 assumes $\gamma \geq 0$.

*Values of μ and σ are IRS population estimates for B and the average of the CRS and IRS population estimates for RA. Percentages positive or negative are computed using estimates under both of the specifications for B and RA.

†Figures shown in Lines 4 and 5 are averages of the four relevant t-statistics from Table 3.

Table 5

Correlates of 1963-1972 Changes in Average and Estimated Zero-Share Profitability*

	Dependent Variable			
	ΔR	ΔA/Pooled	ΔA/CRS	ΔA/IRS
Basic Model				
$\overline{\text{CONC}}$	-.0905	-.0518	-.0500	-.0573
	(3.96)	(2.88)	(2.02)	(2.02)
R^2-Wtd.	-	.057	.057	.057
-Raw	.187	.068	.090	.049
Full Model				
DDUR	-.0201	-.0508	-.0517	-.0531
	(0.55)	(1.74)	(1.27)	(1.26)
DNDR	.0186	.0445	.0560	.0325
	(1.20)	(4.20)	(3.82)	(2.12)
$\overline{\text{CONC}}$	-.0801	-.0355	-.0411	-.0270
	(3.15)	(1.89)	(1.59)	(0.99)
$\overline{\text{AD/K}}$	-.0429	-.2797	-.1585	-.4562
	(0.32)	(2.89)	(1.25)	(3.07)
DDUR*$\overline{\text{PQ/K}}$	.0351	.0615	.0642	.0607
	(1.42)	(3.05)	(2.27)	(2.11)
DNDR*$\overline{\text{PQ/K}}$	.0044	-.0046	-.0098	.0009
	(0.61)	(0.99)	(1.54)	(0.13)
R^2-Wtd.	-	.179	.190	.219
-Raw	.217	.169	.168	.197
P-Levels:				
CNST & $\overline{\text{PQ/K}}$ Equal	.45	<.01	.03	.11
CONC & AD/K Equal	.17	.38	.24	.40
All Coeffs Equal	.27	<.01	.04	.18

*Figures in parentheses are absolute values of t-statistics.

Table 6

Correlates of Estimated 1963-1972 Changes in
Large Firm vs. Small Firm Differentials

	Dependent Variable					
	ΔRA/Pooled	ΔRA/CRS	ΔRA/IRS	ΔB/Pooled	ΔB/CRS	ΔB/IRS
Basic Model						
$\overline{CONC}$	-.0455	-.0439	-.0472	.9003	.5074	1.078
	(2.27)	(1.46)	(1.75)	(2.00)	(0.86)	(1.62)
R^2-Wtd.	.036	.031	.043	.028	.011	.037
-Raw	.010	-.002	.026	.009	-.034	.039
Full Model						
Durables:						
CNST	.0934	.0657	.1152	2.936	2.339	3.118
	(2.74)	(1.24)	(2.34)	(2.82)	(1.33)	(2.02)
$\overline{CONC}$	-.1394	-.1087	-.1638	-1.305	-1.059	-1.428
	(4.14)	(2.07)	(3.40)	(1.23)	(0.61)	(0.90)
$\overline{AD/K}$	1.824	2.026	1.690	21.40	20.67	21.92
	(3.90)	(2.95)	(2.38)	(1.92)	(1.10)	(1.34)
$\overline{PQ/K}$	-.0642	-.0579	-.0694	-2.158	-1.827	-2.245
	(3.19)	(1.87)	(2.38)	(3.13)	(1.44)	(2.25)
R^2-Wtd.	.572	.552	.617	.305	.245	.326
-Raw	.355	.328	.424	.286	.208	.327
Nondurables:						
CNST	-.0377	-.0492	-.0291	-1.272	-1.362	-1.257
	(2.88)	(2.47)	(1.68)	(4.54)	(3.44)	(3.05)
$\overline{CONC}$	-.0079	-.0055	-.0118	1.141	1.119	1.186
	(0.31)	(0.15)	(0.35)	(2.33)	(1.78)	(1.60)
$\overline{AD/K}$	.1425	.0032	.2845	5.377	4.140	5.943
	(1.28)	(0.02)	(1.84)	(2.58)	(1.54)	(1.91)
$\overline{PQ/K}$	.0105	.0161	.0062	.1710	.2262	.1508
	(1.97)	(2.00)	(0.88)	(1.59)	(1.67)	(0.92)
R^2-Wtd.	.070	.089	.100	.144	.142	.150
-Raw	.053	.053	.088	.042	.030	.063
P-Level:						
Slopes =	<.01	.01	.01	.05	.07	.05
All Coeffs =	<.01	.01	.01	<.01	.06	.03

*Figures in parentheses are absolute values of t-statistics.

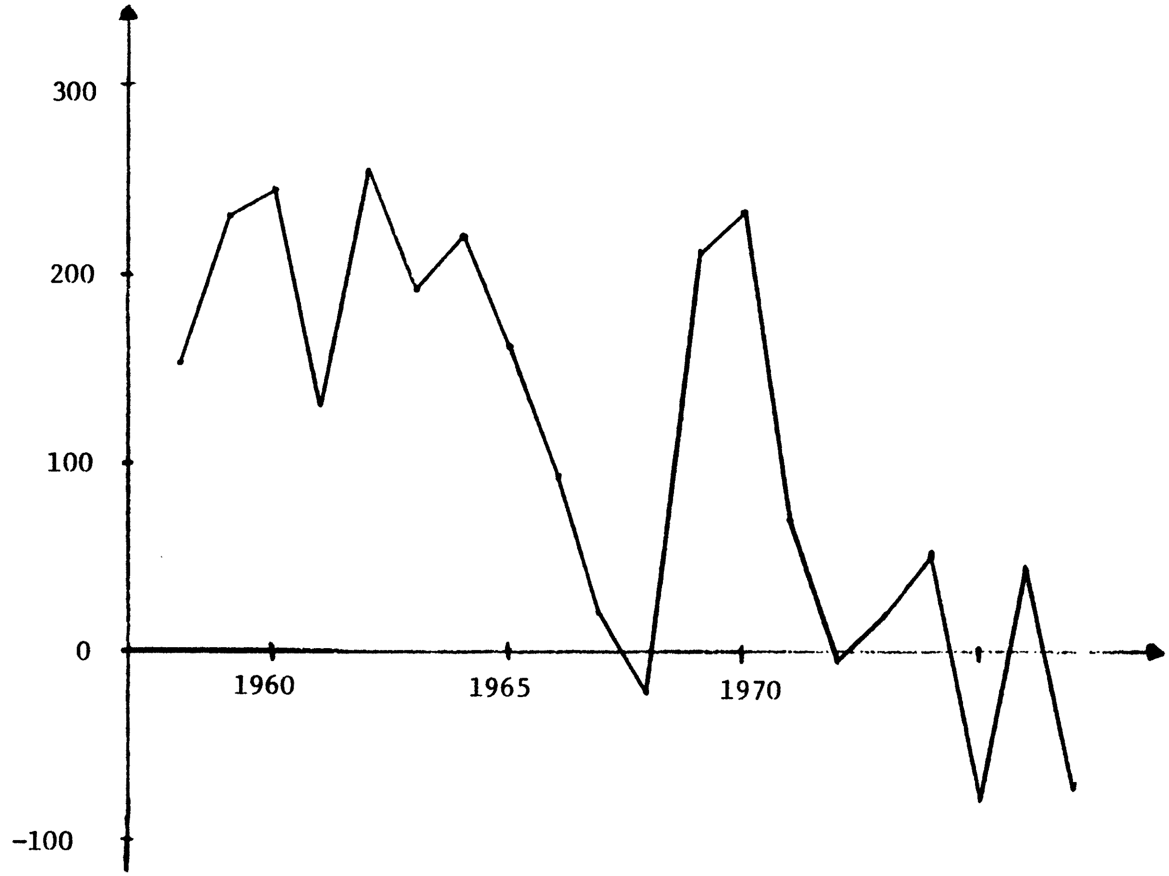

Fig. 1. - Movements of dR Over Time