William J. Lynk
Lexecon Inc.

Information, Advertising, and the Structure of the Market*

This paper suggests that ignorance has a systematic effect of increasing the market shares of larger brands and reducing those of smaller brands, both relative to a costless information environment. Therefore, cheaper information has an effect of making sellers' shares more equal. To determine whether advertising acts in a manner that is consistent with increases or decreases in this information, the introduction of commercial television in the 1950s provides an appropriate test. The evidence suggests that in markets where the message transmission advantages of television were most prominent—where the real costs of advertising fell the most—the largest sellers systematically lost market share to the smaller.

I. Introduction

The thesis of this paper is that consumer information influences the size distribution of competing sellers' market shares in a particular manner. By measuring the response of appropriate measures of the distribution of shares to a reduction in the real cost of advertising messages (and thus to an increase in their rate of transmission), it is, in principle, possible to infer whether advertising messages add to or subtract from the stock of information consumers find useful in making product decisions.

The principal justification for the research presented here is simply that much of the previous work in this area fails to shed much light on the basic nature of advertising. Statistical associations between, say, the advertising-to-sales ratio and the four-firm concentration ratio are found by some researchers and disputed by others, but there is, typically, residual ambiguity

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in the interpretation of the findings.[1] While a systematic correlation between the advertising-to-sales ratio and the concentration ratio may well be interesting as an empirical regularity, it does not by itself offer useful advice on either the nature of advertising or on the underlying economic process generating the relationship. Both the theory and the methodology of the present paper are designed to address those issues more directly.

II. A Model of Consumer Information and Sampling

Free Information

I assume initially, in a reversion to pre-1961 days, instant and complete knowledge of consumers about the products, brands, and prices offered in the market. This will help define the nature of market equilibrium in such an environment for purposes of comparison when information is not free.

Disparity in firm size. That competing firms in the same product market vary in their sales volume is an empirical observation sufficiently commonplace to need no defense. The most obvious theoretical basis for this regularity is simply the recognition of the existence of indivisible specialized resources. The existence of such resources gives rise to a *distribution* of firms' long-run marginal cost curves, rather than a single representative relation, replicable by many

1. Comanor and Wilson (1967), for example, while finding that advertising and concentration are unrelated, hold that advertising leads nevertheless to extraordinary profits. They maintain that ". . . advertising expenditures . . . are both a symptom and a source of differentiation," and that it is the product differentiation which leads to the profits by decreasing firms' elasticities of demand and by creating barriers to entry. The latter are said to arise from: (*a*) economies of scale in advertising, (*b*) increased capital requirements (presumably accompanied by imperfections in the capital market), and (*c*) an increase in entry costs due to increased "buyer inertia and loyalty" as an "effect of advertising." Bain (1959) and Mann, Henning, and Meehan (1967), on the other hand, find a positive relationship between "product differentiation" and concentration, the former using a subjective classification of differentiation levels and the latter using "traceable advertising expenditures as a percentage of sales revenues" as a proxy. Stonebraker (1976) contends that large firms' advertising increases the risk of entry for small firms and thus serves as a true barrier to entry (in the differential cost sense) so that "successful firms are thereby insulated from new competition and can maintain excessive profits in the long run." Benham (1972) and Steiner (1973) find, respectively, that advertising in general and television advertising in particular, respectively, tend to lower product prices in the markets they examined. Brozen (1974) and Nelson (1974, 1975) have analyzed the forces that would associate contemporaneous growth of leading firms' profitability, advertising, and sales (and thus the industry's concentration), while noting that if advertising permits easier new entry, the overall effect on industry concentration is ambiguous. This tends to support Telser's (1964) conclusion that advertising increases the entry of new competition and that the advertising-to-sales ratio is not significantly correlated with the four-firm concentration ratio. Later findings by Telser (1975) in the pharmaceutical industry support the earlier conclusions; higher advertising-to-sales ratios are associated with more rapid entry and, in fact, with lower concentration.

or any, between costs and output. This is the approach taken by Demsetz (1973), who states: "The cost advantage that gives rise to increased concentration may be reflected in scale economies or in downward shifts in positively sloped marginal cost curves . . ." and "It may well be that superior competitive performance is unique to the firm, viewed as a team. . . ." Moreover, this indivisibility permits the disparity in size to persist in the long run.

A similar explanation turns on chance; specifically, on random outcomes of uncertain investments. In an article principally concerned with interfirm profitability differences, Mancke (1974) demonstrated by a simulation study that, even in the absence of scale economies, monopoly power, or inherent differences among firms, stochastic returns on investments are sufficient to generate unequal firm sizes over time, even when firms are initially of equal size. Not surprisingly, this also held true when some firms were likelier than others to make successful investments; this process and Demsetz's explanation are closely related.

None of the logic employed in these arguments requires the existence of ignorance or costly information, and on this basis it will be concluded that the natural state of the structure of the market in the absence of information costs is one of skewed or unequal shares.

Variation in consumer demand. Just as firms differ in the nature of their capacity to supply a given product, so too do consumers differ in their demands for the product. Some, obviously, vary in the quantity of the product they purchase at given prices. Less obviously, however, consumers also vary in their elasticities of demand with respect to product attributes other than price. Both of these classes of differences in purchasing preferences derive from differences in consumers' uses for the product; the latter class generates what is sometimes called the demand for product variety, a concept explored more fully by Lancaster (1966) and Rosen (1974).

This theme is discussed further by Nelson (1975), who notes that ". . . the variance of brands in the qualities about which consumers disagree . . . is 'good' product differentiation rather than 'bad' differentiation because it allows consumers to obtain qualities more closely related to their tastes." Nelson distinguishes this from "bad" differentiation, or variance in qualities about which all consumers agree. The only quality which appears to obviously meet this latter criterion is price. Given the present assumption of perfect information, the latter type of variation cannot exist, and all variation is of the former ("good") type. It is sufficient to conclude here that there will exist a demand for differentiation of the output of the product and, if this differentiation is supplied, consumers will in general not be indifferent to which variant of the product they purchase.

Market equilibrium. To summarize the characteristics of the market in the free information case, it was first noted that the market shares of firms and, by extension, brands will, in general, be unequal in any given product market and will be so for reasons unrelated to conditions of disequilibrium or informational issues. It was also indicated that, because of consumer demand for product variety, the brands offered will not be identical in their specifications but rather will be produced to accommodate differences among consumers in their uses for the product. The picture that emerges is one of a continuous distribution of consumers' demands over several dimensions, each dimension corresponding to an attribute of the product, with the brands offered for sale distributed discretely over the same set of dimensions in such a way as to approximate the consumers' distribution. Consumers are not indifferent among competing brands and purchase their most preferred brands. Brands which are relatively "superior" are the most preferred brands of relatively more consumers and thus have higher market shares. With rents to the responsible superior factors capitalized, firms earn no economic profits.

Costly Information

In this section, all of the assumptions of the previous section are retained except one: information is assumed here to be costly. As Stigler (1961) has shown, this implies that consumers will tend to be ignorant of the full range of prices offered in a product market. More generally, they will be ignorant of the extent of market offerings in all attribute dimensions. It is upon this general aspect—the search of consumers for more preferred brands and the effects of this on the structure of the market—that this section is focused.

Consumer sampling. Due to the depreciation of the accuracy of product knowledge in a nonstatic economy, the consumer is continually engaged in the acquisition of information of one form or another to maintain his desired stock of such knowledge. It may be useful to decompose the consumer's informational relationship with any given product market into two stages. During the first stage, the consumer samples a different brand of the product on each purchase; during the second he habitually purchases one brand for his consumption. The combined process is one of sequential search. (See Kohn and Shavell [1974] for a more detailed treatment.) The optimization problem is to divide this period into two subperiods, one of consumption plus information acquisition and the other of consumption aided by the previously acquired information.

In general, the marginal value of the sampling process declines with additional samples for at least two reasons. First, since the expected utility of the maximal brand encountered in the sampled set rises with the number of samples, the probability of finding a better brand on an additional sample falls. And second, since the consumption horizon is finite, the number of future purchases that will benefit from the additional information produced at the sampling stage falls with each sampling purchase. The marginal cost of sampling rises for a similar reason; it is the opportunity cost of forgoing on a given purchase the utility of the best brand known in favor of the expected utility of the next brand sampled, and with each sample the former quantity tends to rise. In figure 1, the expected optimal sample size is N_1 and the expected value of the sampling activity is $\int_0^{N_1} EMV_s - EMC_s\, dN$, where EMV_s and EMC_s are the expected marginal value and cost, respectively, of sampling.

The configuration of EMV_s and EMC_s is dependent upon the order or selection rule followed during sampling, which in turn depends upon the type of information available to the consumer for guidance in his search. The consumer confronts a universe of B brands from which he will sample. Ex ante, he has some prior probability estimate of the relative utility he will receive from each offered brand. If he is able to

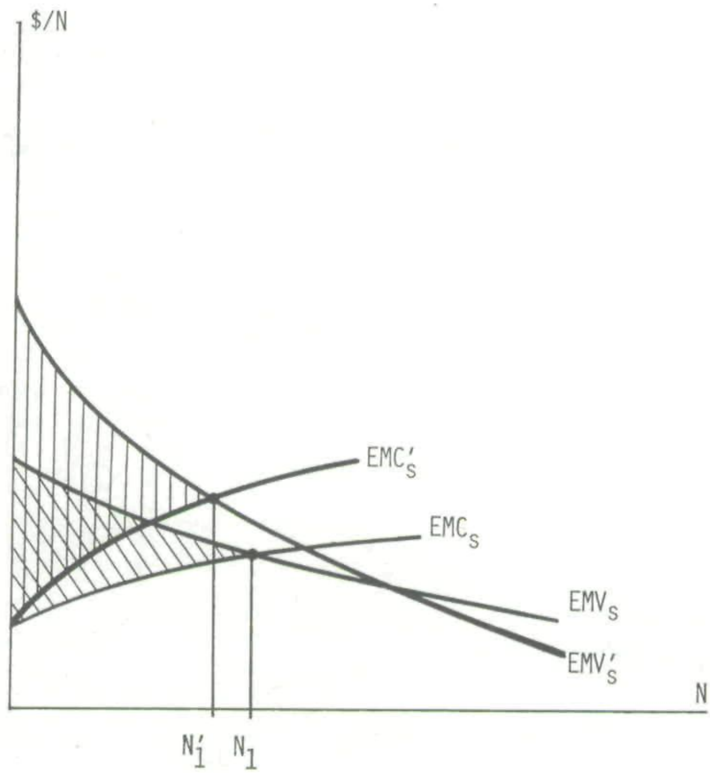

FIG. 1.—The marginal value and cost of sampling

improve the precision of these estimated priors, then initial samples will have relatively higher value and later samples relatively lower value. The effect of any such information is an improvement in the net value of the sampling process; it is represented in figure 1 as a shift to EMV'_s and EMC'_s, resulting in a sample size of N'_1, with $\int_0^{N'_1} EMV'_s - EMC'_s \, dN > \int_0^{N_1} EMV_s - EMC_s \, dN$.[2] Information will be produced by consumers about the brands' prior probabilities of satisfaction until, at the margin, the cost of additional information equals the expected increase in the net value of the sampling process.

When the consumer has literally no information or guidance on his selection of brands, he attaches an equal expected utility to each of the brands of the product of which he is aware and samples randomly. In this context, however, "random sampling" does not carry the implication that a sampling consumer has an equal probability of sampling each of the B brands offered for sale. That is, define $p_i(s_1)$ as the probability that a randomly sampling consumer will select the ith brand on the first sampling purchase. Then in general $p_i(s_1) \neq p_j(s_1)$ for $i \neq j$. The reason, of course, is that brands in general differ in their market shares, and point-of-sale inventory across and within retail outlets varies directly with market share. If by random sampling we mean that a sampling consumer has an equal chance of selecting any item out of the total point-of-sale inventory, then any brand's $p_i(s_1)$ will be proportional to its share of that total inventory for all B brands, defining

$$p_i(s_1) = I_i / \sum_j^B I_j, \; j = 1, 2, \ldots, i, \ldots, B. \tag{1}$$

If we assume that in a given market area each brand's total point-of-sale inventory is proportional to its sales volume,[3] then we have the result that under random sampling each competing brand's probability of being selected on a given consumer's initial sample is equal to its market share, or

$$p_i(s_1) = ms_i. \tag{2}$$

The result in (2) will be used below to demonstrate the effects of consumer ignorance on the equilibrium distribution of market shares. It will be shown that the more ignorance prevails among consumers new to the market—and hence the greater their reliance on sampling—the more inequality will exist in the market shares of sellers.

2. Note that $N_1 = B$ amounts to a complete census of all offerings, and that $\int_0^B EMV_s dN = \int_0^B EMV'_s dN$. Note also that either $N'_1 < N_1$ or $N'_1 > N_1$ is possible, depending on the magnitude of EMC_s relative to EMV_s and on the size of the information-induced shift.

3. Anderson (1979) reports that, empirically, the elasticity of retail shelf space (in terms of brands' shares of the total space for the product class) with respect to brand market shares exceeds unity. This suggests that inventory may be more than proportional to sales volume, a modification which would strengthen the implications of the model developed below.

In an extension of the model,[4] it is easy to show that the option of seeking advice or guidance from experienced consumers—as an alternative to purely random sampling—simply adds a "bias," of a sort, in favor of large brands' chances of selection. The obvious path to this guidance is simply to ask one or more acquaintances what brand they use. The probability that a randomly selected, sampling consumer will receive a recommendation for brand i is simply ms_i, that is, the proportion of his potential acquaintances who use brand i. This advice alters the selection probabilities in favor of brands with higher market shares.

This "large-brand advantage" will increase as the number of inquiries made by consumers increases. For a given distribution of market shares, imagine that an ignorant consumer makes only one inquiry (of a habitually purchasing, experienced buyer), and that he follows the advice he receives for making his initial purchase. Then the probability that he will first sample brand i is ms_i, for brand j it is ms_j, and so on. The sampling probabilities are unchanged from the pure random sampling case. Alternatively, suppose that he canvasses all current consumers of the product in determining his sampling order and samples in descending order of the number of recommendations he receives. Then the highest-share brand will be sampled first with probability 1.0, the second-ranked brand will be sampled second (if there is a second sample) with probability 1.0, and so on. Since the marginal value of requesting advice declines with additional inquiries, while its marginal cost plausibly rises, an intermediate solution would generally be expected.

Figure 2 illustrates, for some assumed share structure, the effect of increasing the number of presample inquiries on brands' probabilities of initial selection (where subscripts indicate the brand's rank, I is the number of inquiries, B is the number of brands, and M is the number of experienced consumers in the market). Additional inquiries always raise the largest brand's chance of selection and lower the smallest brand's. Intermediate brands may be favored or disfavored by initial increases in presample consumer inquiry, but at some level additional inquiry reduces all but the largest brand's $p_i(s_1)$.

Expanding the consumer's expected sample size, on the other hand, increases the probability that a brand will be selected relatively more for a low-share than a high-share brand. (In the limit, obviously, a complete census of all brands requires that small as well as large brands are sampled with probability 1.) Figure 3 illustrates the effect of sample size N on the relationship between market share and the probability of being included in the consumer's (random) sample. The relationship holds qualitatively for sampling both with and without replacement. For any distribution of market shares (taken as given, for the moment),

4. See Lynk (1978) for additional details.

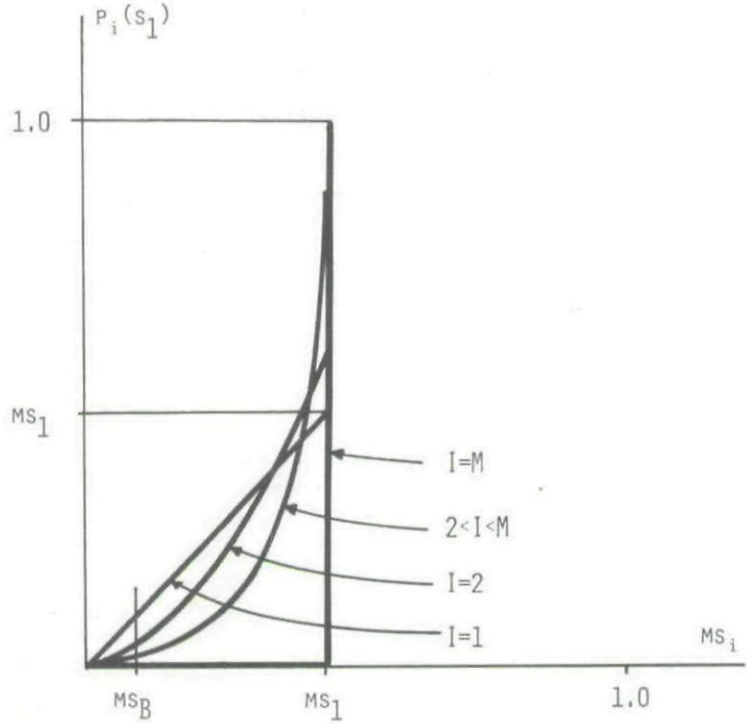

FIG. 2.—The effect of presample advice on the probability of sample selection.

increasing N is seen to cause a proportionately greater improvement in small than in large brands' chances of being sampled.

Sampling and market structure. With this in mind, it is now possible to examine the effect of incomplete information on the equilibrium distribution of market shares. The approach will be to examine a hypothetical market under conditions of perfect information and then to drop that assumption in order to observe any shifting in the pattern of shares due to ignorance.

The market has B brands, each with an observed share ms_i of the market's consumers. The vector of market shares is expressed as $\mathbf{ms} = (ms_1, ms_2, \ldots, ms_B)$. Define $\mathbf{ms}^* = (ms_1^*, ms_2^*, \ldots, ms_B^*)$ as the distribution of consumer preferences for the B brands; that is, the fraction of the market's consumers who absolutely prefer brand 1 to all $B - 1$ others, of those who prefer brand 2, and so on. Under conditions of perfect or costless information, the one-to-one correspondence of the two distributions $\mathbf{ms} = \mathbf{ms}^*$ would be observed; the realized market share for each brand would equal the underlying proportion of con-

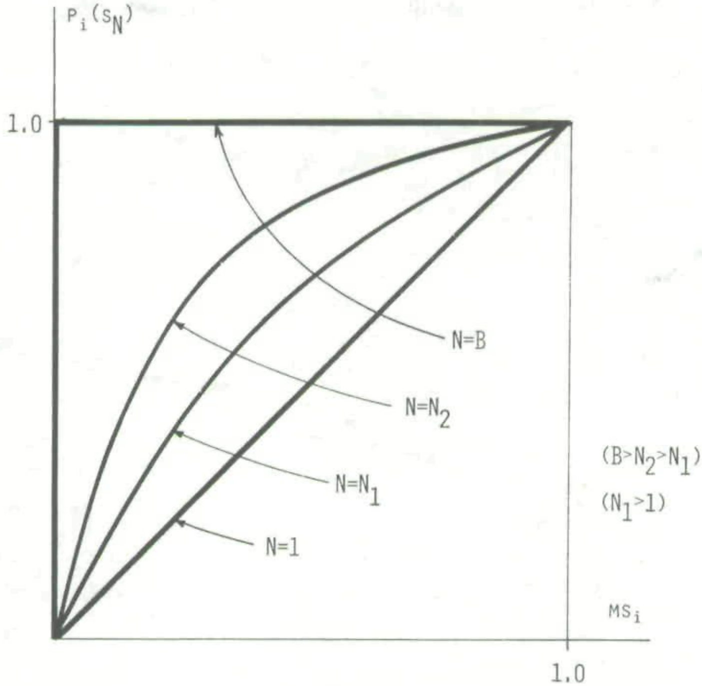

FIG. 3.—The effect of sample size on the probability of sample selection

sumers who most prefer that brand. In each period of time consumer turnover is observed. I assume that the distribution of consumer tastes, **ms***, is stable over time, so that the fraction of the "new" perfectly informed buyers preferring brand i over the other $B - 1$ offerings is constant each period. Thus, market shares are also stable over time.

From this point of equilibrium, drop the free information assumption and assume instead that only some fraction $k(0 < k < 1)$ of incoming consumers are "fully informed." The assumption is made that the distribution of brand preferences, **ms***, is identical for the informed and uninformed groups. Then in each period, each brand i is assured of receiving at least the patronage of kms_i^* of the incoming buyers. The remaining fraction of consumers, $1 - k$, will each sample randomly N brands $(1 < N < B)$ prior to habitually purchasing for the remainder of their tenure in the market the best (for them) brand of the N sampled.

It remains to derive some properties of the function $ms_i = f(ms_i^*, k, N)$, and in particular to see how, if at all, it diverges from the free information case. (Throughout the following derivation, it is assumed for purposes of analytical tractability that all $B - 1$ brands except the ith brand are equal in the proportions of the market's consumers that most prefer them; that is, $ms_j^* = [1 - ms_i^*]/[B - 1]$ for all $j, j \neq i$.) We

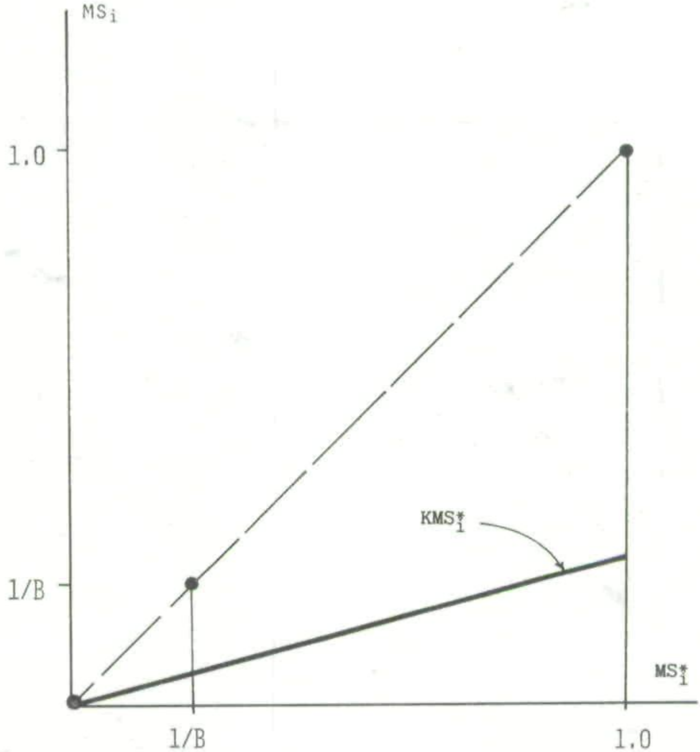

FIG. 4.—Constraints on the relationship between market share and consumer preference.

can then summarize in figure 4 what is known about the relationship between ms_i and ms_i^* at this point:

a) When $ms_i^* = 0$, $ms_i = 0$. This simply says that a brand that is preferred by no consumers will have no sales. (I abstract here, and below, from the possibility of brands existing solely on sampling sales, with no consumer returning to them a second time, and note also that $N \geq 2$ by assumption.)

b) When $ms_i^* = 1$, $ms_i = 1$. This is the converse case; a brand absolutely preferred by all will sell to the entire market.

c) When $ms_i^* = 1/B$, $ms_i = 1/B$. This is simply a symmetry condition. All $B - 1$ brands other than i are, by construction, equal in their underlying "free information" shares ms^*. When $ms_i^* = 1/B$, all B brands have equal ms^* values and, by symmetry, equal market shares.

d) The realized market share is the sum of sales to the fraction k of consumers assumed fully informed, plus sales to that fraction of sampling consumers (denoted r_i) retained as habitual or "loyal" buyers after they have sampled; that is, $ms_i = kms_i^* + (1 - k)r_i$.

Thus the relationship has three fixed points—(0,0), (1,1), and (1/*B*,

$1/B$)—and is the sum of a linear function of unit elasticity plus another function whose form is now to be determined.

To approach this function, begin by determining the expression for r_i. The fraction r_i is itself the product of two probabilities: the probability that brand i will be sampled by an incoming consumer—$p_i(s_N)$—times the conditional probability that, having sampled, the consumer will return to the brand—$p_i(r \mid s)$. This is expressed as

$$r_i = p_i(s_N)p_i(r \mid s), \tag{3}$$

where the N subscript denotes a sample size of N (note that $\Sigma_i^B r_i = 1.0$).

The first factor in (3), the sampling component, depends on brand i's market share ms_i and on the consumer's sample size N. Under random sampling without replacement, the brand's probability of being sampled on any given sampling purchase is equal to its share of the sales of all of the yet unsampled brands, by the logic underlying equation (2). It can be shown that the probability that a consumer will have sampled a brand i in N trials is given by

$$p_i(s_N) = ms_i + \sum_{n=1}^{N-1} \left\{ \frac{ms_i}{1 - n[(1 - ms_i)/(B - 1)]} \right\} \prod_{m=0}^{n-1} \left\{ \frac{1 - ms_i - m[(1 - ms_i)/(B - 1)]}{1 - m[(1 - ms_i)/(B - 1)]} \right\} \cdot \tag{4}$$

Since (4) is not entirely convenient to work with, the analysis will proceed using the expression for $p_i(s_N)$ under sampling with replacement, or

$$p_i(s_N) = 1 - (1 - ms_i)^N. \tag{5}$$

This simplifying substitution does not qualitatively alter the final results.

To express $p_i(r \mid s)$, the "loyal customer" retention probability, recall that ms_i^* was the probability that a customer informed of all brands would choose brand i. Invoking the assumption that excluded alternatives are irrelevant and noting that unsampled brands are, definitionally, excluded alternatives, then the probability that the consumer who has sampled N brands (including i) will choose brand i can be expressed as

$$p_i(r \mid s) = ms_i^* / \sum_j^N ms_j^*, j = 1, 2, \ldots, i, \ldots, N. \tag{6}$$

Since the other $N - 1$ brands in the sample set are assumed to have equal values for ms^*, (6) simplifies to

$$p_i(r \mid s) = \frac{ms_i^*}{ms_i^* + (N - 1)[(1 - ms_i^*)/(B - 1)]}. \tag{7}$$

The expression for r_i is then simply the product of (5) and (7), or

$$r_i = (1 - (1 - ms_i)^N)\left\{\frac{ms_i^*}{ms_i^* + (N - 1)[(1 - ms_i^*)/(B - 1)]}\right\}, \quad (8)$$

recognizing that (8) is an approximation in that (7) assumes sampling without replacement, while (5) assumes replacement. (In [8] the logical condition $\Sigma_i^B r_i = 1.0$ is violated; were [8] formed by the product of [4] and [7] it would hold exactly.) The relevance of r_i to the problem at hand is that it is the "ignorant" component of market share. In a stable equilibrium r_i is constant; shares neither grow ($[1 - k]r_i + kms_i^* > ms_i$) nor shrink ($<ms_i$) over time. Since the kms_i^* component of share is (obviously) a constant fraction of the underlying free information share ms_i^*, the key to the behavior of ms_i with respect to ms_i^* lies in the behavior of r_i and ms_i^*, analyzed below.

The general approach employed here will be to evaluate $\partial r_i/\partial ms_i^*$ and, subsequently, $\partial ms_i/\partial ms_i^*$ at the fixed points (0,0) and (1,1). If the latter pair of derivatives is less than one, then ms_i is a convex function of ms_i^* near the origin and concave near $ms_i^* = 1$; that is, the function cuts the 45° line $ms_i = ms_i^*$ from below at $ms_i^* = 1/B$, and we may conclude that "ignorant" buyers purchase high share brands in greater proportion than they would were they fully informed. Conversely, $\partial ms_i/\partial ms_i^* > 1$ at (0,0) and (1,1) implies the reverse relationship. (Subscripts are suppressed below for visual clarity; the is are understood.)

Beginning with the first factor of $r = p(s_N)p(r|s)$, we have (using the sampling with replacement simplification)

$$p(s_N) = 1 - (1 - ms)^N, \quad (9)$$

$$\frac{\partial p(s_N)}{\partial ms^*} = \frac{\partial p(s_N)}{\partial ms}\left[\frac{\partial ms}{\partial ms^*}\right] \quad (9a)$$

$$= N(1 - ms)^{N-1}\left[\frac{\partial ms}{\partial ms^*}\right],$$

$$\left.\frac{\partial p(s_N)}{\partial ms^*}\right|_{ms^* = ms = 0} = N\left[\frac{\partial ms}{\partial ms^*}\right], \quad (9b)$$

and

$$\left.\frac{\partial p(s_N)}{\partial ms^*}\right|_{ms^* = ms = 1} = 0. \quad (9c)$$

Turning to the second factor we have

$$p(r\,|\,s) = ms^*\Big/\left[ms^* + (N - 1)\left(\frac{1 - ms^*}{B - 1}\right)\right], \quad (10)$$

$$\frac{\partial p(r|s)}{\partial ms^*}$$

$$= \frac{ms^* + (N-1)[(1-ms^*)/(B-1)] - ms^*[1-(N-1)/(B-1)]}{ms^{*2} + (N-1)^2[(1-ms^*)/(B-1)]^2 + 2ms^*(N-1)[(1-ms^*)/(B-1)]}, \tag{10a}$$

$$\left.\frac{\partial p(r|s)}{\partial ms^*}\right|_{ms^* = ms = 0} = \frac{B-1}{N-1}, \tag{10b}$$

and

$$\left.\frac{\partial p(r|s)}{\partial ms^*}\right|_{ms^* = ms = 1} = \frac{N-1}{B-1}. \tag{10c}$$

Combining these expressions yields

$$r = p(s_N)p(r|s), \tag{11}$$

$$\left.\frac{\partial r}{\partial ms^*}\right|_{ms^* = ms = 0} = (1 - [1 - ms]^N)\left[\frac{B-1}{N-1}\right] + \frac{ms^*N}{ms^* + (N-1)[(1-ms^*)/(B-1)]}\left[\frac{\partial ms}{\partial ms^*}\right] = 0, \tag{11a}$$

and

$$\left.\frac{\partial r}{\partial ms^*}\right|_{ms^* = ms = 1} = (1 - [1 - ms]^N)\left[\frac{N-1}{B-1}\right] + \frac{ms^*}{ms^* + (N-1)[(1-ms^*)/(B-1)]}(0) = \frac{N-1}{B-1}. \tag{11b}$$

Extending these results for $\partial r/\partial ms^*$ to $\partial ms/\partial ms^*$, we obtain

$$ms = kms^* + (1-k)r, \tag{12}$$

$$\left.\frac{\partial ms}{\partial ms^*}\right|_{ms^* = ms = 0} = k + 0 = k < 1, \tag{12a}$$

and

$$\left.\frac{\partial ms}{\partial ms^*}\right|_{ms^* = ms = 1} = k + (1-k)\left[\frac{N-1}{B-1}\right] = \frac{k(B-1) + (1-k)(N-1)}{B-1} < 1. \tag{12b}$$

(The inequality in [12b] is obvious when one notes that the numerator is simply a k-weighted average of B and N, less one, and $N < B$ by assumption.)

The economic interpretation of the results in (12a) and (12b) is that the relationship between a brand's realized market share when consumers lack information about brands' utilities and its market share when consumers are fully and costlessly informed is the S-shaped function shown in figure 5. High information costs have the effect of reducing the sales of small brands relative to large; graphically, the more costly (and therefore less prevalent) is information, the greater is the deviation of the function from the linear $k = 1.0$ case. Inspection of (12a) and (12b) reveals that as information becomes more widely available—either as $k \to 1$ or $N \to B$—the (0,0) and (1,1) derivatives of the observed ms_i to the unobservable ms_i^* approach one. Given the fixed point at $(1/B, 1/B)$, this implies that sales deviations from the free information case are in favor of large sellers but are reduced by reductions in the cost of information.[5]

As a final point, reconsider the argument, discussed above, that the rational consumer would, using either explicit or implicit advice from experienced buyers, tend to sample brands in descending order of their market shares. The effect of this activity on the equilibrium distribution of market shares is clear; the advantage that large brands possess over small in being sampled would increase, and so too would their observed shares. Thus a relaxation of the random sampling assumption, made for analytic convenience, serves only to strengthen the conclusions derived under the assumption.

Advertising and market structure. Assume now that advertising is permitted and occurs. Assume also, to formulate the hypothesis, that advertising messages may in fact be informative. In the present context, "informative" has a simple operational definition: Advertising is informative if it provides an improvement in consumers' estimates of brands' prior probabilities of being their most preferred selections. The likeliest reason for this is that it is in the producer's interest to direct his advertising messages to that subset of the public at large who are likeliest to be retained as his "loyal" customers. I have assumed (and

5. One might object that, while the function in figure 5 is sufficient to represent the specified conditions, it is not necessary, since other continuous functions can meet these conditions so long as they have an odd number of inflection points. While such a solution cannot be disqualified on mathematical grounds, it can nevertheless be safely disregarded on the basis of its economic implications. Those implications are that information costs have no effect on actual market share inequality at some particular level(s) of "underlying" share inequality, but have either positive or negative effects at, respectively, slightly higher or lower levels of ms_i^*. This "switching" behavior of the sign of $\partial^2 ms_i / \partial k \partial ms_i^*$ is, as far as I am aware, unsupported by any operative economic principle. Figure 5, on the other hand, represents a relationship between k and deviations from share equality (i.e., a given brand with $ms_i^* \neq 1/B$, the others with $ms_j^* = [1 - ms_i^*]/[B - 1]$) that is continuous. Costlier information (symbolized by lower values of k or N) has an effect uniform in sign on actual share inequality for all levels of underlying share inequality.

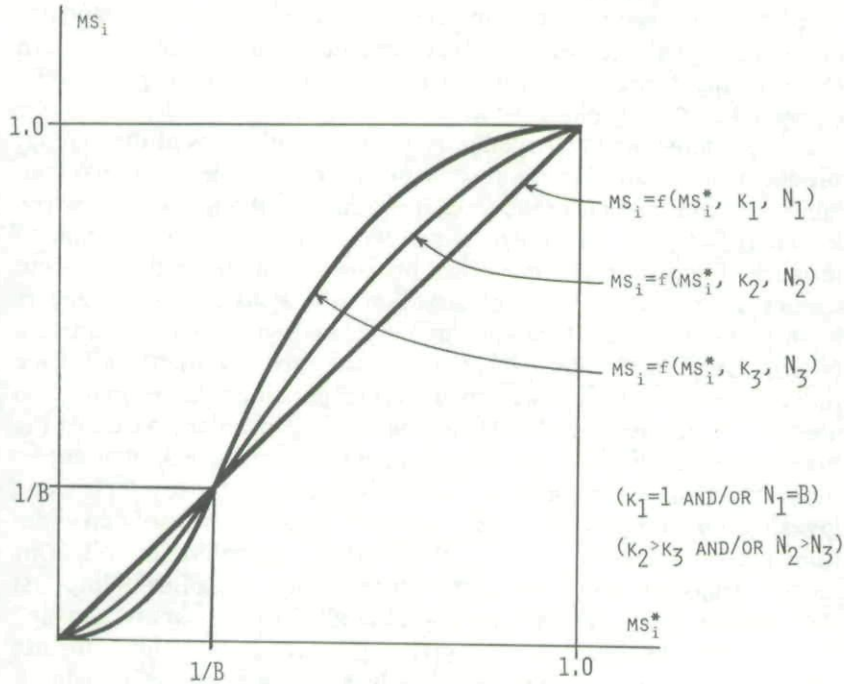

FIG. 5.—Realized market share as a function of consumer preference and information.

will continue to assume) that the volume of purely sampling sales relative to repeat sales is sufficiently small that it can be neglected.[6] Therefore the only return to a firm's messages is through its attraction of future habitual purchasers who are currently sampling. Other things equal (in particular, the costs of reaching different sectors of the population and the proportion of each sector that is currently sampling), a given volume of future sales will be obtained at the least cost by targeting the messages to those most likely to return as habitual customers; that is, to those for whom the advertised brand has the highest net utility. If there exist positive correlations between the likelihood that a customer will prefer the brand and the likelihood that he will view a given advertising-carrying medium, then that medium will be selected for the message. As Nelson (1974), making essentially the same point, put it: "Advertising has the seemingly magical

6. This is something of a departure from Nelson (1974) who, in a discussion of firm demand elasticities, points out that total sales consist of both sampling and repeat customers. To the extent that sales are of the former type, advertising is most profitably directed toward those who are likeliest to try or sample the brand, regardless of the likelihood they will like it enough to continue buying it.

property that those whose tastes are best served by a given brand are those most likely to see an advertisement for that brand. . . . An esoteric, high-price soup gets advertised in the *New Yorker*, while Campbell's soup displays its wares in *Good Housekeeping*."

There is a fundamental symmetry between both sides of the market; producers are searching among consumers in the same sense that consumers search among producers. Both may be thought of as distributed across a grid, the dimensions of which are the product's characteristics. Each presumably knows his own location on this grid but cannot determine by direct observation others' locations. Producers learn that consumers' locations are correlated with their media usage (alternatively, with their "location" in the media market) and place those advertisements in those media corresponding to consumers who are "close" to their own locations. Similarly, consumers learn that the brands whose advertisements they see most often (which may not be those which are advertised most in total) tend to be those which, upon investigation, are best suited for their own circumstances of consumption; that is, closer to them on the product characteristic grid. This model or metaphor is consistent with the rationality of sampling first the brands with the largest shares—a brand which sells more "spans" a larger area on the grid, and given that brands' locations are not known it is likelier to be the consumer's most preferred choice—but it also permits the recognition of the reciprocal nature of search. The net result of advertising is that it permits an allocation of consumers to brands that is closer to the free information case. In terms of the preceding model, advertising messages—if they are informative—are equivalent to either an increase in N, the equilibrium sample size, or in k, the "informed" fraction of potential buyers.[7]

7. Despite this hypothesis about the size distribution of sellers, little can be said about the effect of changes in advertising costs on the absolute concentration of the market (as measured by, say, the concentration ratio), because there are two other factors involved. First, a reduction in the cost per message would in general affect the overall cost structure, including production, distribution, and promotion, of the firms and brands in the industry. If the result is a larger optimal output for all sellers, for example, the concentration ratio would tend to rise for that reason alone. And second, an increase in advertising messages due to a reduction in their cost will, under virtually any hypothesis about the nature of advertising, increase the market demand for the product as a whole. This will tend to reduce the concentration ratio, assuming the usual response of entry to an increase in market demand. A priori, it is not obvious which of these effects, if either, will dominate. For a discussion of the difference between these two concentration concepts, see, e.g., Singer (1968, p. 125) who notes that "economic concentration of business firms within various industries can be measured by different types of indexes. *Absolute* measures of concentration refer to the percentages of assets, employees, or value of shipments accounted for by a given number of leading firms in an industry. *Relative* measures of concentration, which are less frequently employed, consider the size of the competitors in relationship to each other. An industry with sales fairly evenly divided among a few firms may simultaneously possess a high degree of absolute concentration but a low degree of relative concentration [emphasis added]."

III. Empirical Tests of the Implications

Based upon the preceding discussion, the purpose of this section is an empirical estimate of the relationship between an industry's advertising costs and measures of the size distribution of its market shares. The most general empirical specification is

$$\text{Structure} = f(P_a, \mathbf{X}), \tag{13}$$

where the dependent variable is some measure of market structure, P_a is the price of a standardized advertising message, and $\mathbf{X}$ is a vector of other variables which affect the structure of the market.

Television

The specification requires that P_a be taken as an exogenous parameter, to which the industry responds by adjusting its flow of advertising messages (denoted a). One problem in dealing with variables such as the price and quantity of advertising messages is that they are essentially abstract concepts and, as such, are not directly observable. Firms purchase a number of "messages," in the abstract, by the concrete purchase of radio time, magazine pages, and so on, with the marginal revenue product of each medium equal to its marginal cost at the equilibrium media mix. Nevertheless, it is natural to think of firms producing "standard units" of advertising messages (assuming *mutatis mutandis* adjustment of media mix at each level of message production) which have falling marginal revenue products and rising marginal costs. Here, I treat the development and growth of commercial television as the source of an exogenous reduction in the marginal cost to an industry of transmitting messages to its consumers.

To illustrate the use of television as a proxy for communications cost reductions, refer to the production function in figure 6. Isoquants M_1 and M_2 refer to the production of M messages in industries 1 and 2, respectively, using magazine pages and television minutes as the (only) factors of production of these messages. Initially (pretelevision), each produces the same number of messages using only magazine space, at a cost of N_0 pages times the price per page. After its introduction, television time is available to both (and to all others) at a given price per television minute. As constructed in this example, industry 2 is relatively poorly suited for television, perhaps because its relevant audience watches less television or is less homogeneous in its viewing habits, or because its relative advantage in visual portrayal is lower. In any case, the cost-minimizing media mix for each industry (for M messages) is seen at A_1, and A_2, the relative price reductions per standard message are $(N_0 - N_1)/N_0 > (N_0 - N_2)/N_0$, and the percentage of advertising expenditures spent on television ($= \%TV$) is lower in industry 2 than in 1. This is the basis for using $\%TV$ as a proxy for the

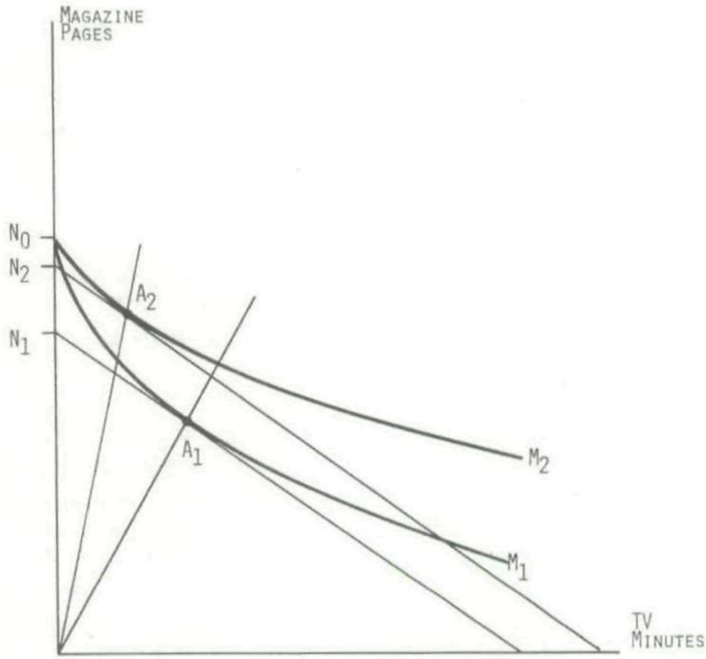

FIG. 6.—Media space and time as factors of the production of messages

industry's reduction in the unit cost of sending advertising messages. The use of this proxy rests on the assumption that industries whose products are relatively well suited for television advertising, and which therefore experienced a greater reduction in P_a, may be characterized as having everywhere (i.e., at every level of $\%TV$) higher marginal rates of substitution of other media for television. To the extent that this assumption is occasionally violated, $\%TV$ will be an imperfect proxy for the true variable of interest, the change in P_a, introducing some degree of error into the measurement of the true causal variable and biasing its estimated coefficient toward zero.

Table 1 indicates the explosive growth of television in the United States during the 1950s, from a curiosity in 1950 with fewer than 10% of all households owning a set, to a medium used by over half of all households only 4 years later. This understates the growth of actual television viewing; the number of transmitting stations grew by nearly 300% over this period, presumably increasing the quality and diversity of the programming, while television time sales, reflecting the value of the medium for transmitting advertising messages, grew by over 500%.

Methodology

Given the occurrence of the exogenous shifts in P_a, inferred from the data in the previous table and from industries' subsequent responses,

TABLE 1 **Growth over Time of National Commercial Television (TV)**

	Stations on the Air		Sets in Use		Time Sales		TV Homes in U.S.	
Year	*N*	Growth (%)	*N*	Growth (%)	10^6 ($)	Growth (%)	Total (%)	Growth (%)
1950	104	...	9,700	...	102.4	...	9.0	...
1951	107	2.9	15,420	59.0	241.0	35.3	23.5	161.1
1952	108	.9	21,220	37.6	330.0	36.9	34.2	45.5
1953	198	83.3	26,940	27.0	445.6	35.0	44.7	30.7
1954	402	103.3	33,165	23.1	614.0	37.8	55.7	24.6
1955	458	13.9	38,960	17.5	783.2	27.6	64.5	15.8
1956	496	8.3	43,565	11.8	958.2	22.3	n.a.	...
1957	519	4.6	47,315	8.6	1,013.2	5.7	...	...
1958	556	7.1	49,020	3.6	1,112.8	9.8	...	...
1959	566	1.8	50,800	3.6	1,249.8	12.3	...	...
1960	579	2.3	52,300	3.0	1,363.9	9.1	...	...

Source.—FCC, *40th Annual Report, Fiscal Year 1974*.

the methodology of an appropriate empirical test suggests itself. The cross-sectional analysis of levels implicit in (13) would be suspect due both to the inherent difficulties in measuring levels of P_a and also to the usual problems of omitted variables. Moreover, cross-sectional empirical tests at a given point in time involving industry structure are invariably plagued by the unavoidably arbitrary definitions of industries, conditioned as they are by the resources and purposes of those who publish the data. Instead, I use a cross-sectional analysis of the changes in the variables over a given time period, or

$$\Delta\text{Structure} = f(\Delta P_a, \Delta \mathbf{X}). \tag{14}$$

This specification has the advantage of holding constant those omitted variables which are industry specific, and the disadvantage of permitting to vary those variables which are time period specific.[8] It should be noted, however, that the arbitrary character of industry definition has an effect similar to that of omitted variables, and it is industry specific. If misclassification is believed to be a serious problem, and if the criteria for classifying output according to industry are constant over time, then (14) is to be preferred to (13). Moreover, the difficulties of a possible simultaneous relationship are avoided by the use of (14). Suppose that the eventual adoption of television (the proxy for ΔP_a) was conditioned by the presence of some unspecified factors which were also correlated with, say, high market concentration. Suppose also that the effect of the reduction in P_a due to television was, in fact, to reduce concentration, but that this effect was mild relative to

8. See Telser (1964); Ekelund and Maurice (1969); Mann, Henning, and Meehan (1969*a*, 1969*b*); and Telser (1969) for a discussion of this and related points.

other factors of cost and demand. Then even after full equilibrium adjustment to the new medium one might, despite the (hypothesized) true negative effect, observe a positive association between television usage and concentration in estimating (13) cross-sectionally. (Telser [1964], in estimating the effect of advertising on brand turnover, makes essentially this point.) All of these difficulties are mitigated by the use of (14) in the empirical analysis.

The elements of **X**, the vector of other variables affecting structure, must also be considered. There is a substantial literature on one part of this area—the concentration issue—which tends to focus on technological economies of scale, regional versus national markets, and barriers to entry. (See, e.g., Goldschmid, Mann, and Weston [1974] for several extensive surveys of this area.) Moreover, the heterogeneity of market demand as well as its overall magnitude also affect the size distribution of producers' sales in each market. It is upon this latter class of the determinants of structure that I focus here.

In isolating the partial effect of changes in advertising cost over a time period, contemporaneous changes in product demand and costs—which could also affect market structure—must be controlled for. At a minimum, growth in population and income would normally be expected to increase demand for each product, though the strength of the effect might vary across products. Similarly, changes in factor prices and the technology of production can safely be assumed to evolve and to affect different products differently. Where there are differential effects on product demand the differences should be roughly reflected in a change in the proportion of the region's population which consumes the product. Similarly, changes in the conditions of supply will ordinarily affect products' relative prices, resulting again in a change in the proportion of the population which consumes the product.

Such shifts in supply and demand will also leave traces in the data on the number of suppliers. A rise in product demand will generally be accompanied by an increased demand for product heterogeneity as well as quantity; the new equilibrium will typically be characterized by a greater number of supplying firms, and of brands sold, in the market. An exogenous expansion in supply is less simple to characterize. Under plausible assumptions about firms' costs, the occurrence of a supply expansion—contingent, say, on lower factor prices or technological innovation—could leave the equilibrium number of sellers higher, lower, or unchanged.

This then is the strategy of the test. The sample consists of different products sold in a given city. Observations of the structure of market shares before (t_0) and after (t_1) the introduction of television are made. The changes in aggregate regional demand over this time period are assumed to impinge on each product similarly (and are, in effect, accounted for in the constant term in the regression estimates). Product-specific exogenous changes in the level and composition of product demand and in the conditions of product supply are accounted for empirically by: (*a*) the observed changes in the fraction of the city's population who consume the product, and (*b*) in the number of brands of the product offered for sale.[9]

Particular measures of the structure of product market shares must now be defined to complete the description of equation (14). The structural aspect that a relevant measure must capture in order to test the theory is the relative size disparity of shares; that is, the size of a brand's sales relative to other brands' sales rather than in relation to the total sales of the market. The simplest and most direct measure is an estimate of the average ratio of each brand's sales to the sales of the next larger brand, or $r = \overline{s_i/s_{i-1}}$, $0 \leqslant r \leqslant 1$, $2 \leqslant i \leqslant B$, where s_i is the market share of the ith-ranked of the B brands. Four variants of r are proposed: the unweighted average of the four largest brands' ratios ($r1$); the unweighted average of all brands' ratios ($r2$); and two weighted averages of all brands' ratios ($r3$ and $r4$), the weights being the market shares of either the smaller or the larger brand, respectively. The standard deviation of brands' shares (σ) in a market is another measure of size inequality that will be included in the analysis. In addition, the Herfindahl index (H) and the entropy index (E) are more familiar measures of market structure which also comprehend the variance or relative size disparity of producers' sales; accordingly, their behavior will also be estimated. Finally, changes in the four-brand concentration ratio ($C4$) will also be estimated. The theory does not contain any implications for this last type of measure; its inclusion should be regarded as a mere heuristic exercise with low costs. Thus I estimate the effects of television's reduction in communicating costs on eight measures of market structure. Where B is the number of brands in the market and is s_i the market share of the ith-ranked brand, we have:

$$r1 = \frac{1}{3} \sum_{i=2}^{4} s_i/s_{i-1}, \tag{15}$$

$$r2 = \frac{1}{B-1} \sum_{i=2}^{B} s_i/s_{i-1}, \tag{16}$$

9. Note that the partial effects of these proxy variables on measures of relative concentration cannot be obviously signed a priori. For example, a shift in product demand could reasonably be expected to result in a higher population percentage of product use associated with a leveling or equalization of firms' shares (perhaps as formerly marginal or specialty sellers expanded relative to the original "main-line" suppliers). On the other hand, innovation by a given firm, not immediately copied, would also result in a higher population usage rate, but here with an increase in the inequality of firms' sales (see, e.g., Peltzman 1977).

$$r3 = \sum_{i=2}^{B} s_i^2/s_{i-1}, \tag{17}$$

$$r4 = \sum_{i=2}^{B} (s_{i-1})s_i/s_{i-1} = 1 - s_1, \tag{18}$$

$$\sigma = \sqrt{\frac{\Sigma(s_i - \bar{s})^2}{B - 1}}, \tag{19}$$

$$H = \sum_{i=1}^{B} s_i^2, \tag{20}$$

$$E = \prod_{i=1}^{B} (s_i)^{s_i}, \text{ and} \tag{21}$$

$$C4 = \sum_{i=1}^{4} s_i. \tag{22}$$

To summarize, the empirical specification calls for some measure of the size distribution of brands' sales as the dependent variable, the change in which is to be explained by the fraction of the product's advertising expenditures later spent on television (as a proxy for the reduction in the real advertising cost per message); changes in both the fraction of the observed population who use the product (denoted $\%U$ below) and also the number of brands (B) offered to that population (as proxies for changes in the conditions of product supply and demand); and changes in other factors unrelated to the model ($\mathbf{X}$). The vector of variables $\mathbf{X}$ is not measured (and is not, for that matter, defined here), but is assumed to be uncorrelated with the included variables. The empirical model is therefore given by

$$\Delta\text{Structure} = f(\%TV, \Delta\%U, \Delta B, \Delta\mathbf{X}). \tag{23}$$

Data

There are two sources of brand data for the principal empirical analyses here. For one sample consisting of 63 products, the *Milwaukee Journal*'s annual survey of consumer households in Milwaukee is the source of data on the number of brands, their market shares, and the fraction of the population who use the product.[10] The same data

10. These estimated shares are actually "recalled brand shares," which differ from shares computed from sales data in two ways. First, interhousehold differences in quantity purchased are ignored. The share here is the fraction of households selecting the brand, rather than the fraction of total sales accounted for by the brand. And second, Telser (1964) has pointed out that recalled brand shares tend to be both more stable and more concentrated than actual sales shares, and that this bias increases as the volume of advertising messages increases. This suggests a possible bias toward a positive estimated relationship between $\%TV$ and measures of relative concentration.

elements, collected in the same way, were obtained for a second sample of 42 products in each of six cities (a total of 252 observations) from *Consolidated Consumer Analysis,* a variant of the *Milwaukee Journal* survey produced in cooperation with several other newspapers. The cities in the sample are Duluth, Indianapolis, Milwaukee, Omaha, Salt Lake City, and St. Paul. An additional source of data is *National Advertising Investments,* a publication of Leading National Advertisers. The information given is 1970 national advertising expenditures (by brand within firm within product market) in each of the six media: network television, spot television, network radio, magazines, newspaper supplements, and outdoor displays. The variable *%TV* is computed by dividing a product's television subtotal by its six-media total.[11] For both samples, it was necessary to match the reported product definitions with those of Leading National Advertisers in order to add the *%TV* variable.

For the 63-product Milwaukee sample, the selection criteria were that the product be a consumer nondurable of apparently low price and be reported for $t_0 = 1952$ (pretelevision) and $t_1 = 1970$ (posttelevision). The criteria for the *Consolidated* sample were somewhat more complex. Since not all products were reported in all cities, adding products reduced the number of cities for which all products were reported, and expansions of $t_1 - t_0$ further reduced the number of included cities. The final selection was 42 products common to six cities, with $t_0 = 1951$ and $t_1 = 1963$. Where a particular product was unreported in only one city, the missing data elements for that product were entered from the geographically nearest city.

In addition to these two data sets, some supplemental data have also been assembled for further testing of the hypothesis. The 63-product *Milwaukee Journal* sample consists of frequently purchased nondurables, most of which have a relatively high fraction of their advertising expenditures spent on television. To test the sensitivity of conclusions based on these products to the particular sample of products selected, one of the selection criteria was relaxed. The resulting expansion involves the inclusion of those products previously excluded as dura-

11. It might be observed that newspapers and spot radio are excluded from these totals, and that they made up approximately 29.5% and 5.6%, respectively, of the national expenditure total in 1966 (reported in Schmalensee [1972, p. 2]). While this exclusion is unavoidable, it may not be too serious a problem. Classifying the advertising expenditures into "national" and "local" content, newspaper and spot radio were seen to carry, on an expenditure basis, only 19.9% and 31.4%, respectively, of national advertising, compared to 76.9%, 100.0%, and 66.2% for television, magazines, and outdoor (Schmalensee 1972). Since the samples analyzed here seem to consist mainly of nationally marketed products—and particularly since most of the local classification is likely to be retail, rather than brand, advertising—newspaper and spot radio advertising may be less relevant to the analysis that their total dollar volumes would at first suggest.

bles. Since such divisions by product type are inherently subjective, this expansion acts as a check on the sensitivity of the results to the stringency of the nondurability criterion.[12]

Finally, a sample of 58 four-digit SIC industries was also compiled. The criteria for inclusion were that the industries produce predominantly consumer products and that consistent data be available for the years in the sample. The initial year, t_0, was set at 1954; the census year 1947 would have required a significantly smaller sample, due to subsequent SIC industrial redefinition, and may have been suspect due to postwar disequilibrium. Two selections—1963 and 1967—were made for t_1.

Data analysis

This section reports ordinary least-squares regression estimates of the relationship in (23). In the form in which it is actually estimated, (23) becomes

$$\Delta S = \beta_0 + \beta_1 \Delta B + \beta_2 \Delta \%U + \beta_3 \%TV + \epsilon, \tag{24}$$

where Δx = natural logarithm of $x(t_1)/x(t_0)$ and the omitted $\Delta \mathbf{X}$ values are assumed impounded in the constant and the error term ϵ. The measures of market structure S are given in (15) through (22). B_1 and B_0 are the total number of brands sold in t_1 and t_0, respectively, subject to the inclusion criterion that a brand have a market share of at least 2% to be included.

The results listed in table 2 are estimates of equation (24) for the eight measures of relative size disparity. Negative coefficient estimates of $\%TV$ when ΔH, ΔE, and $\Delta\sigma$ are the dependent variables, and positive coefficients when $\Delta r1 - \Delta r4$ are dependent, support the informational hypothesis. A growth in the number of brands has, not suprisingly, a uniformly significant effect of lowering the measures of relative market concentration. While some of this relationship may be spurious in the sense that it is a mathematical necessity under certain conditions, the general interpretation is that an increase in the demand for multiple variants of the product (i.e., for additional brands) raises the demand for smaller brands relative to that of the leading brands. Increases in the percentage of consumers who use the product, $\Delta\%U$—interpreted as growth in the overall demand for the good—has generally similar effects, though they are not statistically significant in this sample. The

12. To maintain comparability within the sample of the other causal variables, the fraction of the population using the product ($\%U$) was defined, for durables, to be the fraction which made a purchase within the previous 12 months. This compares with an operational definition of this fraction, in the case of nondurables, as the percentage of families who made a purchase within the past 30 days. Thus the percentages represent, roughly, the fraction of the advertising-receiving audience which is in a position to respond to the ad for both product types.

TABLE 2 **Regressions Explaining Changes in Market Structure, 1952–70; *Milwaukee Journal* Sample ($N = 63$)**

Dependent Variable	Independent Variables			
	ΔB	$\Delta \% U$	$\% TV$	R^2/F
ΔH	−.7701	−.0593	−.5501	.6794
	(8.965)	(.752)	(2.610)	41.676
ΔE	−.9445	−.0296	−.3182	.8688
	(17.539)	(.598)	(2.408)	130.211
$\Delta \sigma$	−.7866	−.0710	−.6340	.6091
	(7.474)	(.734)	(2.455)	30.641
$\Delta r1$	.2566	.0705	.3705	.3023
	(3.053)	(.913)	(1.796)	8.521
$\Delta r2$	.3178	−.0111	.2440	.6354
	(8.542)	(.324)	(2.673)	34.275
$\Delta r3$	.3780	.1034	.7694	.3877
	(3.244)	(.966)	(2.691)	12.453
$\Delta r4$	.2050	.0677	.4285	.3755
	(3.035)	(1.092)	(2.586)	11.826
$\Delta C4$	−.4468	.0076	−.0830	.7326
	(11.836)	(.220)	(.896)	53.885

NOTE.—*t*-ratios shown in parentheses; sample consists of nondurables; variables defined in text.

variable $\% TV$, however, has estimated effects on the dependent variable which are uniformly consistent and statistically significant.[13] In each case, the lower cost of advertising messages implied by $\% TV$ causes relative concentration to decline; that is, the sales volume of small sellers rises relative to that of large sellers.

The data generating the estimates in table 3 differ from the previous table in that seven durables have been added to the sample. The results here are even stronger than those in table 2; $\% TV$ consistently has a significant estimated effect of reducing the relative concentration of the market.

In table 4, I analyze changes in product market variables for 42 products in each of six cities from 1951 to 1963, as reported in the *Consolidated Consumer Analysis* reports. Since there are multiple cities involved, it is now possible to add another demand-related variable—the change in total personal income in the Standard Metropolitan Statistical Area of the city, ΔY—to the empirical specification. One might expect less precise results from this sample than from the *Milwaukee Journal* data for two reasons. First, the time period covered is significantly shorter here, increasing the likelihood that

13. Although not derived here, simultaneous effects of lower information costs on either ΔB or $\Delta \% U$ cannot be ruled out. As an empirical check on the sensitivity of the reported results to the inclusion of these variables, the equations were also estimated excluding each of them from the specification (see Lynk 1978). No material changes were observed in the signs, magnitudes, or significance levels of the estimated coefficients of $\% TV$ in any of these results.

TABLE 3 **Regressions Explaining Changes in Market Structure, 1952–70; *Milwaukee Journal* Sample including Durables ($N = 70$)**

Dependent Variable	Independent Variables			
	ΔB	$\Delta\%U$	$\%TV$	R^2/F
ΔH	−.7728	−.0469	−.5762	.6811
	(9.563)	(.684)	(3.135)	46.982
ΔE	−.9373	−.0223	−.3402	.8669
	(18.352)	(.516)	(2.928)	143.270
$\Delta\sigma$	−.7683	−.0285	−.7334	.5684
	(7.271)	(.318)	(3.052)	28.980
$\Delta r1$	.2626	.0570	.3957	.3128
	(3.396)	(.869)	(2.250)	10.013
$\Delta r2$	.3003	−.0181	.2477	.5429
	(7.484)	(.531)	(2.714)	26.135
$\Delta r3$	.3838	.0673	.8264	.3778
	(3.473)	(.718)	(3.288)	13.361
$\Delta r4$	.2148	.0530	.4452	.3769
	(3.404)	(.989)	(3.102)	13.307
$\Delta C4$	−.4347	.0180	−.1351	.7031
	(11.528)	(.561)	(1.575)	52.100

NOTE.—t-ratios shown in parentheses; sample includes durables; variables defined in text.

industries had not yet reached a new equilibrium following the introduction of television. And second, the measured values of $\%TV$ are for calendar year 1970, not for 1963, the terminal year in this sample. The true variable of interest is $\%TV$ in 1963, which is proxied only imperfectly by $\%TV$ in 1970.[14]

Turning to table 4, we see that the demand variables ΔB, $\Delta\%U$, and ΔY all tend to reduce relative concentration (though the effect generally is statistically significant only for the first two variables, ΔB and $\Delta\%U$). This is in accord with the previous results for Milwaukee. The coefficients for $\%TV$ are also qualitatively consistent (save only for the estimate of $\Delta r2$) with the earlier analysis, lending additional support to its findings.

Based upon the coefficients' t-ratios, the results here for $\%TV$ appear to be somewhat lower in statistical significance than the earlier estimates. As it happens, this is due solely to the lower absolute magnitude of the estimated coefficients. A comparison of tables 4 and 2 shows that the estimates in the *Consolidated* sample are generally less than half the size estimated with the Milwaukee data. In table 5 a comparison of the standard errors of the estimated coefficients across the two samples, however, actually indicates lower standard errors for the *Consolidated* sample. (It may be interesting to note that the sole exception

14. While it is conceivable that the industries in this sample had identical $\%TV$ ranks and proportions in 1963 and 1970, the strong likelihood that this condition is violated introduces another element of measurement error into the independent variable $\%TV$.

TABLE 4 **Regressions Explaining Changes in Market Structure, 1951–63** ***Consolidated Consumer Analysis* Sample (N = 252)**

Dependent Variable	Independent Variables				
	ΔB	$\Delta\%U$	ΔY	$\%TV$	R^2/F
ΔH	−.3579	−.1839	−.1996	−.2047	.3477
	(8.153)	(5.165)	(1.131)	(1.605)	32.913
ΔE	−.5707	−.1311	−.1715	−.1759	.6433
	(17.885)	(5.066)	(1.336)	(1.897)	111.350
$\Delta\sigma$	−.3062	−.1914	−.1598	−.2462	.1916
	(5.074)	(3.910)	(.658)	(1.404)	14.632
$\Delta r1$	.1724	.0990	.0972	.0521	.0943
	(3.484)	(2.465)	(.489)	(.362)	6.430
$\Delta r2$	.4061	.0359	.0193	−.1567	.3256
	(9.913)	(1.081)	(.117)	(1.317)	29.818
$\Delta r3$	.4457	.2342	.5681	.1036	.2073
	(5.469)	(3.542)	(1.733)	(.438)	16.153
$\Delta r4$	.2193	.1353	.2830	.1403	.1924
	(4.941)	(3.758)	(1.585)	(1.088)	14.714
$\Delta C4$	−.1515	−.0452	.0017	−.0121	.3833
	(10.263)	(3.771)	(.028)	(.282)	38.373

NOTE.—Sample consists of 42 products in six cities; t-ratios shown in parentheses; variables defined in text.

TABLE 5 **Standard Error of Estimate of Coefficients of %*TV***

Sample	Dependent Variable							
	ΔH	ΔE	$\Delta\sigma$	$\Delta r1$	$\Delta r2$	$\Delta r3$	$\Delta r4$	$\Delta C4$
Milwaukee Journal	.2108	.1321	.2582	.1506	.0913	.2859	.1657	.0926
Consolidated	.1275	.0927	.1754	.1439	.1190	.2365	.1290	.0429

is for $\Delta r2$, the one dependent variable for which the sign of $\%TV$ is inconsistent.) This suggests an answer to the puzzle of the low significance levels: Equilibrium adjustment to the television-induced lower P_a had not yet been reached by 1963.[15] If so, this is wholly consistent with finding, were the data available, that the *Consolidated* sample by 1970 had estimates of $\partial S/\partial\%TV$ indistinguishable in magnitude and statistical reliability from those reported in the Milwaukee sample. Given this, table 4 is properly interpreted as a confirmation of the results obtained in table 2.

The final source of data with which I confront the theory is the sample of 58 four-digit SIC industries matched to similar industry categories in the LNA television data. In this data set, the appropriate analog to the previous ΔB is ΔF, the (log) change in the number of firms

15. And, of course, it may not have been reached by 1970, although presumably the adjustment process was closer to completion.

in the industry. No suitable proxy for $\Delta\%U$ is readily available.[16] On the other hand, Ornstein (1977) reports advertising-to-sales ratios for 1963 and 1967 (denoted $ATS63$ and $ATS67$ below), derived from the Commerce Department's input-output tables. These values are included in the empirical specification to explore, if only crudely, the earlier speculation that the possible total cost effects related to changes in advertising message prices (P_a) would confound any unambiguous prediction about the effect of P_a on absolute concentration.[17]

The unavailability of any share data more detailed than concentration ratios forces a redefinition of the market structure variables used to measure relative size differences among sellers. In addition, it remains possible to simply use the concentration ratios themselves as dependent variables. Given these limitations, the analysis employs the following measures of market structure:

$$C4 = \sum_{i=1}^{4} s_i, \tag{23}$$

$$C8 = \sum_{i=1}^{8} s_i, \tag{24}$$

$$C20 = \sum_{i=1}^{20} s_i, \tag{25}$$

$$Z1 = (C8 - C4)/C4, \tag{26}$$

$$Z2 = (C20 - C8)/C8, \tag{27}$$

and

$$Z3 = (C20 - C4)/C4. \tag{28}$$

Table 6 reports the empirical results for the 1954–63 period, and table 7 for 1954–67. With minor and insignificant exceptions, the effects of ΔF on relative firm sizes ($Z1$ through $Z3$) and absolute market concentration ($C4$ and $C8$) are analogous to those of ΔB in the previous brand analyses, though, again, some part of that effect may be spurious. The end-of-period level of the advertising-to-sales ratio, despite the very real methodological objections to its inclusion in this form, seems to have some effect on the observed changes in market structure. Though the coefficients are not statistically significant by con-

16. The change in sales volume, in either dollars or units, is available and initially seemed a plausible substitute. In no case, however, did its inclusion materially affect the other coefficients, nor was its own coefficient statistically significant. For this reason, I have omitted if from the empirical specifications reported here.

17. It would be preferable, of course, to use the change in ATS rather than its level at t_1, but 1954 data are not readily obtainable for this sample. The use of $ATS63$ and $ATS67$, in spite of this objection, might reasonably be termed an implicit appeal to the regression phenomenon.

TABLE 6 **Regressions Explaining Changes in Market Structure, 1954–63; SIC Industry Sample (N = 58)**

Dependent Variable	Independent Variables			
	ΔF	$ATS63$	$\%TV$	R^2/F
$\Delta Z1$	−.0384	−.9244	.2560	.0798
	(.264)	(1.133)	(2.025)	1.561
$\Delta Z2$	.3156	−1.4030	.1932	.0755
	(1.603)	(1.272)	(1.130)	1.471
$\Delta Z3$	.0970	−1.1625	.2813	.0792
	(.596)	(1.274)	(1.990)	1.548
$\Delta C4$	−.1487	.7273	−.2380	.1380
	(1.440)	(1.256)	(2.652)	2.881
$\Delta C8$	−.1573	.4021	−.1529	.1437
	(2.101)	(.958)	(2.350)	3.022
$\Delta Z1$	−.0475	. . .	.2152	.0579
	(.326)		(1.771)	1.690
$\Delta Z2$	.3019	. . .	.1313	.0479
	(1.527)		(.796)	1.382
$\Delta Z3$	.0857	. . .	.2300	.0515
	(.524)		(1.688)	1.492
$\Delta C4$	−.1416	. . .	−.2058	.1128
	(1.366)		(2.381)	3.496
$\Delta C8$	−.1534	. . .	−.1352	.1292
	(2.053)		(2.169)	4.080

NOTE.—t-ratios shown in parentheses; variables defined in text.

TABLE 7 **Regressions Explaining Changes in Market Structure, 1954–67; SIC Industry Sample (N = 58)**

Dependent Variable	Independent Variables			
	ΔF	$ATS67$	$\%TV$	R^2/F
$\Delta Z1$	.0456	−1.2000	.1841	.0354
	(.383)	(1.024)	(1.229)	.661
$\Delta Z2$	.3049	−2.3206	.1799	.1067
	(2.055)	(1.586)	(.962)	2.149
$\Delta Z3$	.1666	−1.6050	.2170	.0686
	(1.328)	(1.298)	(1.373)	1.325
$\Delta C4$	−.2612	.6451	−.2419	.1788
	(2.946)	(.738)	(2.164)	3.919
$\Delta C8$	−.2424	.2644	−.1789	.2332
	(3.689)	(.408)	(2.160)	5.473
$\Delta Z1$	.0390	. . .	.1335	.0167
	(.329)		(.944)	.466
$\Delta Z2$	.2923	. . .	.0820	.0650
	(1.946)		(.458)	1.193
$\Delta Z3$	.1578	. . .	.1493	.0395
	(1.252)		(.994)	1.131
$\Delta C4$	−.2577	. . .	−.2147	.1705
	(2.922)		(2.043)	5.653
$\Delta C8$	−.2409	. . .	−.1677	.2308
	(3.700)		(2.162)	8.251

NOTE.—t-ratios shown in parentheses; variables defined in text.

ventional standards, higher advertising-to-sales ratios seem to be weakly associated with both higher market concentration and greater disparity in size between large and small sellers. While the lengthy debate over the theoretical significance of such an association, if it in fact exists, will not be summarized here, I do note in passing that such a relationship seems entirely consistent with Demsetz's (1973) and Peltzman's (1977) characterizations of the process of market rivalry.

The theory advanced above suggests that it is the variable *%TV*, not the advertising-to-sales ratio, that is the better measure of changes in "advertising intensity." And in this sample, as in the preceding results, *%TV* consistently has the effect of increasing the sales of smaller competitors relative to large. Moreover, the results for $C4$ and $C8$ show a significant reduction in absolute concentration (as it was defined earlier), much more so than in other samples. While the theory does not imply such a reduction in the concentration ratio, this empirical finding (at the SIC industry level, at least) suggests that it is an absolutely small number of firms who yield the most sales when advertising becomes cheaper.

Table 8 clarifies this observation. In each of the two sample time periods, *%TV* causes a large and significant decline in the combined share of the largest through fourth largest sellers (i.e., $\Delta C4$). The effect on the next four sellers in size order (fifth through eighth) is essentially zero; any advertising-induced gains they make at the expense of the four largest are essentially offset by more effective competition from the ninth largest and smaller firms. The net effect is similar for the ninth through twentieth largest firms. Comparing the pattern of *%TV* coefficients between the 1954–63 and the longer 1954–67 samples suggests a substantial lag in full adjustment to the changes in P_a, in which most of the 20 largest firms lost or would eventually lose market share as a result of the new medium. The effect of lower P_a on the shares of firms one through four was negative through 1963 and caused further declines through 1967. Firms five through eight apparently gained share initially, as a result of the introduction of television; the net effect on their shares was still positive by 1963. This gain was eroded, however, presumably by firms still smaller, until by 1967 the net effect on their combined share was negative. Similarly, the positive effect through 1963 on the shares of the ninth through twentieth firms had faded to essentially zero by 1967.

Thus, this final data source supports the results of the previous analyses, and does so using firm rather than brand market share data, and national rather than local market definitions. These results, again, are that lower real advertising costs, as proxied by *%TV*, result in a gain in the sales of a market's smaller sellers at the expense of the larger.

Table 8 **Regressions Explaining Changes in Market Structure; SIC Industry Sample (N = 58)**

Dependent Variable	Independent Variables			
	ΔF	$ATS(t_1)$	$\%TV$	R^2/F
		1954–63		
$\Delta C4$	−.1487	.7273	−.2380	.1380
	(1.440)	(1.256)	(2.652)	2.881
Δ ($C8$–$C4$)	−.1871	−.1971	.0180	.0698
	(1.934)	(.363)	(.214)	1.350
Δ ($C20$–$C8$)	.1591	−1.0020	.0401	.0372
	(.983)	(1.104)	(.285)	.695
$\Delta C8$	−.1573	.4021	−.1529	.1437
	(2.101)	(.958)	(2.350)	3.022
$\Delta C20$	−.1139	.1415	−.0662	.1092
	(2.238)	(.496)	(1.497)	2.207
		1954–67		
$\Delta C4$	−.2612	.6451	−.2419	.1788
	(2.946)	(.738)	(2.164)	3.919
Δ ($C8$–$C4$)	−.2156	−.5548	−.0578	.1432
	(2.823)	(.737)	(.600)	3.007
Δ ($C20$–$C8$)	.0628	−2.0580	.0008	.0596
	(.506)	(1.683)	(.005)	1.141
$\Delta C8$	−.2424	.2644	−.1789	.2332
	(3.689)	(.408)	(2.160)	5.473
$\Delta C20$	−.1927	−.0746	−.1023	.2580
	(4.103)	(.161)	(1.727)	1.619

NOTE.—t-ratios shown in parentheses; variables defined in text.

IV. Conclusion

The findings of this study are not difficult to summarize. These findings are based on three separate and independent sources of data for the samples analyzed, each of which, when differences in their time periods and units of observation are taken into account, behaves in a manner consistent with the others.

The specific empirical finding is a relationship between the degree to which industries responded to a newly available medium—television—and changes in the sales volume of their smaller members relative to their larger. The nature of the relationship is that a relatively larger shift of an industry's advertising into television results in a reduction in the size disparity among its sellers. By the logic of the methodology outlined earlier, this finding can be restated: An increase in the real volume of advertising messages causes an increase in the sales of smaller sellers relative to the sales of larger sellers. Given the methodology, this is only an empirical finding; its meaning lies in the relevant theory. The central implication of that theory was that increases in the level of information transmission cause small sellers to grow relative to large.

The conclusion is therefore that, in response to additional advertising, consumers readjust their patterns of purchase and, on balance, shift their patronage from larger, widely known brands and firms to smaller, preferred but previously unknown, sellers. This resultant shift toward size equality occurs because the greater real flow of advertising messages, however one might characterize their intended effects, in fact fosters a wider distribution of information about the products and sellers in the market.

References

Anderson, E. E. 1979. An analysis of retail display space: theory and methods. *Journal of Business* 52 (January): 103–18.

Bain, J. S. 1959. *Industrial Organization*. New York: Wiley.

Benham, L. 1972. The effect of advertising on the price of eyeglasses. *Journal of Law and Economics* 15 (October): 337–52.

Brozen, Y. 1974. Entry barriers: advertising and product differentiation. In Goldschmid, Mann, and Weston 1974.

Comanor, W., and Wilson, T. 1967. Advertising, market structure and performance. *Review of Economics and Statistics* 49 (November): 423–40.

Demsetz, H. 1973. Industry structure, market rivalry, and public policy. *Journal of Law and Economics* 16 (April): 1–9.

Ekelund, R., and Maurice, C. 1969. An empirical investigation of advertising and concentration: comment. *Journal of Industrial Economics* 18 (November): 76–80.

Goldschmid, H. J.; Mann, H. M.; and Weston, J. F. 1974. *Industrial Concentration: The New Learning*. Boston: Little, Brown.

Kohn, M., and Shavell, S. 1974. The theory of search. *Journal of Economic Theory* 9 (October): 93–123.

Lancaster, K. 1966. A new approach to consumer theory. *Journal of Political Economy* 74 (April): 132–57.

Lynk, W. 1978. Information, advertising, and the structure of the market. Ph.D. dissertation, University of Chicago.

Mancke, R. 1974. Causes of interfirm profitability differences: a new interpretation of the evidence. *Quarterly Journal of Economics* 88 (May): 181–93.

Mann, H.; Henning, J.; and Meehan, J. 1967. Advertising and concentration: an empirical investigation. *Journal of Industrial Economics* 16 (November): 34–45.

Mann, H.; Henning, J.; and Meehan, J. 1969*a*. Testing hypotheses in industrial economics: a reply. *Journal of Industrial Economics* 18 (November): 81–84.

Mann, H.; Henning, J.; and Meehan, J. 1969*b*. Statistical testing in industrial economics: a reply on measurement error and sampling procedure. *Journal of Industrial Economics* 18 (November): 95–100.

Nelson, P. 1974. Advertising as information. *Journal of Political Economy* 82 (July): 729–54.

Nelson, P. 1975. The economic consequences of advertising. *Journal of Business* 48 (April): 213–41.

Ornstein, S. 1977. *Industrial Concentration and Advertising Intensity*. Washington, D.C.: American Enterprise Institute.

Peltzman, S. 1977. The gains and losses from industrial concentration. *Journal of Law and Economics* 20 (October): 299–63.

Rosen, S. 1974. Hedonic prices and implicit markets: product differentiation in pure competition. *Journal of Political Economy* 82 (January/February): 34–55.

Schmalensee, R. 1972. *The Economics of Advertising*. Amsterdam: North-Holland.

Singer, E. 1968. *Antitrust Economics*. Englewood Cliffs, N.J.: Prentice-Hall.

Steiner, R. 1973. Does advertising lower consumer prices? *Journal of Marketing* 37 (October): 19–26.

Stigler, G. 1961. The economics of information. *Journal of Political Economy* 69 (June): 213–25.

Stonebraker, R. 1976. Corporate profits and the risk of entry. *Review of Economics and Statistics* 58 (February): 33–39.

Telser, L. 1964. Advertising and competition. *Journal of Political Economy* 72 (December): 537–62.

Telser, L. 1969. Another look at advertising and concentration. *Journal of Industrial Economics* 18 (November): 85–94.

Telser, L. et al. 1975. The theory of supply with applications to the ethical pharmaceutical industry. *Journal of Law and Economics* 18 (October): 449–78.