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3

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The Effects of Advertising on Intraindustry Shifts in Demand

ABSTRACT: The effects of advertising on market shares are investigated for five industries—cigarettes, soft drinks, cereals, beer, and gasoline. A nonlinear model employing the Nerlove-Arrow formulation of advertising as a capital good is specified and estimated using conditional regression techniques. The empirical analysis suggests a significant effect of advertising on market shares, for both current and future periods, in all industry classes except gasoline. In addition, in three of the industries—cigarettes, soft drinks, and cereals—calculated optimal advertising-to-sales ratios are in close accord with actual values. These findings, taken in conjunction with my earlier study of the interindustry effects of advertising on demand, indicate that the main impact of advertising is on the consumer's choice of brands or products within a particular industry class rather than across product classes.

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In a prior paper, the interindustry effects of advertising on demand were investigated for several broad industry categories (Grabowski 1976). It was found that, with the exception of certain advertising-intensive industry categories, advertising has a relatively insignificant effect on demand at this level. This finding appears to be consistent with most other empirical work on this question.[1] This suggests, in turn, that the primary impacts of advertising are intraindustry in nature. This question is considered in the current paper where the relation of advertising to market shares is examined in five industry classes.

A number of prior studies have investigated the intraindustry effects of advertising, and most published studies have, in fact, found a significant impact of advertising on sales or market shares.[2] However, most past work has been done in the context of a single-industry case study or a few related industries. Because researchers have often used different models and examined different samples or time periods, it is difficult to compare or check the consistency of the findings of past analysis.

In the current paper, the effects of advertising on market shares are analyzed for five nondurable categories—cigarettes, cereals, soft drinks, beer, and gasoline. A dynamic framework is employed in the empirical analysis, which is based on the Nerlove-Arrow (1962) model of advertising as a capital good. This type of model appears to have a number of advantages for empirical analysis. Specifically, the Nerlove-Arrow analysis of optimal advertising behavior under dynamic conditions provides a basis for taking account of some of the simultaneous equation interactions between advertising and market demand.[3] Second, after regression estimates are obtained on various parameters such as advertising elasticities and depreciation rates, the Nerlove-Arrow optimality conditions can be used to compute optimal advertising-to-sales ratios. These may then be compared with actual ratios in each industry sample. This provides a check on the plausibility of the regression estimate, as well as allowing some insights into the question of whether firms on average are investing too little or too much in advertising relative to other investment activities.

The plan of the paper is as follows. In the following section, the Nerlove-Arrow model is reviewed in some detail. The next two sections contain discussions of the nature of the industry data samples and the empirical specifications of the model to be tested. Section IV contains the empirical findings, using both single-stage and two-stage estimation techniques. The final section is focused on the question of the optimality of and returns to advertising in the five industry samples investigated here.

[I] THEORETICAL CONSIDERATIONS

Most recent theoretical and empirical work concerning the effects of advertising on demand has utilized a dynamic framework in which advertising impacts are assumed to persist beyond a single time period. The general form of the demand function is

$$(1)\quad Q_t = f(A_t, A_{t-1}, A_{t-2}, \ldots, X_t)$$

where

Q_t = product demand in period t;
A_t = product advertising in period t;
X_t = other factors influencing demand in period t (price, consumer income, etc.).

A number of reasons why advertising effects might persist beyond the period of initial outlays have been advanced in the literature. These include the hypothesis of a cumulative effect of advertising on consumer demand in which continued exposure over time is necessary for "buyer inertia" to be overcome. In addition, advertising will have lagged effects on demand if there are bandwagon effects between consumers or intergenerational effects between parents and children. Lagged effects can also exist as a result of using durable media (e.g., magazines). Finally, they can occur if only a portion of the consumers exposed to a particular message are in the market for the good at the time it is advertised.[4]

[A] The Nerlove-Arrow Model

In theoretical and empirical work, it is usually necessary on grounds of analytical tractability to impose some further conditions or constraints on the dynamic lag structure for advertising in equation 1. Nerlove and Arrow (1962) (hereafter N-A) have performed an extensive theoretical analysis of optimal advertising behavior under one set of assumptions concerning the nature of advertising dynamic effects on demand. Because their model is used extensively in the empirical analysis presented below, its main assumptions and implications are reviewed here at the outset of the paper.

Nerlove and Arrow basically assume that the choice of optimal advertising inputs constitutes an investment decision to the firm. Specifically advertising outlays are envisioned as contributing over time to a stock of "goodwill" for the firm's product. Like the other capital assets, this goodwill stock is subject to depreciation over time.

Since it is goodwill stock which directly influences demand in the N-A model, the firm's demand curve may be written in the simplified form

$$(2)\quad Q(t) = f[P(t), G(t), Z(t)]$$

where

$Q(t)$ = output demanded at time t;
$P(t)$ = product price at time t;
$G(t)$ = the goodwill capital stock at time t produced by current and past advertising outlays;
$Z(t)$ = the set of other factors influencing demand.

The stock $G(t)$ is further related to advertising investments in the N-A model by the equation

$$(3)\quad \dot{G} = A - \lambda G$$

(where λ = the rate of depreciation on the goodwill stock, G, and time indices have been omitted for notational convenience).

Equation 3 assumes that the firm's goodwill stock depreciates at a rate which is proportional to the value of the stock at any moment of time. This is a prevalent assumption in the literature on capital theory. Its discrete counterpart (which is relevant for empirical analysis) is a distributed lag structure with geometrically declining weights (i.e., the Koyck distributed lag structure).

Assuming the firm operates under monopoly conditions and wishes to maximize the net discounted value of profits, $V(t)$, its objective function becomes

$$(4)\quad V = \int_t^{\infty} e^{-rt}\,[PQ - C(Q) - AT]\,dt$$

where

r = the firm's discount rate;
P = product price;
Q = rate of output;
$C(Q)$ = total costs excluding advertising;
A = real advertising inputs (in "viewer messages");
T = advertising cost per viewer message.

Advertising expenditures in equation 4 are expressed explicitly as the product of inputs in real terms (in viewer messages) times the cost per unit of these inputs. This allows for possible changes over time in the cost of producing viewer messages.[5]

N-A show that in order for the firm to maximize $V(t)$ subject to equations 2 and 3, it should select a goodwill stock G at each point in time such that

$$(5)\quad \frac{GT}{PQ} = \frac{\eta_G}{r+\lambda}\left(\frac{P-MC}{P}\right) = \frac{\eta_G p}{r+\lambda}$$

where η_G = elasticity of demand with respect to goodwill capital and p is the markup of price over marginal costs (excluding advertising).

This condition can also be expressed in terms of optimal advertising-to-sales ratios. Specifically, multiplying both sides of equation 5 by A/G and given that $\partial Q/\partial G = \partial Q/\partial A$, one obtains the relation

$$(5')\quad AT/PQ = \eta_A p/(\lambda + r)$$

The optimal advertising-to-sales ratio therefore will be directly proportional to the elasticity of demand with respect to advertising and the markup of price over marginal costs and inversely related to the firm's discount rate and depreciation rate on goodwill capital.[6] It is this basic relation that will be used extensively in the empirical analysis.

While the N-A model assumes a monopoly situation, some simple generalizations of that analysis to oligopoly conditions have been made using the conjectural variation approach. For example, the oligopolistic counterpart to the optimality condition given by equation 5' is

$$\text{(6)} \quad \frac{A_i T_i}{P_i Q_i} = \frac{\eta'_{Ai} p_i}{\lambda_i + r_i}$$

where

$$\eta'_{Ai} = \frac{A_i}{Q_i}\frac{\partial Q_i}{\partial A_i} + \sum_{j \neq i} \frac{\partial Q_i}{\partial A_j}\,\frac{dA_j}{dA_i}$$

In effect the advertising elasticity for each firm now incorporates the expected response of rival firms to any change in its own advertising outlays. A similar response pattern, of course, can be defined with regard to other decision variables such as product price. The analysis, of course, becomes correspondingly more complicated (in terms of interaction terms) as one introduces more general response patterns and additional decision variables.

[B] Implications for Empirical Analysis

A number of points may be made concerning the relevance and implications of the above theoretical analysis for empirical estimations of advertising effects on demand. First, it is usually impractical to estimate a general unconstrained distributed lag formulation like equation 1, because of severe multicollinearity in the lagged advertising terms. The N-A concept of a stock of goodwill capital, with its attendant assumptions concerning the stock's accumulation and depreciation, provides a plausible a priori basis for constraining the lag terms. It utilizes assumptions that have received considerable attention in the literature on capital theory. A constant proportional depreciation pattern also has some attractive features from the standpoint of empirical estimation.

The N-A analysis of optimal advertising behavior further underscores the fact that a two-way relation will generally exist between advertising and sales,[7] that is, advertising changes will not only shift firm demand over time, but a feedback relation of sales on advertising will also exist. This means that in econometric analysis, simultaneous equation techniques are appropriate for estimating the effects of advertising on demand. Simple least square estimators will be biased in this situation. In constructing simultaneous equation estimation techniques that are unbiased, it is important that all functional relations be mutually consistent. An important advantage associated with employing the N-A dynamic assumptions is that their optimality analysis may be used to structure the simultaneous equation estimates in a consistent manner. This is highly preferable to ad hoc specifications concerning advertising expenditure behavior.

Another advantage associated with the N-A model in applied work is that the optimality conditions given above may be used to calculate advertising-to-sales ratios. These can then be compared with the actual ratios for each industry, and the results can be used to evaluate the rationality of (and returns from) advertising outlays as well as providing a rough consistency check on the plausibility of the estimates derived from the empirical analysis.

In sum, the N-A model has a number of desirable attributes and provides a consistent dynamic framework for empirically analyzing the effects of advertising. It is used throughout the remainder of the paper as the underlying theoretical basis for my empirical work.

[II] CHARACTERISTICS OF INDUSTRY SAMPLES

Information on the basic characteristics of the five industry samples investigated in the empirical analysis is presented in Table 1. The five industry classes presented in the table are those for which firm or brand data on both output and advertising could be obtained for a significant portion of industry activity. All five industries involve nondurable products,[8] and all except gasoline have advertising intensities that are significantly above the average advertising-to-sales ratio of 1.5 percent for the whole manufacturing sector.

TABLE 1 Basic Characteristics of the Five Industry Samples

Industry	Number of Firms or Brands	Time Period	Output Measure	Market Share of Sample Firms	Advertising-to-Sales Ratio of Sample Firms
Cigarettes	20 brands	1962–1969	Billions of cigarettes	96%	7.1%
Soft drinks	6 firms	1962–1970	Cases	75	5.7
Gasoline	8 firms/brands	1961–1968	Gallons	56	1.4
Cereals	6 firms	1963–1970	Dollars	96	14.1
Beer	19 firms/brands	1961–1970	Barrels	76	7.1

The data were collected on as disaggregate a basis as possible. The most detailed information was obtained in the cigarette industry where data on output and advertising outlays were assembled for twenty major brands. For the other four industries, output data were available only at the firm level, and the analysis is conducted at that level. However, in two of these industries, gasoline and beer, firm shares effectively denote brand shares as well, because firms generally market only under a single brand name. In the remaining two industries, cereals and soft drinks, firm shares are aggregated over several brands produced by each firm.

The advertising expenditure data were obtained from audits of individual media. Advertising expenditure data for the four major media—network TV, spot TV, newspapers, and magazines—are included in the advertising measure for all industries. These data were supplemented by advertising data in two other media--radio and outdoor—for those industry classes where the data (available in selected years) indicated they were a significant percent of total firm outlays. Where this was the case, data on missing years were approximated using a simple statistical extrapolation procedure. Details are provided in a statistical appendix available from the author on request.

Because the data on firm output levels were available only on an annual basis, the empirical analysis is conducted using the calendar year as the unit of observation for all variables. In general this means there are insufficient degrees of freedom to do purely time series analyses of advertising effects for individual firms or brands. As a consequence, the empirical regression analysis is performed on pooled time series of cross-sectional industry samples. In effect, therefore, one is examining the dynamic effects of advertising on demand for the "representative" firm or brand in each of these industries and abstracting from differences in advertising quality or effectiveness across brands or firms. Thus, a basic issue which this type of analysis addresses is whether the average or representative firm in these industries is earning a rate of return on advertising that is greater than, equivalent to, or less than alternative investment opportunities. This question is explicitly considered in the final section of the paper.

[III] SPECIFICATION OF THE MODELS FOR EMPIRICAL ANALYSIS

[A] Market Share as the Dependent Variable

As noted at the outset, the main objective of the empirical analysis is to estimate the dynamic effects of advertising on demand for the five industry categories described above. As also emphasized, the focus of this paper is on the intraindustry effects of advertising on demand. Interindustry impacts have been analyzed at some length in an earlier paper (Grabowski 1976). Consequently, considerable economies of model specification can be achieved by employing market share rather than the absolute level of sales as the dependent variable. This allows us to abstract from aggregate factors such as consumer income and focus on intraindustry determinants of demand. This type of approach has been employed in a number of prior research studies of advertising for particular industries.

In particular, I assume that the demand function given by equation 1 can be expressed as

$$(7) \qquad Q_t = \bar{Q}_t(Y_t)\, f\left(\frac{A_t}{\bar{A}_t}, \frac{A_{t-1}}{\bar{A}_{t-1}}, \ldots, \frac{A_{t-m}}{\bar{A}_{t-m}}, \ldots, Z_t\right)$$

or

$$MS_t = \frac{Q_t}{\bar{Q}_t} = f(AS_t, AS_{t-1}, \ldots, AS_{t-m}, \ldots, Z_t)$$

where

$\bar{Q}_t$ = industry demand in period t;
$\bar{A}_t$ = industry advertising in period t;
Y_t = aggregate and interindustry demand factors influencing demand in period t;
Z_t = intraindustry factors (besides advertising) influencing demand in period t;
MS_t = firm market share in period t;
AS_t = firm advertising share in period t.

Equation 7 assumes that consumers collectively decide on the *total demand* for an industry's goods on the basis of *aggregate* factors (such as consumer income, interindustry differences in prices, etc.). This demand is then allocated among the *various firms* or *brands* in this industry on the basis of *intraindustry* differences in relative advertising levels and other supply-side variables. It further implies that any shifts that occur in total industry demand will produce parallel shifts in the demand curves of individual firms and leave market shares unchanged.[9]

This type of specification has in fact been employed in most prior studies of advertising and market shares.[10] Although this formulation embodies some strong assumptions, it also offers significant advantages on empirical grounds. Problems often arise in empirically untangling the effects of a firm's advertising from that of its competitors when these expenditures are often highly correlated. The formulation given by equation 7 assumes that only relative shifts in advertising affect market shares and therefore avoids this multicollinearity problem.

The advertising share terms are constructed in our empirical analysis on the basis of real rather than absolute dollar expenditures; that is, both the numerator and denominator of the advertising share variable are calculated in terms of constant 1958 dollars. To express these variables in real terms, each of their individual media components is deflated by a media price index obtained from trade sources. Further details are presented in the statistical appendix.

[B] The Dynamic Effects of Advertising

As discussed in the previous section, it is usually necessary to constrain the dynamic lag structure of advertising in some a priori fashion in order to obtain reasonable coefficient estimates. As discussed above, in this paper, I employ the N-A concept of a goodwill stock of advertising capital that depreciates at a constant proportional rate to generate the lag structure on advertising.

In particular, given the N-A assumptions on the goodwill advertising stock, equation 7 can now be expressed as

$$(8) \quad MS_t = f(G_t, Z_t)$$

where G_t, the goodwill stock, is generated by the discrete analogue of equation 2 or

$$(9) \quad G_t = AS_t + (1 - \lambda)\, G_{t-1}$$

and λ = rate of depreciation on goodwill capital. Equation 9 can then be solved recursively to obtain

$$(10) \quad G_t = AS_t + (1 - \lambda)AS_{t-1} + (1 - \lambda)^2 AS_{t-2} + \ldots + (1 - \lambda)^m AS_{t-m} + \ldots$$

Thus the goodwill stock is a weighted combination of current and past relative advertising expenditures in which the weights decline geometrically as we proceed back in time (i.e., the Koyck distributed lag structure).

In selecting a specific functional form for equation 8 for empirical estimation, both linear and multiplicative formulations were considered. A multiplicative relation appears preferable on theoretical grounds. This is because a linear functional relation imposes a proportionate relation between the goodwill stock and market shares, whereas a multiplicative relation allows diminishing, constant, or increasing returns. A diminishing returns relation would seem more plausible in this situation given that the dependent variable is formulated in market share terms. Furthermore, even if the relation has an initial phase of increasing or constant returns, one would still expect a profit-maximizing firm to operate on the diminishing returns portion of the curve. Because of these considerations, primary attention is focused on the multiplicative functional form in the empirical analysis. Hence, in symbolic terms, the principle model analyzed is

$$(11) \quad MS_t = \alpha\, G_t^{\beta}\, Z_t^{\gamma}\, u_t$$

and substituting equation 10 for G_t, this can be expressed in terms of advertising shares as

$$(11') \quad MS_t = \alpha\,[AS_t + \ldots + (1-\lambda)^m AS_{t-m} + \ldots]^\beta Z^\gamma u_t$$

In most past empirical work where a geometrically declining lag structure is assumed between market shares or sales and advertising, the models have been estimated using the Koyck transformation (Koyck 1954), that is, the original model is transformed into one in which the dependent variable is regressed on a lagged value of itself and first- or second-order lagged terms of the independent variables. However, because of the particular nonlinear character of equation 11′, this method of estimation is not feasible here.

An alternative approach to the estimation of equation 11′ is to obtain these coefficients directly using nonlinear estimation procedures. In particular, the goodwill stock in the equation can be approximated by a finite number of lags, or

$$(12) \quad G_t(\lambda) \cong AS_t + (1-\lambda)\,AS_{t-1} + \ldots + (1-\lambda)^n AS_{t-n}$$

and then a conditional regression approach can be used to find the value of λ and other coefficients that maximize the coefficient of determination on equation 11.

This approach has been employed in my earlier study of interindustry effects of advertising as well as in some recent studies of advertising by others for particular industries.[11] While it is computationally more complicated than the Koyck transformation approach, it does have the advantage of not generating autocorrelated residuals and related types of problems associated with the Koyck transformation. Some measurement error will be introduced in the G variable by truncation, but this is not likely to introduce serious biases if a sufficient number of lagged terms are included and the rate of depreciation is not close to zero.

In the econometric analysis, I estimate the model given by equation 11′, using this conditional regression procedure. For comparative purposes, I also estimate some other functional forms (e.g., the linear Koyck case) for which the Koyck transformation can be employed.

In accordance with the discussion in section I, estimation of (11′) as a single-equation model will be subject to simultaneous equation bias. In particular, the N-A optimality conditions indicate a behavioral relation also exists between current advertising and output. Because of this feedback relation between advertising and output, the goodwill stock will not be independent of the error terms in the above equations. This leads to a positive bias in the estimated coefficients for advertising and goodwill stock.

The basic strategy for dealing with this problem here is to use an instrumental variable approach to "purge" the positive relation of current advertising with the error term. Specifically a reduced form equation on advertising is formulated, based on a simultaneous equation system that incorporates both the N-A optimality conditions and the market share equation presented above. The reduced form estimates on current advertising, $\hat{A}_t$, are then used as instruments in estimating the above market share relation. Specific details on this approach are presented in the next section in the context of the particular models employed.

[C] Other Determinant Factors

In addition to advertising outlays, two other dimensions of intraindustry competition might be expected to have a significant influence on market shares for our industry samples. These are product price and product quality.

The only price data that could be obtained, however, were list prices and this was much more fragmentary in character than the advertising data. Moreover, in cigarettes and gasoline, there was virtually no differences in list prices across the major brands in our sample. In beer, the main differences were in the list prices of national versus regional or local brands. Some variation in the list prices across brands was also observed for cereals and soft drinks. However, the market share data in these industries are aggregated over several brands, and without output or market share weights on particular brands, it is difficult to construct meaningful price indexes at the firm level.

Empirical measures of intraindustry differences in quality are subject to related, but conceptually more difficult, problems. One approach that has been applied in studies of durable goods (like automobiles), with some success, is to estimate a hedonic price index to get at differences in quality.[12] Basically this approach involves regressing product price on various quality characteristics (such as horsepower, gas mileage, etc.) and using the resulting coefficient estimates as market utility weights for these characteristics. However, this approach is difficult to apply to nondurable categories where product qualities are basically subjective in character and quantitative indexes of the characteristics do not exist. As a consequence, the hedonic price index approach has been confined to studies of durable goods, and none of the previous investigations of advertising effects for nondurable products has included any quality-adjusted measures.

Because of these various problems, no attempt is made to include direct measures of product price or quality in the regression analysis undertaken here. Rather, the alternative procedure is employed of attempting to capture the effects of these factors through the use of firm or brand dummy variables. This approach is equivalent to measuring all our variables as variations around firm (or brand) means and excluding interfirm variation from the estimation process. Hence, to the extent that differences in price or qualities are firm (or brand) related and have been stable over the time period spanned by our sample, this approach should provide an adequate control for these factors. This would appear to be true for much, if not all, the variations in product prices and quality in our samples.

To the extent that some variation in product prices and/or quality remains that is not adequately captured by this dummy variable approach, some bias can be expected in the estimates for the advertising variables. The exact nature of this bias will depend on the relation of the omitted determinant variable to both the dependent variable in the analysis (i.e., market share) and the included explanatory variable (i.e., advertising). As an example, let us assume that some firms increase their average product quality over the time period covered and this further results in increased advertising and market shares. If the changes in product quality are omitted while advertising is included in the regression equations, the result will be an upward bias for the estimates on the advertising variable. On the other hand, the opposite kind of bias might also plausibly occur. For example, changes in prices over time might also be positively correlated with advertising, but negatively correlated with market shares, and this would create a negative bias on the advertising variable.

It should also be emphasized that we are abstracting from any differences in advertising quality across firms. To the extent that there have been stable advertising quality differences for the firms or brands in our sample for the period under study, the firm and brand dummies should also reflect the influence of this factor. However, if relative quality has been significantly changing across firms, this would also tend to introduce bias into our coefficient estimates.[13]

It is thus difficult to assess the net effect or sign of any bias resulting from omitted variables. Potentially, the most important source of such bias would appear to be from significant new-product introductions or changes in product characteristics. However, the gasoline, beer, and soft drink industries were in fact characterized by very stable product characteristics over the time spans covered. Therefore, any bias associated with the exclusion of product quality changes should be minimal for those industries. On the other hand, the cereal and cigarette industry did experience some changes in product composition over this period. Further analysis is necessary, however, to determine how sensitive the estimated coefficients below are to this and other omitted factors. In the absence of specific data on transactions prices or product quality, a dummy variable approach is the best one can do to take account of interfirm differences in nonadvertising factors.

[IV] EMPIRICAL RESULTS

[A] Single-Equation Analysis

Initially, model estimates are obtained using single-equation methods. In particular the model to be estimated is

$$MS_{it} = (\Pi a_i^{D_i})\, C_{it}\, (\lambda)^{\beta}\, v_{it} \tag{13}$$

or

(13') $MS_{it} = (\Pi a_i^{D_i})[AS_{it} + (1 - \lambda)AS_{it-1} + \ldots + (1 - \lambda)^n AS_{it-n}]^{\beta} v_{it}$

where

MS_{it} = market share of the i^{th} firm or brand in period t, i.e., the ratio of the i^{th} firm's, or brand's, output to total industry output;

D_i = dummy variable taking the value 1 for the i^{th} firm or brand and zero otherwise;

G_{it} = goodwill stock of the i^{th} firm in period t;

AS_{it} = advertising share of the i^{th} firm in period t, i.e., the ratio of the i^{th} firm's, or brand's, advertising to total industry advertising where both are measured in real terms;

v_{it} = error term.

The values of a_i, B, and λ are estimated by a nonlinear search algorithm which minimizes the standard error of estimate of equation 13.[14] As noted above, the process of approximating the goodwill stock by a finite number of lags will necessarily introduce some measurement error into this model. Advertising data consistent with that used in the previous estimates were available back as far as 1956. Since our sample periods begin in 1961 or later, at least five years and in some cases as many as eight years of lagged data were available to construct the approximations on the goodwill stock given by equation 13'. Except in the cases where the rate of depreciation on goodwill capital is very slow, the measurement error arising from finite truncation of equation 13' should not be very great, given these many periods of lagged terms.

In estimating the parameters of this model, the value of λ was constrained to the region $0.10 \leq \lambda \leq 1.0$. Values of λ which are negative or in excess of 100 percent are, of course, nonsensical. The rate of depreciation was further constrained to be at least 10 percent because a zero rate creates convergence problems for the model used here.

The estimated coefficients for (13) are presented in Table 2. The goodwill stock variable takes on the postulated positive sign in all cases. Furthermore, it is statistically significant (at the 1 percent level) for all industries except gasoline. The coefficient values for β, which represents the elasticity of market shares with respect to the goodwill stock, indicate that a less than proportionate relation (i.e., diminishing returns) exists in each industry with the possible exception of soft drinks. The coefficient in that industry suggests constant returns to scale. However, the problems of simultaneous equation bias have not yet been considered. Since this would tend to result in a positive bias for β across all industries, diminishing returns may also hold in the soft drink industry when the estimates are adjusted to take this effect into account. This issue is considered in the next section.

The estimated values in Table 2 indicate sizable long-run impacts of advertising on sales for three of the five industries. The rate of depreciation on ad-

TABLE 2 Estimation of Market Share Equation 13, Using Conditional Regression Estimation Procedure (figures in parentheses are standard errors)

Industry	Period	Dummy Variables	β	λ	R^2
Cigarettes	1962–1969	20 brands	0.725 (0.095)	0.259 (0.049)*	.99
Soft drinks	1962–1970	6 firms	1.03 (0.203)*	0.169 (0.045)*	.99
Gasoline	1961–1968	8 firms/brands	0.033 (0.039)	1.00 (1.10)	.99
Cereals	1963–1970	6 firms	0.708 (0.125)	0.100 (0.075)*	.99
Beer	1961–1970	19 firms	0.241 (0.041)	0.839 (0.088)*	.99

*Statistically significant at 1 percent level.

vertising capital is between 10 and 25 percent in the cigarette, cereal, and soft drink industries. The corresponding (long-run) elasticities of market share with respect to changes in goodwill capital range from 0.7 to 1.0. On the other hand, the estimated coefficient on depreciation in the beer industry is 84 percent, and the elasticity of market share is only 0.24. Finally, as noted above, the estimated coefficient in the gasoline industry is not significant, and its value suggests a negligible long-term impact of advertising on sales.

The estimates in Table 2, hence, suggest there are considerable differences in the long-run impact of advertising on market shares among the five industries. Consideration of the possible reasons for these differences will be deferred until later so that other variants of the model, including the two-stage estimation, can also be taken into account.

For comparative purposes, I also estimated linear and log-linear variants of the Koyck transformation model. In the linear case, the basic model is

$$(14) \quad MS_{it} = a_0 + \Sigma a_i D_i + b_1 G_{it} + u_{it}$$

where MS_{it} and G_{it} are market share and goodwill stock of the i^{th} firm in period t, D_i are firm or brand dummies, and G_{it} is given by the following infinite series:

$$(15) \quad G_{it} = AS_{it} + (1 - \lambda)\, AS_{it-1} + \ldots + (1 - \lambda)^n\, AS_{it-n} + \ldots$$

Substituting (15) for G_{it} into (14) and transforming, using the standard Koyck procedures, one obtains the following functional form for empirical estimation

$$(16) \quad MS_{it} = (1 - \lambda)a_0 + (1 - \lambda)\, \Sigma\, a_i D_i + b_1 AS_{it} + (1 - \lambda) MS_{it-1} + u_{it} + (1 - \lambda) u_{it-1}$$

Similarly, if multiplicative functional forms are assumed for the relations given by (14) and (15), the log-linear version of the Koyck model is obtained:[15]

$$(17) \quad \log MS_{it} = (1 - \lambda) \log a_0 + (1 - \lambda) \Sigma (\log a_i) D_i + b_1 \log AS_{it}$$
$$+ (1 - \lambda) \log MS_{it-1} + \log u_{it} + (1 - \lambda) \log u_{it-1}$$

In these models, the first-period impact of advertising on market share is obtained directly from the coefficient estimate of the current advertising variable, and the rate of depreciation on goodwill capital is calculated from the lagged market share terms. The advantages and statistical problems associated with this lagged dependent variable formulation obtained from the Koyck transformation have been extensively discussed in the literature (see, for example, Griliches 1967).

In the present situation, the linear variant of the Koyck model did not perform very well for our five-industry sample. The current advertising variable was significant in only the cigarette and soft drink industries. In addition, the values on the lagged market shares were close to 1 in three of the five industries (soft drinks, beer, and gasoline). This would imply very low or even zero rates of depreciation on goodwill capital in these industries, an implausible result.[16]

However, the log-linear Koyck transformation given by (17) performed much better and exhibited qualitatively similar findings compared to the nonlinear model presented in Table 2. In particular, the current advertising variable was positive and statistically significant for four of the five industries (all except gasoline). Furthermore, the estimated coefficient values for the log-linear Koyck model imply a diminishing returns relation between advertising and market share, consistent with expectations based on economic theory.

Although the qualitative similarities in findings between the log-linear Koyck model (17) and my basic model (13') employing conditional regression techniques is reassuring, the latter formulation still seems preferable on both theoretical and econometric grounds. First, in contrast to the log-linear Koyck model, my original model does not have to assume a multiplicative pattern on the depreciation of goodwill capital.[17] Rather, it incorporates the theoretically more plausible N-A assumption of a constant proportional rate of depreciation. Second, in empirically estimating both structures, the biases arising from truncation of the goodwill stock seem potentially less severe than those arising from a lagged dependent variable approach in which serial correlation is likely to be present. Along these lines, it may be noted that when I estimated the model underlying the log-linear Koyck case by conditional regression techniques rather than the Koyck transformation relation of (17), I obtained much more conservative estimates of the impacts of advertising on market share, i.e., higher estimated depreciation rates on goodwill capital and lower lagged effects of advertising on market shares.[18]

Because of these considerations, attention is focused throughout the remainder of the paper on the model given by (13′) and estimated by nonlinear conditional regression techniques. A key unresolved question, of course, is the extent to which the coefficient estimates in Table 2 are influenced by simultaneous equation bias. This question is now considered.

[B] Two-Stage Estimates

As I pointed out earlier in this paper, the estimates presented in Table 2 for our basic model

$$(18) \quad MS_{it} = (\Pi a_i^{D_i}) G_{it}^{\beta} v_{it} = (\Pi a_i^{D_i}) [AS_{it} + (1-\lambda)AS_{it-1} + \ldots + (1-\lambda)^n AS_{it-n}]^{\beta} v_{it}$$

are subject to simultaneous equation bias because of the expected positive relation between the firm's current output and its advertising. On the basis of the N-A analysis discussed in section I, one expects a behavioral or feedback relation, arising from the optimality conditions on advertising, of the form

$$(19) \quad \left(\frac{AT}{PQ}\right)_{it} = \left(\frac{\rho\eta_A'}{\lambda + r}\right)_{it}$$

or rearranging terms and adding a stochastic term to the equation

$$(20) \quad A_{it} = \left[\frac{P}{T}\frac{\rho\eta_A'}{(\lambda + r)}\right]_{it} Q_{it} v_{it}$$

If prices are assumed to be exogenous, equations 18 and 20 together with the identities

$$(21) \quad MS_{it} = Q_{it}/\bar{Q}_t$$

and

$$(22) \quad AS_{it} = A_{it}/\bar{A}_t$$

can be taken as a simultaneous system determining the values of the two endogenous variables, output and advertising, in both absolute and relative terms. In view of the complexity of this two-equation system and the unavailability, in any event, of satisfactory data on transaction prices, the assumption that prices are exogenous is adopted in the analysis undertaken here.

Even under this simplifying assumption, the above is a complex, nonlinear, functional system that cannot be directly estimated by standard linear methods. Accordingly, rather than try to identify and estimate a full nonlinear simultaneous equation system, the above relations are used as guidelines for deriving a reduced form equation on current advertising. This is then used in an instrumental variable analysis to purge the relation of this variable with the error term in equation 18. Using this approach, the following reduced form equation for advertising was constructed:

$$(23)\quad A_{it} = (\Pi b_i^{D_i})\,(P/T)_{it}^{c_1}\, r_t^{c_2}\, A_{it-1}^{c_3}\, AC_{it-1}^{c_4}\, Y_t^{c_5} PI_t^{c_6}\, v_{it}$$

Thus, from the advertising determinant relation, i.e., equation 20, two variables are included in equation 23, one reflecting the relative price of advertising, $(P/T)_{it}$, and the other indexing the firm's cost of capital, r_t. The former is formulated as the ratio of product price (measured at the industry level) to the firm's price index on advertising. The cost-of-capital measure, r_t, is formally defined as the ratio of net income and interest payments to the market value of debt and equity in any given period. This is the same as the measure used by Jorgenson in studies of other types of investment activity.[19] Two other variables included in the advertising determinant relation, the markup of price above marginal cost, p, and the net advertising elasticity variable, $\eta'_{A_{it}}$, were not included in (23) because insufficient data exist to construct time series of them.

From the market share equation, only the first-order lag terms on advertising and competitors' advertising are included. The higher-order lag terms have a high degree of collinearity with the first-order lags, and the latter can plausibly be assumed to have the most direct influence on the firm's current expenditure.

Finally, the industry output variable, which appears in the original reduced form because of the identity equations, was replaced in (23) by two variables that have been significant determinants of industry output in past empirical studies: disposal income, I_t, and relative industry price, PI_t. This was done because total industry output is obviously not a completely exogenous determinant of *firm output* and hence if included in (23) would not be independent of the error term.

A multiplicative, i.e., linear in logarithmic, specification was used for reduced form equation 23 because of the interactive character of the equations underlying that form. Firm dummies were also included in (23) because it was estimated on the same pooled cross-sectional time series industry samples as the previous specifications.

The two-stage estimating process therefore involved initially obtaining first-stage structural estimates on current advertising, $\hat{A}_{it}$, for each industry sample, using equation 23. These were then substituted for A_{it} in equation 18, and the second stage of the model, namely

$$(24)\quad MS_{it} = (\Pi a_i^{D_i})\left(\frac{\hat{A}_{it}}{\bar{A}_{it}} + (1-\lambda)\frac{A_{it-1}}{\bar{A}_{it-n}} + \ldots + (1-\lambda)^n \frac{A_{it-n}}{\bar{A}_{it-n}}\right)^{\beta} v_{it}$$

was estimated using the conditional estimation procedures previously described.

TABLE 3 Two-Stage Estimates of Market Share Equation 24 (figures in parentheses are standard errors)

Industry	Period	Dummy Variables	β	λ	R^2
Cigarettes	1962–1969	20 brands	.576 (.112)*	0.241 (0.083)*	.99
Soft drinks	1962–1970	6 firms	.730 (.216)*	0.163 (0.083)**	.99
Gasoline	1961–1968	8 firms/brands	−.027 (.073)	1.100 (–)	.99
Cereals	1963–1970	6 firms	.661 (.143)*	0.100 (0.091)*	.99
Beer	1961–1970	19 firms/brands	.305 (.045)	0.904 (0.153)*	.99

*Statistically significant at 1 percent level.
**Statistically significant at 5 percent level.

Table 3 presents the coefficient estimates that resulted from estimation of (24) by this two-stage approach. In general, the results are qualitatively similar to the single-stage estimates presented in Table 2. However, the estimated elasticity coefficients for the goodwill stock variable are on the average 20 percent lower than those in Table 2. This coefficient estimate declines in all industries except beer. Hence, these findings are consistent with the notion that prior estimates were upwardly biased due to simultaneous equation interactions between advertising and output.

The elasticity estimates in Table 3 further indicate that a diminishing returns relationship holds across all industry classes. The elasticity coefficient ranges from 0.31 to 0.73 for the four industries in which it is statistically significant. This is in accordance with the theoretical expectation that firms will operate only on the diminishing returns portion of the relationship.

Aside from the lower coefficient estimates on the elasticity of the goodwill stock variable, the other findings remain virtually unchanged. The estimated coefficients on depreciation are essentially identical to those in Table 2, except in the beer industry, where the coefficient increased by about 10 percent over its former value. Hence, the previously observed pattern of relatively low rates of depreciation in cigarettes, soft drinks, and cereals and rapid depreciation in the other two industries also holds for the two-stage estimates of this model.

In sum, the two-stage estimates do not in any way alter the major finding emerging from the single-equation estimates of this model. They, too, indicate a statistically significant impact of advertising on market shares in both the short and long run in four of the five industries studied. The exception is the gasoline industry, for which no statistically significant effect of advertising on market shares in our sample of the eight largest firms could be discerned with this or any of the other models employed here.

While the estimates in Table 3 indicate a positive impact on market shares associated with increases in relative firm advertising in all industries except gasoline, they do not necessarily imply that the marginal return to advertising of the representative firms in those industries is equal to opportunity costs or even that the marginal return is positive. This general question is considered in the final section where the marginal returns to advertising and the rationality of advertising investment activity are evaluated.

[V] THE OPTIMALITY OF AND MARGINAL RETURNS TO ADVERTISING

The N-A optimality conditions presented in section I require that the profit-maximizing firm invest in advertising up to the point where marginal returns equal opportunity cost. This in turn implies the following condition on the advertising-to-sales ratio:

$$(25)\quad \frac{AT}{PQ} = \frac{\eta_A'}{\lambda + r}\,\frac{P - MC}{P}$$

where all time and firm subscripts have been omitted for notational convenience.

This relation can be used to gain some insights into the optimality of and marginal returns to advertising. In particular, the coefficient values in Table 3 provide estimates on advertising elasticities and depreciation rates for the mean or representative firm in each of the five industries. These can be combined with industry estimates on the average markup of price over marginal cost and the opportunity cost on capital. Given these measures, optimal advertising-to-sales ratios can then be calculated using (25). The comparison of these calculated optimum values with the actual ratios provides an insight into whether the rate of return to the investment in advertising capital of these firms is on average higher, lower, or about the same as the rate obtainable on other types of investment activity. This type of analysis is undertaken on four of the five industries for which elasticity and depreciation coefficients were estimated in the previous section. The gasoline industry is excluded here because of its highly insignificant advertising coefficients in all the models tested.

The N-A conditions given by (25) actually require an estimate of elasticity of firm sales with respect to advertising, whereas the previously estimated models provide estimates of the elasticity of firm market shares with respect to advertising shares. However, under two assumptions discussed below it is easy to show that a simple relation exists between the two elasticities, namely,

$$(26)\quad \eta_{Q\cdot A} = (1 - AS)\,\eta_{MS\cdot AS}$$
$$= (1 - AS)\left(\frac{AS}{G}\right)\eta_{MS\cdot G}$$

where η_{QA} is the elasticity of firm output with respect to advertising outlays, and the other elasticities are defined in corresponding fashion.

In particular, equation 26 holds under the assumption that (1) total industry output is unaffected by changes in advertising, i.e., the effects of advertising are all intraindustrial in nature; and (2) the advertising expenditures of rival firms are unaffected by changes in other firms' outlays, i.e., Cournot behavior.[20]

Both assumptions are polar in nature, and therefore it is appropriate to consider how their relaxation would affect the above analysis. In general, relaxation of these assumptions has opposite effects on the calculated elasticities and optimal advertising-sales ratios; that is, to the extent that industry output is influenced by firm advertising, a positive relation would be expected between the two. This would mean that the elasticity of demand calculated by equation 26, which ignores this component of increased demand, will tend to underestimate true advertising elasticities. Correspondingly, the optimal advertising-to-sales ratio based on that estimate will also be underestimated. However, to the extent that firms in an industry positively shift advertising in response to each other's increases in advertising, the gains in sales associated with increased advertising would be offset in part or in whole. Hence, ignoring the intraindustry response factor will tend to produce the opposite kind of bias from that associated with ignoring interindustry shifts in demand.

In the absence of any quantitative estimates of the importance of these two phenomena, it is impossible to say what will be the net effect of these polar assumptions on the calculated values of optimal advertising-to-sales ratios. My own past work on advertising, as well as most other studies on this subject, tends to indicate that the interindustry effects of advertising are not strong[21] and that the main effects are intraindustrial. To the extent that this is the case, and competitive interactions in advertising are also strong, the present analysis might be expected to overestimate advertising elasticities and optimal advertising-to-sales ratios. While there is some fragmentary evidence consistent with the hypothesis of strong rivalry in advertising, further analysis is necessary before it can be stated that this is in fact the case.[22] For the moment, (26) is employed in the expectation that it provides a good first approximation.

In order to calculate optimal advertising-to-sales ratios using equation 25, estimates are also needed of the firm's opportunity cost on capital and the percent markup of price over marginal cost. For the opportunity cost variable a value of 10 percent is assumed in all industries. This is roughly equal to the after-tax return on equity capital for corporate firms over this period[23] and is, therefore, what the firm's shareholders could be expected to earn on rival investments during that time.

The average percent markup of price over marginal cost in each of the industries can be approximated by average firm profit margins on sales gross of advertising.[24] Accordingly, a weighted average of profit margins on the firms in each industry sample was computed using balance sheet data on total firm revenues and costs. Firms which were obviously conglomerate in character or had the majority of their sales in unrelated industrial activities were excluded from this calculation. This procedure yielded estimates of after-tax margins (gross of advertising) between 12.5 and 16.5 percent for the four industries.[25] Pretax margins would be roughly double these values.

When these various assumptions and approximations are pulled together, the optimal advertising-to-sales ratio in each industry can be calculated by the relation

$$\text{(27)}\quad \frac{A^*}{S} = \frac{\eta_{MS\cdot C}(1-AS)}{\lambda + r}\,\frac{AS}{G}\,\frac{\Pi'}{S}$$

where Π'/S is the weighted profit margin variable and the other variables are defined as above.

In calculating optimal advertising-to-sales ratios, $\eta_{MS\cdot C}$ and λ are obtained directly from the estimates presented in Table 3. The values of $(1 - AS)$, AS/G and Π'/S are all calculated as sample means in, or centered around, the year 1965 (a midpoint year for our sample). Correspondingly, the calculated optimal advertising-to-sales ratios are then compared with mean ratios for the samples in the same year.

Table 4 presents a summary of the various statistics used in calculating the optimal advertising-to-sales ratios. The final two columns show the predicted and actual values in each industry for 1965. They exhibit reasonably good conformity for three of the four industries (cigarettes, soft drinks, and cereals). The predicted optimal ratios in these industries are all within 20 percent of the ac-

TABLE 4 Comparison of Actual and Predicted Optimal Advertising-to-Sales Ratios for Four Industry Classes

Industry	$\eta_{MS\cdot C}$	$\eta_{Q\cdot A}$	λ	Π'/S	$(A/S)^*$	(A/S) 1965
Cigarettes	.576	.146	.241	.176	.075	.071
Soft drinks	.730	.140	.163	.135	.072	.057
Cereals	.661	.111	.100	.209	.116	.141
Beer	.305	.262	.904	.128	.032	.071

NOTE: $\eta_{MS\cdot C}$ and λ are from Table 3. $\eta_{Q\cdot A}$ was calculated according to formula

$$\eta_{Q\cdot A} = \eta_{MS\cdot C}(1 - AS)(AS/G)$$

where the last two terms are taken as industry averages in 1965. Π'/S was estimated as a weighted average of firm data (1963–1967) in each industry sample. A discount rate of 10 percent is assumed for all industries in the calculation of $(A/S)^*$. Actual ratios of advertising to sales in 1965, (A/S) 1965, were computed using advertising data from media sources and shipment data from Census Bureau adjusted to conform to the definitions of our particular industry samples.

tual ratios. For beer, however, the actual ratios are roughly double the predicted optimal ones.

Given that the N-A condition may be interpreted as a marginal condition requiring yields on advertising to equal firm opportunity costs, the rather close conformity in predicted and actual advertising-to-sales ratios in the cigarette, cereal, and soft drink industries further suggests that marginal returns in these three industries are roughly in line with yields earned on other types of investment activities. On the other hand, the mean ratio is much higher than the calculated optimum in beer, suggesting that advertising there has increased to the point where returns are below what can be earned elsewhere, i.e., the 10 percent rate of return on overall corporate manufacturing embodied in the above calculation. While I have not included any formal calculations for the gasoline industry, the regression estimates for this industry, taken at face value, would also imply that advertising outlays are excessive and that returns to advertising are below the opportunity cost of capital in this industry as well.

In interpreting the results of Table 4, it is important to keep in mind that these are estimates of *mean* behavior in each of the industries. Some firms may do much better than the average (and other much worse). Moreover, the qualifications made above concerning advertising elasticities must also be kept in mind, namely, the calculated elasticities in Table 4 abstract from both interindustry effects of advertising on demand, as well as intraindustry reactions of firms to changes in each other's advertising. The former simplification causes optimal advertising-to-sales ratios to be underestimated, whereas the latter simplification causes the opposite effect. Further analysis is necessary to see how sensitive the above estimates are to these simplifying assumptions.

Nevertheless, despite these qualifications, the close conformity between calculated optimal and actual advertising-to-sales ratios in the cigarette, cereal, and soft drink industries is a rather striking aspect of the results presented in Table 4. These three industries are also the ones for which the lagged effects of advertising on demand were estimated to be relatively large and, hence, the industries for which the model of advertising as a capital good is most applicable.

The coefficient estimates emerging from our models suggest as well that advertising has expanded beyond optimal levels in the beer and gasoline industries. We can only conjecture whether that is indeed the case or whether these findings simply reflect shortcomings in the above analysis. Competition in both these industries does have a much greater regional and local character and output is much less concentrated among firms than in the cereal, soft drink, or cigarette industries.[26] In principle, these factors could contribute to a decision-making environment in which advertising outlays tend to expand beyond the point where marginal returns equal opportunity costs.

Alternatively, the results for beer and gasoline may signal greater technical difficulties in applying the above models to industries where local or "unbranded" competition is more important. While this may be so, the proposition that advertising under certain industrial circumstances may expand beyond the point where returns are commensurate with other investment activities is hardly a novel notion. Indeed, Lambin (1972) in a recent empirical study of gasoline advertising for three European countries concluded that the returns on the margin to gasoline advertising were negative. However, a previous study of advertising in the U.S. beer industry by Peles (1971) did not find advertising to be excessive; rather, his study suggests the opposite may be the case. However, his study was based on the Koyck transformation model and employed only ordinary least squares estimating techniques, and this undoubtedly explains some of the differences between his findings and mine here.

The question of advertising effects on market share has also been analyzed in a recent English study using a somewhat similar analytical framework to that employed here (Cowling et al. 1975). Their results indicate a relatively close conformity of actual to optimal advertising-to-sales ratios for margarine and toothpaste but a considerable higher predicted optimal ratio than the actual one for coffee. Two durable industries, cars and tractors, also exhibit this type of behavior to an even more pronounced degree.

The pattern of results observed for our five industry samples, as well as past studies of particular industries, clearly suggests important interindustry differences. While the results observed here suggest further hypotheses that might be tested concerning these differences, a larger sample of industries is obviously necessary before the question can be explored in any depth.

[VI] SUMMARY AND CONCLUSIONS

The effects of advertising on market shares were investigated for five nondurable industry classes. A model employing the Nerlove-Arrow formulation of advertising as a capital good was formulated and tested. The empirical analysis suggests a significant effect of advertising on market shares, for both current and future periods, in all industry classes except gasoline. In addition, in three of the industries—cigarettes, soft drinks and cereals—calculated optimal advertising-to-sales ratios are in close accord with actual values, lending further credence to the observed results in those industries.

The analysis is subject to a number of qualifications discussed in the text. In terms of future work, a high-priority item would appear to be the development of data to do an analysis of the interactions of advertising with other types of competitive decision variables: changes in product quality, other marketing activities, etc. An important open question, for example, is whether advertising can create goodwill capital for a firm's product apart from or only in conjunction with differences in the quality or price of the firm's product relative to competitors'. Much of the normative debate about advertising defects clearly centers around this issue and more work on it of a positive economics character is certainly necessary and desirable.

The results of this paper, taken in conjunction with my earlier study of the interindustry effects of advertising on demand, indicate that the main impact of advertising is on consumer's choice of brands or products within a particular industry class rather than across classes. At the intraindustry level, there is also strong support for the view that advertising has significant long-run lagged effects on demand (i.e., it has capital good characteristics), a condition that was not generally observed at the interindustry level.

NOTES

1. A review of past work on this subject is presented in the first section of my earlier paper. A survey is also presented in Schmalensee (1972, pp. 113–117). A dissenting view to the notion that advertising has a relatively insignificant effect on demand at the industry level is provided by Comanor and Wilson (1974). Their analysis is extensively discussed in my earlier paper.
2. Partly because of the abundance of data, the cigarette industry has been studied by a number of researchers. Telser (1962), Peles (1971), Schmalensee (1972), and Schnabel (1972) have made studies of this industry using a distributed lag formulation. All but Schmalensee found a statistically significant effect of advertising on firm sales or market shares. Distributed lag analyses of other industries or products have been undertaken by Palda (1964), Lambin (1969, 1972), Simon (1969), Schultz (1971), Cowling and Cubbin (1971), Montgomery and Silk (1972), Bass and Clarke (1972), Beckwith (1972), Wildt (1974), Houston and Weiss (1974), and Cowling et al. (1975).
3. Schmalensee (1972) in particular has been highly critical of much of the prior empirical literature for ignoring simultaneous equation problems and biases. After adjusting for this and other conceptual and econometric problems in earlier work, he found no statistically significant relation between advertising and demand in his empirical analysis of the cigarette industry. However, since his study, several studies of this and other industries have appeared that have employed a simultaneous equation framework and incorporated various other statistical refinements and found a statistically significant relation between advertising and demand (see Lambin 1972, Bass and Clarke 1972, Wildt 1974, and Cowling et al. 1975).
4. For a further elaboration of these points, see the discussions in Cowling and Cubbin (1971) and Palda (1964).
5. In particular, it would seem plausible to postulate that consumer demand will be influenced only by those changes in advertising expenditures that represent actual changes in viewer messages (or their quality) and not those associated with changes in the cost of producing a viewer message. This distinction, which is important in empirical application, is maintained throughout the current analysis, and demand functions are always formulated with variables expressed in terms of real advertising units.
6. When product price is endogenous and chosen also to maximize net discounted present value, then the familiar static optimality condition for a profit-maximizing monopoly holds here as well, namely, $\rho = (P - MC)/P = 1/\eta_P$, where η_P = the price elasticity of demand. In this case, equation 5 may be further simplified to $GT/PQ = 1/(\lambda + r)\ (\eta_C/\eta_P)$, and analogously, equation 5′ may be expressed as $AT/PQ = 1/(\lambda + r)\ (\eta_A/\eta_P)$. However, if product price is exogenously imposed on the N-A decision model (say, because of limit price considerations or for other reasons) then (5) and (5′) cannot be simplified as shown and the formulation given in the text in terms of advertising elasticity and the markup of price over marginal cost is appropriate. For reasons discussed elsewhere in the paper, I assume product price is exogenous throughout the empirical analysis.

7. The notion that sales will be a major factor determining advertising outlays also receives support from empirical surveys and case studies of advertising decision making. See for example, Bullen (1961) and the discussion of various survey studies in Schmalensee (1972, pp. 17–18).
8. Nondurable categories were selected for analysis here principally because the available advertising data are for media activities. A high percent of total marketing activity of nondurables is generally allocated to media advertising, whereas durables advertising is typically concentrated in other activities, e.g., point of purchase displays, promotional activities, etc. This is reflected in the fact that nondurables collectively account for over three-fourths of total media outlays. Another reason for focusing on nondurables is that in my earlier interindustry analysis of demand, which covered fifteen durable and nondurable classes, the latter generally exhibited the greatest advertising effects (Grabowski 1976).
9. In fact, one might expect aggregate factors like income to affect consumer choice significantly at the firm or brand level in many situations. However, the above decomposition of firm demand into inter- and intraindustry components does not seem unreasonable in the present case, given the particular nondurable products involved as well as the relatively short period of time under consideration. At best one would expect these to be very secondary factors influencing market shares. On the other hand, this decomposition offers significant benefits by empirically isolating the impacts of advertising from other factors.
10. For example, in the studies cited above of Peles (1971), Lambin (1972), Schmalensee (1972), Cowling et al. (1975), as well as by a number of other researchers investigating the impact of advertising on market shares in particular industries.
11. In my prior analysis (1976) this approach was actually combined with a stock adjustment mechanism for industry demand that independently introduced a lagged output term into the equation. Other studies of advertising that have employed the conditional regression approach outlined above are Lambin (1972) and Cowling et al. (1975, chap. 8).
12. For an example of this approach applied to the British car and tractor markets, see Cowling et al. (1975, chap. 4). In the three nondurable classes analyzed in their study, a dummy variable procedure similar to that outlined in the text was utilized to capture the effects of quality differences.
13. To the extent that an increase in a firm's advertising quality causes a subsequent increase in both the firm's equilibrium advertising share and market share, omission of the quality changes will cause an upward bias in the estimated coefficients on advertising effects. However, it cannot be ruled out on logical grounds that firms experiencing positive changes in advertising quality would end up with a lower equilibrium advertising share and higher market share. That would lead to the opposite type of bias.
14. Schmalensee (1972) has argued that a further restriction should be incorporated into the estimation of the market share model, namely, that market shares summed over all firms must equal 1.0. However, since our samples do not include observations for *all* industry brands or firms, no equality relation necessarily exists among the firms or brands contained in our sample; only an inequality one. In effect, there is an "other" category in each industry that is included in total industry output and advertising. This is in contrast to Schmalensee's procedure of taking total industry activity as the sum of included firms only, which thereby allows further constraints to be imposed on the above relation.
15. The basic model underlying equation 17 is

$$MS_{it} = a_0\, a_i^{D_i}\, C_{it}^{b_1}\, u_{it}$$

where

$$C_{it} = AS_{it}\, AS_{it-1}^{(1-\lambda)} \cdots AS_{it-n}^{(1-\lambda)^n}$$

16. For two of the industries, beer and soft drinks, the coefficients are not statistically different from 1.0. This means the hypotheses of zero depreciation cannot be rejected for these in-

dustries. Since this is implausible, it would seem that at least for these two industries, and perhaps for the others as well, some of the potential econometric problems associated with a lagged dependent variable formulation are present here. I also experimented with other linear Koyck specifications, such as separate variables for firm and rival advertising and various differenced relations, but all those tried performed poorly.

17. One undesirable property of the multiplicative specification on the formation of goodwill capital underlying equation 17 (see footnote 15) is that a zero observation on advertising share in any period implies a zero value for goodwill capital independent of advertising shares in any other period. The N-A assumption on depreciation, which results in a linear weighted sum of advertising shares, does not have this property and seems intuitively more plausible on economic grounds than the multiplicative one.

18. Ferguson (1966) and Lambin (1972) have also estimated the geometrically declining distributed lag structure on advertising using the Koyck transformation model, as well as the conditional regression approach, and both authors found the former tended to give lower implied depreciation rates and higher lagged effects on advertising.

19. See, for example, Jorgenson and Stephenson (1967), especially their statistical appendix (pp. 217–218) for details on how this cost-of-capital variable is constructed from available data sources.

20. By definition,

$$\frac{\partial MS}{\partial AS} = \frac{\partial(Q/\bar{Q})}{\partial(A/\bar{A})} = \frac{\bar{Q}\partial Q - Q\partial\bar{Q}}{\bar{Q}^2} + \frac{\bar{A}\partial A - A\partial\bar{A}}{\bar{A}^2}$$

under the assumptions made above, namely, $\partial\bar{Q} = 0$ and $\partial\bar{A} = \partial A$, this simplifies to

$$\frac{\partial MS}{\partial AS} = \frac{\partial Q}{\partial A} \frac{\bar{A}}{\bar{Q}} \frac{1}{1 - (A/\bar{A})}$$

Multiplying both sides of this equation by AS/MS we obtain $\eta_{MS:AS} = \eta_{Q:A}/(1 - AS)$. The second relation in the text, namely, $\eta_{MS:AS} = (AS/G)\,\eta_{MS:G}$, follows immediately from the definition of G used in the estimated regression equations.

21. Past work on the interindustry effects of advertising is discussed in Grabowski (1976, sect. I).

22. An analysis of this question for the U.S. cigarette industry indicated fairly strong competitive response patterns (see Grabowski and Mueller 1971).

23. In particular, Federal Trade Commission data indicated a range of 9 8 to 12.7 percent in the ratio of after-tax profits to stockholder equity for nondurable goods over the period 1960–1970.

24. Specifically, if constant returns to scale are assumed for nonadvertising costs then

$$(P - MC)/P = (\hat{P} - AC)Q/PQ = \Pi'/S$$

where MC and AC are marginal and average cost per unit for all activities besides advertising, and Π' is after-tax profits (gross of advertising). The profit margin measure, Π'/S, is computed in the above analysis using an average of firm values weighted by firm output shares.

25. In order to be consistent with the data on the advertising-to-sales ratios in Table 4 which are based on industry value of shipments data and are *exclusive* of federal and state excise taxes, the profit margin calculation is also net of federal and state excise taxes.

26. Specifically, the market share data indicate concentration ratios of over 70 percent for the cereal, soft drink, and cigarette industries in 1965, whereas the corresponding ratios for beer and gasoline are 35 and 32 percent, respectively.

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