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The Effects of Advertising on the Interindustry Distribution of Demand

ABSTRACT: An empirical investigation is undertaken of the effects of advertising on the pattern of consumer demand across different product classes. Demand functions are estimated for several consumption categories (e.g., food, clothing, automobiles, etc.) over the period 1956–1972 using both single equation and simultaneous equation techniques. The particular dynamic models analyzed are most applicable to nondurable categories. ¶ The most interesting results emerge from a comparison of the simultaneous equation and least squares results. Least squares estimates suggest a statistically significant effect of advertising on demand in several categories. However, after adjustments are made for both external advertising and simultaneous equation effects, insignificant coefficients are observed except in a few very advertising-intensive categories. On the other hand, in almost all consumption categories considered, the level of sales is a strong explanatory variable of advertising outlays. ¶ These findings therefore do not provide much support for the hypothesis advanced by Galbraith and others that advertising has strong effects on consumer budget allocations even across product classes which are not close substitutes.

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INTRODUCTION

The effect of advertising expenditures on the overall pattern of consumer demand has been the subject of considerable speculation and debate by economists. At one end of the spectrum, Galbraith [1967] [1973] has argued that advertising has strong effects of a broad character on consumer preferences and demands. In this regard he suggests advertising outlays will significantly influence both the interindustry distribution of consumption expenditures and the aggregate level of consumption versus saving. On the other hand, a quite different perception of advertising effects has been made by Solow [1968] in a well-publicized critique of Galbraith's work. In particular, Solow argues that the main impact of advertising will likely be on the market shares within a particular industry or between product classes which are close substitutes. He expresses serious doubts about whether advertising outlays can significantly influence either the distribution of demand across broad product classes such as food, clothing, automobiles, housing or the level of aggregate consumption versus saving.[1]

The issues raised by the Galbraith-Solow exchange are ultimately empirical in nature. At the macro level, three recent studies have attempted to test whether total advertising expenditures influence the aggregate consumption function. Taylor and Weiserbs [1972] find that advertising does significantly influence aggregate consumption and savings behavior. On the other hand, Simon [1970] and Schmalensee [1972] conclude that the causal relation is from aggregate consumption and sales to advertising rather than vice versa.

In this paper an empirical investigation is undertaken of the effects of advertising on consumption across product classes. To this end, demand functions are estimated for several broad consumption categories. The other explanatory variables included in the demand function, in addition to advertising, are relative prices and disposable income. The effects of these variables on consumption are estimated using both single equation and simultaneous equation methods.

Most past empirical work on the effect of advertising on demand at the industry level has involved case studies of a single industry or a small group of related industries. While quite limited in scope, those studies offer little support for the view that advertising has strong interindustry effects as postulated by Galbraith. However, a more extensive investigation performed by Comanor and Wilson [1974a] [1974b] seems to offer support for the Galbraithian hypothesis. On the basis of demand functions estimated for a large number of industries, Comanor and Wilson conclude that estimated advertising effects on demand are generally much larger than corresponding price effects. If sustainable, their results would have significant implications for economic analysis and policy.

[I] PAST EMPIRICAL WORK

Empirical studies intended to evaluate the effect of advertising on sales at both the firm and industry level date back at least to the 1930s. The earliest studies involved simple linear regression models and a static formulation. Later the models progressed to a multiple regression framework and a little over a decade ago, became dynamic in character. Until recently most focused on either a single industry (very often cigarettes) or a small group of industries.

Several of those studies clearly demonstrate a significant effect of advertising on market shares and firm sales *within* particular industries.[2] Relatively few studies, however, have been addressed to the question of whether the total level of industry advertising influences total industry demand. In a recent book, Richard Schmalensee [1972] provides an extensive review of the econometric studies of advertising undertaken before 1972. He cites only five studies of advertising performed at the industry level. Of these, only one, a study of oranges by Nerlove and Waugh [1961], offered support for a significant effect of advertising on industry sales.[3] Since the Schmalensee review, Lambin [1972] has undertaken a study on the gasoline industry. He found a statistically significant positive impact of advertising on gasoline demand in two of three countries studied, but advertising elasticities were very small relative to price elasticities and other factors.

Schmalensee has also conducted his own analysis of the question using cigarette industry data. He advances the analysis over past work by utilizing a simultaneous equation framework (with advertising depending on sales as well as vice versa) and by taking explicit account of the effect of advertising external to the cigarette industry, through the use of a relative or net formulation of the advertising variable. Despite these refinements, Schmalensee's findings are also very negative in character. He concludes: "We find no evidence suggesting that total cigarette advertising has an effect on the total consumption of cigarettes."[4]

Overall, Schmalensee's literature review and cigarette industry analysis lead one to a skeptical view of Galbraith's hypothesis that advertising has strong impacts on consumption across industry classes.

Over the same time period that these case studies of advertising effects were undertaken, some large scale multi-industry studies of consumer demand also have evolved. These studies, undertaken primarily with the objective of forecasting future consumption patterns, have omitted consideration of advertising and instead have focused on the role of income and prices as primary determinant variables. The best known and most extensive work of this nature is by Houthakker and Taylor [1970]. They use historical data to estimate demand functions for essentially all the consumption categories in the national income accounts. For most industries, dynamic models outperform static ones and the income variable is the dominant economic factor explaining interindustry patterns of consumer demand. The explanatory power of their models is quite high, despite the omission of potentially significant factors such as advertising.

In a recently published work, Comanor and Wilson [1974a and 1974b] (henceforth C&W) utilize the methods and approach of Houthakker and Taylor to estimate industry demand functions that include advertising as well as income and price variables. Their main analytical model is a simple generalization of the Houthakker and Taylor dynamic state or stock adjustment model. They estimate demand functions for thirty or so manufacturing classes at roughly the three-digit level over the period 1946–1964. While the impact of the explanatory variables differs significantly across industry classes, a general finding of their work is that advertising outperforms other factors in terms of statistical significance and total explanatory power.

They particularly stress the differential impacts on consumer demand of advertising versus relative prices. In this regard they suggest:[5]

> . . . the adjusted advertising effects are generally far larger than the corresponding price elasticities of demand. Indeed, in many cases, the differences represent a substantial order of magnitude. What this suggests is that, for the most part, advertising has a far greater impact on the level of industry demand than relative prices and therefore is likely to be a more important determinant of the interindustry allocation of resources.

While relative prices generally have had a much smaller estimated effect on demand compared to income in past consumption studies, C&W results also suggest relatively weak income effects compared to advertising. Their income variable is statistically significant in less than half the industries studied.[6] Because this result is in sharp contrast to all prior estimates of industry demand functions, it would appear appropriate to examine the potential sources of these differences. Questions of data composition are considered first and then issues of model formulation are examined.

Apparently because of data availability considerations, C&W do not use the consumption data of the national income account employed by Houthakker and Taylor. Instead they obtain data on industry sales and advertising from income statistics of the Internal Revenue Service. Since IRS source materials have no price or aggregate income information, Bureau of Labor Statistics wholesale price series and national income account data are used to construct these variables. Overall this merged set of data series does permit a more disaggregate analysis than would be possible using the consumption categories in the national income accounts.

Nevertheless, a number of potential difficulties arise from the merging of IRS-based data on industry demand and advertising with non-IRS data in time series analysis. Two related points would seem to deserve particular emphasis. First, because IRS data are constructed from consolidated corporate tax forms, industry aggregates based on them are subject to considerable compositional error. Second, and more important, this compositional error is common to C&W's measures of industry sales and advertising (but not their price and income data) and hence acts to produce a spurious positive correlation in time series relation between these two variables.[7]

The compositional error in IRS data results from the consolidated character of corporate tax data. Because tax forms provide no breakdown on a firm's costs and revenue by industry or product category, the firm's entire accounts are assigned to the single industry class which it designates as its principal activity. In an economy where there is sizable firm diversification, this method of generating industry measures can lead to significant compositional error associated with misclassified activities. Used in a time series context, the possibility of discrete shifts in a firm's accounts from one industry to another compounds the measurement error problem. Specifically, if a firm changes its principal activity from one period to the next, either because of a merger or some other factor, this has the effect under the IRS classificatory scheme of simultaneously increasing sales and advertising in one industry and decreasing them in another. Such shifts of a purely compositional character therefore will produce a positive correlation in the time series data on sales and advertising in both industries. While it is difficult to determine the overall importance of such spurious correlation, the 1946–1964 period was characterized by vigorous merger and diversification activity. These factors increase the likelihood of such spurious correlation due to firm shifts across categories.

As noted above, C&W's samples merge the IRS data on sales and advertising with BLS wholesale price data and national income account aggregate measures of disposable income. Both of these latter data series use a product basis for classifying and aggregating industry activity. Hence, any measurement errors present in the price and income variables arise from completely different constructional procedures and should be uncorrelated with those in IRS industry aggregates. As a consequence, observed correlations of income and prices with industry demand will be biased toward zero in C&W's sample.

Whether compositional errors of this kind significantly bias C&W's estimates of the relative impacts of advertising and other variables on industry demand is, of course, conjectural. They do acknowledge considerable data imperfections. Nevertheless, they feel on balance that measurement error is unlikely to distort their findings toward rejection of the null hypothesis on advertising.[8] Whether or not this is the case, there is some independent evidence that the compositional errors present in IRS time series data are not inconsequential.

An earlier unpublished study by Taylor [1968] on the effects of advertising on industry demand illustrates the compositional problems inherent in IRS data sources. In his demand study, Taylor obtained his consumption and price data from national income account classifications and only utilized IRS data for the advertising variable. Using this data construction procedure, he was able to obtain data for twenty-two consumption categories over the same period, 1946–1964, that C&W studied. He then estimated a number of dynamic demand functions with income, prices, and advertising as the determinant variables. In contrast to the C&W findings in which IRS sales measures were used as the dependent variable, when Taylor substituted a national income account measure of demand, advertising performed rather poorly and was significant in only a handful of categories.[9] Even in the instances where it was significant, he had to omit some of the other variables and employ very specialized models. At the very least, this suggests considerable compositional error is present in IRS-based statistics in comparison to the conceptually purer national account data.[10]

Turning from considerations of data quality to model formulation and interpretation, a second possible criticism of C&W's work centers on the nature of the causal relation between sales and advertising. C&W recognized the possibility that the strong positive relation they observed could result from the effect of sales on advertising rather than vice versa. To examine this question, they formulated a simultaneous equation model incorporating a simple behavioral relation of advertising to sales. They then used the reduced form equation of this model to reestimate the dynamic equation coefficients. The effect of this two-stage estimation procedure is to reduce the average size of the advertising coefficients and reduce somewhat the high t values associated with the advertising variable. Nevertheless, the qualitative character of their results remain intact. However, whether this two-stage estimating procedure adequately isolates the true effect of advertising on sales remains open to question. Owing to the complex nonlinear simultaneous equation generated by their assumptions and the small number of observations present in their time series analysis, they were forced to use a very truncated and approximate version of the reduced form equation to obtain coefficient estimates.[11] This question will be discussed in further detail below where a somewhat different approach for simultaneous equation estimates is developed.

In summary, various attempts prior to C&W's recent work to relate industry advertising to sales met at best with limited success. The relation was usually weak and often neither economically nor statistically significant. Those attempts therefore seemed to support Solow in his debate with Galbraith, at least in so far as he conjectured that advertising had at best a very secondary influence on the interindustry allocation of resources.

C&W's recent study represented a more extensive attempt to test the effect of advertising on industry sales, both from the standpoint of the number of industries considered and the type of models utilized. In contrast to previous work, they found advertising to be the most dominant factor influencing interindustry sales over the period studied, 1946–1964. Their results appear to swing the weight of evidence more toward Galbraith's point of view. Nevertheless, there are both compositional errors in C&W's sample that produce biases in the direction of their findings and possible problems of model formulation and interpretation. Before their findings can be accepted, further work dealing with these problems would seem in order.

In the following analysis, the effect of industry advertising on demand is undertaken using national income account data for consumption, income, and prices. These data are merged with advertising data from trade media sources on television, magazines, and newspapers. Because media advertising data are available on a comprehensive basis only for more recent periods than were covered by C&W, the analysis presented here covers the later time period, 1956–1972. These data have a number of advantages but also some disadvantages in comparison to IRS advertising data which will be discussed below. The most important reason for developing this alternative data base, however, is to attempt to eliminate the spurious positive correlation that plagues IRS-based time series of sales and advertising.

[II] FORMULATION OF THE DEMAND MODELS

In common with prior work, my starting point is the concept of a consumption function of the general form

$$(1) \quad C^*_{it} = f_i(Y_t, P_{it}, A_{it}, X_{it}, u_{it})$$

where

C^*_{it} = equilibrium or desired real consumption per capita of the ith commodity in period t;
Y_t = real disposable income per capita in period t;
P_{it} = relative price of the ith commodity in period t;
A_{it} = gross or net advertising on the ith commodity in period t;
X_{it} = the set of other exogeneous factors influencing the ith commodity in period t;
u_{it} = error term.

In order to transform this equation into an estimable form, some dynamic assumptions must be made concerning how actual consumption adjusts to desired consumption over time. Because of consumer inertia and other such factors, it is usually implausible to assume that actual consumption adjusts instantaneously to desired consumption in each period. Perhaps the most frequently employed dynamic assumption in past work is that the rate of change in consumption at any point in time is directly proportional to the difference between desired and actual consumption. In symbolic terms (omitting i subscripts for convenience),

$$(2) \quad \dot{C}(t) = \alpha[C^*(t) - C(t)] \qquad 0 < \alpha < 1$$

or in discrete form

$$(2') \quad C_t - C_{t-1} = \alpha(C_t^* - C_{t-1}) \qquad 0 < \alpha < 1$$

Equation 2′ implies that a common dynamic response pattern holds between consumption and all the explanatory variables present in equation 1. For example, in equation 1, if a linear relation is assumed between desired consumption and income, prices, and advertising, so that

$$(1') \quad C_t^* = a_0 + a_1 Y_t + a_2 P_t + a_3 A_t + u_t$$

the latter may be combined with equation 2′ to obtain, after some transformations, the dynamic formulation

$$(3) \quad C_t = b_0 + b_1 Y_t + b_2 P_t + b_3 A_t + b_4 C_{t-1} + u_t'$$

where

$$b_i = a_i \alpha \quad \text{for} \quad i = 0, 3$$
$$b_4 = 1 - \alpha$$

This is equivalent to the transformed version of the familiar Koyck distributed lag mechanism. The cumulative long-run impacts on consumption for each variable, B_i, are related to their initial impact by the simple relation

$$(4) \quad B_i = \frac{1}{1 - b_4} b_i \qquad i = 1, 3$$

In addition to the proportional adjustment response lags present in equation 3, several authors have postulated that advertising be treated as a capital investment good. In particular, advertising outlays are hypothesized to influence the level of desired consumption over future periods as well as the current one. Cowling and Cubin [1971, p. 382] have summarized some of the reasons why this might be true.

1. Advertising may have a cumulative effect in molding consumer behavior.
2. There is consumer uncertainty about the price and specification of a product.

The price and quality "image" may be derived from observations in earlier time-periods. Limited search by consumers may be interpreted as the outcome of predicting the likely costs and benefits associated with the acquisition of more information.

3. There is consumer uncertainty about the utility to be derived from any known specification.
4. Consumer behavior may show bandwagon effects. . . .
5. Consumers influenced by current strategies may not enter the market immediately. This will particularly be true in the case of consumer durables where purchases are typically made relatively infrequently.

In terms of modeling these capital investment effects, Nerlove and Arrow [1962] and other researchers have proposed the concept of a stock of "goodwill" capital built up from past advertising outlays. Advertising expenditures in each period increase this stock, while depreciation in it occurs as buyers forget or competitive advertising offsets it.

While a number of assumptions might be employed regarding how goodwill capital depreciates over time, Nerlove and Arrow and most other theoreticians have assumed that the stock depreciates at a constant proportional rate over time. Thus,

$$(5) \quad \dot{K}(t) = A(t) - \lambda K(t)$$

where λ = the depreciation rate on advertising capital.

The discrete analog of equation 5 implies that the stock in any period is a weighted combination of all past advertising outlays, or

$$(5') \quad K_t = A_t + kA_{t-1} + k^2A_{t-2} + k^3A_{t-3} \ldots$$

where $k = 1 - \lambda$.

If equation 1 is correspondingly modified to allow the desired level of consumption in each period to depend on the stock of advertising goodwill, rather than just current advertising, the relation obtained is

$$(6) \quad C_t^* = a_0 + a_1Y_t + a_2P_t + a_3K_t + u_t$$

Equations 2′, 5′, and 6 constitute a dynamic system that includes common proportional adjustment effects for all variables as well as a capital stock effect for advertising. After substitution and some algebra, the relation obtained is

$$(7) \quad C_t = b_0 + b_1Y_t + b_2P_t + b_3(A_t + kA_{t-1} + k^2A_{t-2} + k^3A_{t-3} \ldots) + b_4C_{t-1} + u_t$$

The long-run impact of a change in advertising no longer has the same symmetric effect as other variables, except in the limiting case of the Koyck model ($k = 0$ or, in effect, a 100 percent rate of depreciation in each period).

Equation 7 may be further transformed and put into a closed form involving second-order lag terms of the variables on the right-hand side.[12]

Because this results in a complex nonlinear combination of the underlying parameters, it presents significant problems of estimation. Alternatively, the capital stock variable in equation 5 may be approximated by using a finite number of lagged advertising terms, provided the depreciation rate is not too close to zero. Equation 5 can then be estimated by using an iterative procedure for different values of *k*. This latter estimation approach has a number of advantages over the second-order lag formulation.[13] Further discussion of the method used in this paper to estimate equation 7 is deferred to the next section, where estimation procedures are discussed more fully.

A number of variants of the above dynamic assumptions are possible and have been employed in the literature. For example, if a multiplicative rather than a linear relation is assumed for the adjustment mechanism,

$$(8)\quad C_t/C_{t-1} = (C_t^*/C_{t-1})^{\gamma} \qquad 0 < \gamma < 1$$

and a corresponding multiplicative relation is assumed between desired consumption and the explanatory variables in equation 1,

$$(9)\quad C_t^* = \beta_0 Y_t^{\beta_1} P_t^{\beta_2} K_t^{\beta_3} u_t$$

then equations 5′, 8, and 9 may be combined to yield the relation

$$(10)\quad \log C_t = \beta_0' + \beta_1' \log Y_t + \beta_2' \log P_t + \beta_3' \log (A_t + kA_{t-1} + k^2A_{t-2} \ldots) + \beta_4' \log C_{t-1} + u_t'$$

Equation 10 is the log-linear analog of equation 7. Other variants of this lagged dependent variable dynamic structure include semilog formulations (allowing for diminishing returns) and the incorporation of unrestricted lag terms in the explanatory variables to allow for more general types of decay patterns.

Houthakker and Taylor (H-T) provide another type of generalization to the Koyck model that differentiates the response pattern for durable and nondurable goods. Instead of assuming consumers fractionally adjust in each period toward some desired consumption level, they impart dynamic motion to their system by a stock or state variable. In each period this stock variable is replenished by new purchases and is depleted by some form of depreciation of existing stocks. In symbolic terms, the differential equation is

$$(11)\quad \dot{S}(t) = C(t) - \delta S(t)$$

The actual level of consumption in any period is determined by the current values of the other explanatory variables as well as this stock variable embodying the influence of past purchases. Assuming a linear relation between consumption and the explanatory variables, one has

$$(12)\quad C(t) = \alpha_0 + \alpha_1 Y(t) + \alpha_2 P(t) + \alpha_3 A(t) + \beta S(t) + u(t)$$

Equation 12 is the variant of the H-T model used by C&W to investigate the influence of advertising on consumption. Advertising is brought into the H-T system in a symmetric fashion to prices and income, and is not assumed to have the special properties of a capital investment good.

A critical parameter in this model is the coefficient on the stock variable in equation 12. In the case of durable goods, increases in stocks are postulated to have a negative effect on the demand for current consumption (i.e., $\beta < 0$). On the other hand, in the case of nondurable goods, because the stock variable is interpreted as a cumulative habit-formation effect of past purchases, a positive coefficient is expected (i.e., $\beta > 0$). This difference in assumptions on β gives rise to qualitatively different behavior in the response patterns of durable and nondurable goods. In the case of nondurables, long-term elasticities will be greater than short-term ones, and convergence to a long-run equilibrium will occur through successively smaller incremental positive changes over time. In the case of durable goods, long-run elasticities will be smaller than short-term ones, and a movement back toward equilibrium in successively smaller increments will occur after an initial response that overshoots the equilibrium point.

The Houthakker-Taylor model given by the above equations may be transformed into estimable form by substitution of (12) into (11) so as to eliminate the state (stock) variable, which is normally unobservable.[14] After transformation and approximation of the continuous variables by discrete terms, an equation of the following form is obtained:

$$(13)\quad C_t = B_0 + B_1\Delta Y_t + \lambda B_1 Y_{t-1} + B_2\Delta P_t + \lambda B_2 P_{t-1} + B_3\Delta A_t + \lambda B_3 A_{t-1} + B_4 C_{t-1} + u_t$$

This equation, although now containing only observable variables, is nonlinear in the coefficients, and nonlinear techniques must be employed to estimate it. As in (7) above, this model also includes the linear transformation of the Koyck distributed lag as a special case, in particular when $\lambda = 1$.

The above discussion of alternative dynamic lag structures suggests three general types of dynamic demand models in the empirical analysis. The simplest dynamic model considered is the Koyck lag structure in linear or log form. The Koyck model follows from the assumption of a constant proportional adjustment response pattern for consumption over time. It involves a geometrically declining set of identical lag coefficients for all of the explanatory variables in the consumption function. Second, a generalization of the Koyck model is considered in which advertising is separately treated as a capital investment good. Advertising is permitted to have a more general lag structure that embodies the capital stock effect on desired consumption of past advertising outlays. The third is the Houthakker-Taylor dynamic model, which permits a qualitatively different type of response pattern for durable and nondurable goods.

In the empirical work that follows, an essentially inductive approach is employed with regard to the analysis of these alternative dynamic specifications. Simpler models (i.e., forms of the Koyck lag structure) are tried first and then compared with results for more complex forms. It might be argued that on a priori theoretical grounds, more general and flexible lag structures should be preferred to simpler, more specialized dynamic formulations. However, we will be dealing with time series samples that have small numbers of observations (i.e., fewer than twenty) and which also may contain a high degree of multicollinearity. In such circumstances it is an empirical question whether more complex models with their corresponding extra demands on data are preferable to simpler formulations where the response pattern is more constrained. Another reason for employing simpler dynamic lag structures is that they are much more amenable to nonlinear specification (multiplicative, semilog, etc.), whereas more complex lag structures such as the Houthakker-Taylor model must be linear in order to reduce them to an estimable form like equation 13.

Up to this point I have been discussing models of industry consumption completely in terms of one-way causal flows. On theoretical and intuitive grounds, there are reasons for expecting that an industry's prices and advertising also will be a function of its sales and consumption. In the first part of the following empirical analysis, this simultaneous equation problem is ignored. and I operate as if the causal flow is in complete accordance with the assumptions embodied in the above materials. After making a number of ordinary least square (OLSQ) estimates with various models, the simultaneous equation issue is then considered. At that point the nature of the bias from OLSQ as well as the cost and benefits of employing more involved causal relations are considered.

[III] DATA SAMPLES AND VARIABLES

Data Samples

A major objective of this study was to construct advertising measures that would be more consistent with consumption and price data available from the national accounts. As noted above, a potentially significant problem with the data samples utilized by C&W concerns the noncomparability of IRS data with time series of the Bureau of Economic Analysis and the Bureau of Labor Statistics. On the other hand, one reason that IRS advertising data have been utilized so intensively by C&W and others in past work is that that source offers an extensive data base on advertising at the industry level for which there are no easily available substitutes.[15]

An alternative source of advertising data is that collected for the national media by various private data-gathering services.[16] These are the data that have been employed in most of the case studies of individual industries discussed in section I. After conducting an investigation of the availability and characteristics of the various media-oriented services, it was found that annual advertising expenditures at a disaggregate industry level could be compiled for the period 1956–1972 for the four major media—network TV, spot TV, newspapers, and magazines. Since these industry data are generated from individual brand and product advertising information, they do not have the diversification bias arising for industry statistics that sum total firm data classified in polar fashion by major product class.

The chief drawback of the media-based data is their incompleteness. The possibility of a firm shifting expenditures from measured to unmeasured media from one year to the next could introduce significant errors in the advertising series. However, there are ways to check on the importance of this bias in various industry classes. Advertising expenditures are available for a number of minor media—network radio, spot radio, and outdoor advertisements—over segments of the seventeen-year period studied here, especially the most recent years. It turns out that the four major media for which complete data are available comprise a very high percentage of total media outlays for several industry classes. Omission of minor media expenditures causes little error for these industries. In a few cases where the minor media are very important to a particular industry, the data from available years can be used to determine whether media allocations in those other media have different patterns. Where they do, those industries can be excluded from the analysis.

The classification procedures used for the media advertising data also have a similar format to those used in NI accounts for personal consumption. For most durable and nondurable goods categories, the advertising data tend to be much richer in detail, but they are very sparse or nonexistent for the service categories. The product classes were thus constructed using standard NIA definitions with merged media advertising data where the latter were available on a comparable basis.

In Table 1, a list of seventeen major consumption categories is presented for which compatible data could be constructed across all four major media and the NIA categories. As is indicated in the table, the seventeen categories in the aggregate account for over three-quarters of major media advertising and about one-half of total consumption expenditures. The list includes a high percentage of manufactured goods but excludes all services except airline travel. The latter is the only service category with significant advertising expenditures in the major media.

TABLE 1 Consumption Categories Constructed from National Income Accounts and Media Advertising Sources

Category	Percent of Total Consumption, 1972	Outlays in Four Major Media as Percent of Total Advertising, 1972
Alcoholic beverages	3.1	5.0
Food (for off-premises consumption)	17.0	16.4
Tobacco products	1.4	4.4
Clothing	8.3	2.6
Watches and jewelry	0.7	0.5
Toilet articles	1.1	10.4
Furniture and furnishings	4.0	1.1
Appliances	2.2	1.4
Cleaning and polishing preparations	1.0	6.9
Drug preparations	1.5	6.4
Automobiles	7.8	7.8
Tires, tubes, and parts	1.2	2.0
Gas and oil	4.0	2.4
Publishing	0.9	1.9
Sporting goods and toys	2.3	3.2
Radio, television, and musical equipment	2.2	2.4
Airline travel	0.4	2.2

Before doing any statistical work on the data, some further checks were employed on the accuracy of the advertising variable as generated from the four major media totals. In particular, data from specific major and minor media were compared in those years when both types were available. The period 1966–1972 was given particular scrutiny because all seven media were available then. On the basis of that analysis, it was decided to drop two of the seventeen categories, tobacco products and gas and oil. Expenditures on radio and outdoor advertising exceeded 20 percent for those two industry groups, and the percentage allocations to those media varied considerably from one year to the next.[17] On the other hand, radio and outdoor outlays accounted for less than 10 percent of total advertising in twelve of the other fifteen categories over the years in which data could be compared. The omission of the outdoor and radio media for those categories therefore did not appear to pose any significant problems. Between 10 and 20 percent of the total outlay of the remaining three categories—alcoholic beverages, automobiles, and airline travel—was allocated to minor media. Because the allocation pattern between the major and minor media appeared to be fairly stable in years when both data series were available, it was decided to tentatively retain those three categories in the analysis which follows.[18] Further discussion of the characteristics of the advertising data for those industries and others is provided in a separate statistical appendix available from me on request.

One further qualification concerning the data should be noted. Ideally, advertising effects should be studied in the context of a general marketing mix. This is because other forms of marketing outlays may substitute for or complement the effects of advertising on demand. Marketing outlays that may assume particular importance in given classes include point-of-purchase outlays and other more direct sales techniques (free samples, mail campaigns, etc.). This study, in common with most other social science work in this area, focuses on the role of media advertising and ignores other marketing outlays. This is dictated largely by the nature of the available data.

Fifteen separate consumption categories thus emerge for which empirical demand curves will be estimated. Those categories account for over 70 percent of total major media advertising in the U.S. economy. The fifteen categories do differ widely in size and coverage. Some are equivalent to two-digit SIC classes while others are closer to three-digit ones in aggregation. It obviously would be desirable to have more disaggregate data for some of the broad categories in Table 1, for example, food, which accounts for almost one-fifth of total consumption and advertising. Nevertheless, such categories correspond to those Solow had in mind when he conjectured that advertising would have little significant effect on consumer choice as one moved toward higher levels of aggregation and away from closely substitutable product groups. These national income account data are thus not inappropriate for testing his hypothesis.

Empirical Specification of Variables

All the dynamic models discussed in section II reduce to a form for estimation in which current consumption is regressed on current and lagged values of the three explanatory variables: income, prices, and advertising (or goodwill capital) as well as lagged values of consumption. In this section, a discussion is presented of the specific definitions of each of the variables employed in the empirical analysis.

In all cases, the dependent variable—consumption expenditures in each industry category—is expressed in real per capita terms. This is in accordance with past studies. Conceptually, we wish to abstract from common impacts on our variables produced by population changes and inflation. For national income account data classes, information on real consumption per capita is obtained from published Census calculations based on the implicit price deflator for each class.

The income variable employed here is real disposable income per capita. In past studies, both this measure and total personal consumption expenditures per capita have been used as measures of income. On theoretical grounds, disposable income per capita would seem to be the superior measure. The level of consumer saving—the difference between disposable income and consumption—is neither a fixed nor a residual factor but rather a variable subject to similar influences as consumption items. Thus disposable income would seem to be a better measure of overall resource availability. As a practical matter, there is a very high correlation between the two measures over the seventeen-year period spanned by our data samples. Sample regressions run with these alternative measures produced very little difference in final results.

The price variable in our analysis is a relative one. It is the ratio of the price index of the particular category to the price index for total personal consumption expenditures. This relative formulation embodies the usually assumed property of the absence of money illusion on the part of consumers. A more sophisticated formulation would also include relative prices of close substitutes and complementary goods. This is precluded not only because the number of observations is small, but also because economists have little operational knowledge concerning the general equilibrium thicket of relative price interactions.

One further characteristic of the relative price variable should be noted. When national income data are employed, the relative price variable is based on implicit deflators for each consumption category and total personal consumption expenditures. These deflators in effect use current-year consumption weights. This is in contrast to the BLS practice of using constant base-period weights to construct price indices.

Specification of the advertising variable as a relative or per capita measure is more debatable than in the case of the other explanatory variables. In the most recent work, both C&W and Schmalensee have argued that a relative advertising variable is superior. They argue that, analogous to prices, if all industries were to double their advertising outlays, the consumer would be essentially in the same initial position as before the doubling.[19] While there may be some factors pointing in this direction—i.e., most advertising has a demand-substituting characteristic and its ability to cause increases in total consumption is severely limited—it does not follow that a relative formulation is necessarily correct. The mix of consumption may change when all categories experience a proportionate increase in advertising. A strong assumption is necessary to produce this condition, namely, that advertising is equally effective for each category. This is a much stronger assumption than is normally employed to justify a relative price variable, i.e., the absence of the money illusion.

While a relative advertising variable embodies a strong assumption, it would seem superior to a formulation completely ignoring advertising expenditures for other industries.[20] This is the other practice common in the literature. In the empirical work below, both real expenditure per capita and relative advertising measures are utilized. The per capita measure is constructed in symmetric fashion to the consumption and aggregate income variables and ignores external advertising outlays.[21] The second measure is a relative advertising measure similar to that employed by other researchers, namely, the ratio of real advertising expenditures for the industry to total real expenditures for all industries. The method of constructing real measures from monetary outlays is described in the statistical appendix. In effect an implicit price deflator like that employed in national income account data is constructed from the price indices for each medium.

In one set of dynamic models described in section II, advertising enters as a stock variable rather than as a flow. In accordance with the discussion above, if a constant proportional depreciation rate, λ, is assumed for this stock of advertising, it is related to past advertising investment outlays by the relation

$$(1)\quad K_t(\lambda) = \sum_{i=0}^{t} (1 - \lambda)^{t-i} A_i$$

In my empirical work, the stock, K_t, is approximated by taking five years of prior advertising investments. Hence, the approximation used is

$$(1')\quad K_t(\lambda) \simeq A_t + (1 - \lambda) A_{t-1} + (1 - \lambda)^2 A_{t-2} + \ldots + (1 - \lambda)^5 A_{t-5}$$

Unless advertising capital depreciates at a very slow rate, this should provide a good approximation to the capital stock. In past microeconomic studies of depreciation rates for particular industries, annual depreciation rates of 30 percent or higher have been found.[22] At those rates, most of the lagged impact of advertising would be completed in five years, given the geometric rate of decline on the coefficients in the above lag structure.

In order to construct the capital stock variable by this procedure, advertising outlays prior to 1956 are necessary to calculate the values of K_{56} through K_{62}. The advertising data were available back to 1951 for network TV, magazines, and newspapers, but not for spot TV. However, total national spot TV expenditures were available over the period 1951–1955. Hence, spot TV data prior to 1956 were approximated using an extrapolative procedure in which it was assumed that spot TV in each category in the period 1951–1955 had the same ratio to total expenditures that it had in the years just following that period. The ratios in the later period exhibited considerable stability. The approximation was not expected to introduce any significant bias into the analysis, since spot TV was a relatively small portion of total media expenditures in the early fifties.

Also the back years affect only the first few time series observations on K_t and are discounted by successively higher powers of $1 - \lambda$ as one goes back in time.

[IV] EMPIRICAL WORK: SINGLE-EQUATION MODELS

The procedure employed in analyzing and reporting results is to begin with simpler demand function specifications and then proceed to more complex ones. Ordinary least squares models are considered in this section and simultaneous equation models in the following one. All of the demand equations reported here are dynamic in character. While some static models were considered in preliminary runs, they were inferior to dynamic specifications in a number of dimensions.

The first dynamic models considered involve variants of the Koyck lag specification. As the analysis presented above suggests, these models may be formulated in linear or multiplicative form. After transformation, they take the following empirically estimable form for the linear case:

$$(1) \quad C_t = b_0 + b_1 Y_t + b_2 P_t + b_3 A_t + b_4 C_{t-1} + u_t$$

For the case of multiplicative consumption and adjustment functions, the log-linear analog to equation 1 is obtained, or

$$(2) \quad \log C_t = b'_0 + b'_1 \log Y_t + b'_2 \log P_t + b'_3 \log A_t + b'_4 \log C_{t-1} + u'_t$$

As indicated in the previous section, two different formulations of the advertising variable are used in the analysis—real advertising per capita and a relative advertising measure.

Tables 2 and 3 present estimates of the linear and log-linear formulations of the Koyck model. All equations are estimated using annual time series over the period 1956–1972. Some general considerations emerge from the estimates of the demand models in the two tables. The R^2 are very high but not unusually so for this type of time series analysis. In addition, most of the coefficient estimates have the predicted sign, although many are not statistically significant. The latter fact undoubtedly reflects the relatively few degrees of freedom and the high intercorrelation among variables in time series work. The results also suggest that the linear and log forms perform quite similarly, although the log specification is slightly better in terms of conformance to theoretical predictions, particularly for the advertising and price variables.

In both tables 2 and 3, income is clearly the dominant independent variable. In each of the four cases, it takes on the predicted positive sign and is statistically significant in all but a few instances. No other variable approaches this type of consistency in terms of both conformance to theoretical predictions and statistical significance.

Perhaps the most interesting result that emerges from the estimated equations in tables 2 and 3 is the very different performance of the advertising variable when measured in per capita terms versus the relative formulation. For example, the advertising variable is positive and statistically significant in almost half of the categories for the per capita formulation in Table 3 (seven industries) but in considerably fewer cases when a relative advertising measure is employed (four industries). While the poorer performance of the relative advertising variable could result from its smaller degree of variation compared to the per capita measure, it might also reflect simultaneous equation bias in the estimates of per capita advertising coefficients. The latter would be more directly influenced by industry sales. On theoretical grounds, the relative advertising variable should be a superior formulation in that it incorporates advertising outside the industry. Industry demand should experience negative shifts from external advertising in similar fashion to the positive shifts produced by its own advertising. While one may quarrel with the particular specification of this effect implied by a relative measure, the significantly weaker result of this "net" measure compared to the absolute one suggests that the estimates in tables 2 and 3 may reflect a causal flow more from sales to advertising than vice versa. This hypothesis is analyzed further in the next section.

The estimated coefficients for the relative price variable in tables 2 and 3 generally take on a negative sign but are statistically significant in only a minority of instances. These findings for the price variable are not unlike the results observed by Houthakker and Taylor in their more extensive investigation of this question.[23] A few problem cases are also evident here as in earlier work. The price variable takes on a significant positive coefficient in radio and TV equipment in three of the four estimated equations. This undoubtedly reflects the presence of quality changes in this technologically progressive industry that are inadequately captured by the implicit price deflator constructed for the national accounts data. The other industries that generally have positive (but insignificant) price coefficients are also ones characterized by considerable quality change (e.g., appliances, automobiles, and tires).

The final variable present in the empirical analysis is of course the lagged consumption term, which comes into the equation as a result of the dynamic Koyck adjustment process. This variable is generally in the predicted range of 0 to 1 and is statistically significant in slightly less than half the consumption categories. In a few cases, both the linear and log estimates of these coefficients seem quite high (e.g., alcoholic beverages, toiletries, and tires), implying a fairly slow adjustment process. Alterna-

TABLE 2 Estimation of Demand Equation 1, Section IV, for 1956–1972 (figures in parentheses are t ratios)

Industry	b_0	Y_t	P_t	A_t Per Capita[a]	A_t Relative[b]	C_{t-1}	R^2
Alcoholic beverages	.007 (0.46)	.009 (3.26)*	−.005 (0.38)	−2.05 (0.54)	—	0.695 (6.84)*	.99
	.007 (0.44)	.007 (2.68)*	−.004 (0.28)	—	−0.032 (0.26)	0.746 (5.40)*	.99
Food	.236 (3.28)*	.033 (3.82)*	.039 (0.53)	9.30 (3.26)*	—	0.056 (0.29)	.97
	.214 (1.93)*	.039 (3.25)*	−.018 (0.18)	—	0.104 (0.80)	0.249 (1.02)	.96
Clothing	.076 (2.40)*	.067 (5.96)*	−.072 (2.00)*	52.3 (2.31)*	—	−0.075 (0.35)	.99
	.102 (2.88)*	.074 (5.17)*	−.138 (2.58)*	—	1.06 (1.62)	0.073 (0.35)	.99
Watches and jewelry	.010 (0.98)	.004 (1.11)	−.012 (1.59)	−5.22 (0.56)	—	0.537 (1.70)	.98
	.012 (1.18)	.003 (0.94)	−.012 (1.72)	—	−0.174 (1.27)	0.581 (2.00)*	.99

Toiletries	.006 (0.40)	.000 (0.00)	−.005 (0.39)	2.46 (3.42)*	—	0.703 (4.72)*	.99
	.013 (0.73)	.001 (0.04)	−.013 (0.98)	—	0.047 (1.85)*	0.766 (4.09)*	.99
Furniture	.086 (2.28)*	.052 (3.62)*	−.109 (2.47)*	66.9 (1.85)*	—	−0.499 (1.04)	.98
	.096 (2.03)*	.051 (3.32)*	−.131 (2.10)*	—	1.09 (1.58)	−0.199 (0.55)	.97
Appliances	−.053 (2.09)*	.033 (2.93)*	.018 (1.20)	−2.88 (0.33)	—	0.053 (0.17)	.98
	−.050 (1.66)	.032 (2.71)*	.016 (0.82)	—	−0.028 (0.16)	−0.084 (0.81)	.98
Cleaning and polishing preparations	.008 (0.60)	.002 (1.88)*	−.003 (0.26)	4.19 (2.18)*	—	0.233 (0.94)	.98
	.017 (1.49)	.003 (2.31)*	−.015 (1.65)	—	0.072 (2.51)*	0.322 (1.62)	.98
Drugs	−.006 (0.46)	.006 (2.88)*	.000 (0.03)	−0.715 (1.06)	—	0.771 (7.71)*	.99
	−.005 (0.37)	.005 (2.15)*	.000 (0.41)	—	−0.010 (.058)	0.782 (6.48)*	.99
Automobiles	−.537 (1.79)*	.117 (4.17)*	.322 (1.41)	55.3 (3.79)*	—	0.213 (0.76)	.99

TABLE 2 (concluded)

Industry	b_0	Y_t	P_t	A_t Per Capita[a]	A_t Relative[b]	C_{t-1}	R^2
	−.478 (1.88)*	.148 (5.69)*	.200 (1.05)	—	1.25 (4.72)*	−0.004 (0.02)	.97
Tires and accessories	−.009 (2.29)*	.003 (1.41)	.005 (1.45)	−0.20 (0.03)	—	0.991 (8.38)*	.93
	−.008 (2.30)*	.003 (1.47)	.004 (0.88)	—	0.04 (0.21)	0.967 (6.17)*	.99
Publishing	.010 (2.78)*	.007 (2.11)*	−.007 (1.41)	−0.433 (0.08)	—	0.167 (0.66)	.93
	.010 (2.81)*	.007 (2.57)*	−.008 (1.59)	—	−0.042 (0.47)	0.176 (0.72)	.93
Sporting goods and toys	−.012 (0.16)	.010 (1.19)	−.003 (0.03)	−11.3 (0.95)	—	1.03 (3.32)*	.98
	−.003 (0.04)	.006 (0.73)	−.005 (0.07)	—	−0.227 (0.81)	1.07 (3.35)*	.98

Radio and TV	−.105	.036	.044	21.4	—	0.316	.99
	(2.64)*	(3.99)*	(1.67)	(1.88)*		(1.13)	
	−.127	.042	.052	—	0.647	0.240	.99
	(3.72)*	(5.46)*	(2.31)*		(3.03)*	(1.00)	
Airline travel	−.003	.003	−.002	2.40	—	0.539	.99
	(2.37)*	(3.93)*	(1.94)*	(1.78)		(6.28)*	
	−.004	.004	−.002	—	0.072	0.504	.99
	(3.10)*	(5.21)*	(2.16)*		(2.01)*	(5.91)*	

*Statistically significant at 5 percent level or better.
[a]Industry advertising expenditures measured in per capita terms.
[b]Industry advertising expenditures measured relative to total national advertising expenditures.

TABLE 3 Estimation of Demand Equation 2, Section IV, for 1956–1972 (figures in parentheses are t ratios)

				Log A_t			
Industry	b'_0	Log Y_t	Log P_t	Per Capita[a]	Relative[b]	Log C_{t-1}	R^2
Alcoholic beverages	−1.14 (1.74)	0.284 (3.11)*	−0.086 (0.42)	−.012 (0.18)	—	.692 (6.58)*	.99
	−1.03 (3.25)*	0.257 (2.71)*	−0.073 (0.29)	—	−.019 (0.17)	.713 (4.88)*	.99
Food	−0.640 (2.72)*	0.197 (3.76)*	0.105 (0.55)	.066 (2.40)*	—	.050 (0.25)	.98
	−0.890 (3.57)*	0.243 (3.89)*	−0.038 (0.16)	—	.036 (0.66)	.152 (0.66)	.97
Clothing	−1.40 (2.56)*	0.894 (6.23)*	−0.360 (1.75)	.166 (2.40)*	—	−.094 (0.47)	.99
	−1.89 (3.68)*	1.01 (5.24)*	−0.687 (2.38)*	—	.178 (1.60)	.018 (0.08)	.99
Watches and jewelry	3.33 (1.89)*	0.790 (1.35)	−0.458 (0.94)	−.052 (0.82)	—	.472 (1.36)	.98
	−2.94 (1.77)	0.639 (1.16)	−0.498 (1.11)	—	−.087 (1.65)	.533 (1.72)	.99

Toiletries	0.550 (1.00)	−0.071 (0.28)	−0.140 (0.25)	.226 (3.08)*	—	.760 (6.60)*	.99
	−0.070 (0.11)	−0.019 (0.06)	−0.238 (0.35)	—	.188 (1.42)	.863 (6.31)*	.99
Furniture	−3.12 (3.70)*	1.38 (3.50)*	−1.19 (2.32)*	.159 (1.60)	—	−.298 (0.75)	.98
	3.31 (3.26)*	1.30 (2.75)*	−1.20 (1.66)	—	.123 (1.04)	−.094 (0.24)	.98
Appliances	−4.55 (3.39)*	1.89 (3.78)*	0.202 (0.64)	.028 (0.39)	—	.007 (0.04)	.99
	−4.26 (3.78)*	1.72 (3.60)*	−0.002 (0.01)	—	.070 (0.86)	.043 (0.24)	.99
Cleaning and polishing preparations	−1.34 (2.45)*	0.233 (1.71)	−0.149 (0.30)	.286 (2.57)*	—	.215 (0.93)	.98
	−2.00 (3.17)*	0.281 (1.89)*	−0.653 (1.47)	—	.262 (2.54)*	.367 (1.99)*	.98
Drugs	−1.56 (4.59)*	0.506 (3.24)*	−0.107 (0.38)	.019 (0.40)	—	.645 (5.45)*	.99
	−1.76 (3.50)*	0.577 (3.16)*	−0.094 (0.38)	—	.035 (0.56)	.616 (4.40)*	.99
Automobiles	0.79 (0.75)	1.30 (2.18)*	−0.403 (0.21)	.672 (4.87)*	—	−.208 (0.73)	.98

TABLE 3 (concluded)

Industry	b'_0	$\text{Log } Y_t$	$\text{Log } P_t$	$\text{Log } A_t$: Per Capita[a]	$\text{Log } A_t$: Relative[b]	$\text{Log } C_{t-1}$	R^2
Tires and accessories	−2.14 (3.81)*	2.31 (3.92)*	0.382 (0.20)	—	.791 (5.11)*	−.150 (0.54)	.98
	−0.76 (0.61)	0.390 (1.61)*	0.218 (0.84)	−.007 (0.05)	—	.880 (6.53)*	.99
Publishing	−0.70 (0.97)*	0.395 (1.77)	0.185 (0.53)	—	.017 (0.11)	.866 (5.14)*	.99
	−3.74 (2.88)*	0.794 (2.39)*	−0.481 (1.75)	.031 (0.43)	—	.121 (0.53)	.93
Sporting goods and toys	−4.10 (3.85)*	0.884 (3.08)*	−0.537 (1.98)*	—	−.008 (0.14)	.120 (0.52)	.94
	−2.89 (2.28)*	0.509 (1.52)	−2.11 (1.62)	.039 (0.47)	—	.223 (0.58)	.99
Radio and TV	3.15 (2.32)*	0.597 (1.92)*	−2.05 (1.69)	—	.060 (0.57)	.190 (0.48)	.99
	−4.10 (1.02)*	3.27 (6.75)*	1.12 (3.02)*	.211 (2.23)*	—	.042 (0.21)	.99

	−4.94	3.67	1.46	—	.247	.071	.99
	(5.61)*	(7.80)*	(4.10)*		(2.64)*	(0.40)	
Airline travel	−2.13	1.50	−0.180	.321	—	.327	99
	(2.17)*	(4.48)*	(1.41)	(3.93)*		(3.35)*	
	−3.91	2.04	−0.164	—	.444	.217	.99
	(4.46)*	(5.72)*	(1.12)		(3.17)*	(1.76)	

*Statistically significant at 5 percent level or better
[a]Industry advertising expenditures measured in per capita terms.
[b]Industry advertising expenditures measured relative to total national advertising expenditures.

tively, this could reflect the presence of an omitted explanatory variable which is significantly correlated with the first-order lag term, causing an upward bias in this coefficient.

The estimated coefficients in both tables could also have some bias if autocorrelation is present in the residuals. While most of the equations have Durbin-Watson statistics close to 2.00, that test is of course biased in the presence of a lagged consumption term. Since my main purpose is to evaluate the relative impacts of different factors from a qualitative standpoint, rather than obtain precise quantitative estimates of their effects on demand (which is hardly practical with current data sources), I operate under the presumption that any autocorrelation present in the residuals is not so large as to basically alter the qualitative nature of the results presented above.[24] There are a number of reasons to suppose that simultaneity between advertising and consumption is a much more serious statistical problem in this regard; and consequently, it is given greater attention below.

The next set of dynamic models that was estimated involved the generalized Koyck model in which advertising outlays enter as a capital stock variable rather than as a flow. In particular, I wished to examine whether allowing the advertising variable to have a cumulative lagged impact on consumption, over and above the adjustment lags common to other factors, results in improved performance for that variable and otherwise provides results that are intuitively plausible on economic grounds.

In symbolic terms, the model to be estimated now becomes

$$(3)\quad C_t = b_0 + b_1 Y_t + b_2 P_t + b_3 K_t + b_4 C_{t-1} + u_t$$

and for the multiplicative case,

$$(4)\quad \log C_t = b'_0 + b'_1 \log Y_t + b'_2 \log P_t + b'_3 \log K_t + b'_4 \log C_{t-1} + u'_t$$

As discussed in the previous section, K_t in each period is approximated by six years of current and prior advertising expenditures:

$$(5)\quad K_t = A_t + (1-\lambda)A_{t-1} + (1-\lambda)^2 A_{t-2} + \ldots + (1-\lambda)^5 A_{t-5}$$

where λ is the depreciation rate of advertising capital.

In estimating equations 3 and 4 I used nonlinear techniques to find the value of λ over the range 0 to 1 (i.e., depreciation rates from 0 to 100 percent in each period) that maximizes the estimated R^2 for the two equations.

Overall, the results obtained from estimating equations 3 and 4 differed little in qualitative terms from those obtained from the simple Koyck model presented above. As before, advertising measured in per capita terms significantly outperformed that in relative terms. For individual industries, none of the advertising coefficients that were statistically insignificant or negative in the Koyck model presented in tables 2 and 3 became positive and statistically significant when advertising was reformulated as a stock effect. Likewise, advertising flow variables that were positive and statistically significant in tables 2 and 3 were generally so in the capital stock case.

One question on which the generalized Koyck model given by equations 3 and 4 might be expected to provide some insights is the value of the depreciation rate of advertising capital. In point of fact, in many cases the estimated R^2 were not very sensitive to the value of λ, and the maximum R^2 over the range searched frequently occurred for the case $\lambda = 1$ (i.e., the Koyck model). Perhaps this result is not too surprising, given the high explanatory power of the latter structure in the current data set as well as the fact that simultaneous equation problems also would tend to produce a bias toward an estimate of a 100 percent depreciation rate.

To illustrate these points further, Table 4 contains the nonlinear estimates for equation 3 for the eight industry classes which exhibited significant (or near significant) positive coefficients for the advertising stock variable. As before, the first equation for each industry includes advertising measured in per capita terms; and the second, advertising measured in relative terms.

In the set of equations in which advertising is measured in per capita terms, the results taken at face value would suggest relatively slow depreciation rates for cleaning and polishing and toiletries (26 and 32 percent, respectively) and a much faster depreciation rate for airlines (73 percent); but in all other industries (food, wearing apparel, furniture, autos, and radio and TV) the maximum R^2 occurs at a 100 percent depreciation rate on advertising (in effect reducing to the Koyck limiting case).

A quite different picture is presented when advertising is measured in relative terms. Although the advertising stock variable usually has much lower t values, estimates of 100 percent depreciation rates are obtained only for the two durable classes, autos and furniture. Three of the classes that had 100 percent depreciation rates in the per capita formulation (food, clothing, and radio and TV) now show much smaller estimated rates.[25] The remaining three classes (cleaning and polishing, toiletries, and airlines services) have about the same rates in both cases.

The high depreciation rates for the two durable classes, autos and furniture, are consistent with past estimates of depreciation based on brand or firm data.[26] In addition, relatively low depreciation rates (in the range of 30 percent) for cleaning and polishing and toiletries also do not appear unreasonable, given published estimates for the few high-advertising-intensive nondurable product classes previously examined in the literature.[27]

On the other hand, the results for three of the classes (food, clothing, and

TABLE 4 Estimation of Demand Equation 3, Section IV, for 1956–1972, for Selected Industry Classes (figures in parentheses are t ratios)

Industry	b_0	Y_t	P_t	K_t: Per Capita[a]	K_t: Relative[b]	C_{t-1}	$1 - \lambda$
Food	.236 (3.28)*	.033 (3.82)*	.039 (0.53)	9.30 (3.26)*	—	.056 (0.29)	0 [c]
	.187 (1.38)	.039 (2.98)*	.024 (0.20)	—	0.038 (0.24)	.160 (0.68)	1.00 (0.66)
Clothing	.076 (2.40)*	.067 (5.96)*	−.072 (2.00)*	52.3 (2.31)*	—	−.075 (0.35)	0 [c]
	.130 (2.95)*	.077 (5.16)*	−.188 (2.72)*	—	0.555 (0.59)	.126 (0.57)	0.60 (1.02)
Toiletries	.011 (0.75)	.000 (0.18)	−.008 (0.68)	1.95 (3.42)*	—	.360 (1.25)	0.68 (4.53)*
	−.003 (0.19)	.002 (0.89)	−.011 (1.00)	—	0.044 (3.54)*	.244 (0.85)	0.95 (7.66)*
Furniture	.086 (2.28)*	.052 (3.62)*	−.109 (2.47)*	66.9 (1.85)*	—	−.499 (1.04)	0 [c]
	.096 (2.03)*	.051 (3.32)*	−.131 (2.10)*	—	1.09 (1.58)	−.199 (0.55)	0 [c]

Cleaning and polishing	.019 (1.48)	.002 (1.81)*	−.009 (0.84)	1.92 (1.25)	—	−.140 (0.38)	0.74 (2.48)*
	.007 (0.67)	.005 (3.32)*	−.007 (0.82)	—	0.040 (2.22)*	.007 (0.03)*	0.73 (3.82)*
Automobiles	−.537 (1.79)*	.117 (4.17)*	.322 (1.41)	55.3 (3.79)*	—	.213 (0.76)	0 c
	.478 (1.88)*	.148 (5.69)*	.200 (1.05)	—	1.25 (4.72)*	.004 (0.02)	0 c
Radio and TV	−.105 (2.64)*	.036 (3.99)*	.044 (1.67)	21.4 (1.88)*	—	.647 (3.03)*	0 c
	−.212 (4.00)*	.067 (4.92)*	.090 (0.31)	—	0.707 (3.50)*	−.217 (0.76)	0.49 (4.17)*
Airline travel	−.003 (2.28)*	.003 (3.82)*	−.001 (1.66)	2.13 (1.16)	—	.510 (2.02)*	0.27 (0.16)
	−.004 (2.87)*	.003 (5.07)*	−.001 (1.76)	—	0.068 (1.66)	.477 (2.53)*	0.23 (0.20)

*Statistically significant at 5 percent level or better.
[a]Advertising capital stock based on past advertising per capita expenditures.
[b]Advertising capital stock based on past relative advertising expenditures.
[c]Maximum R^2 occurs at Koyck special case.

radio and TV) suggest there may be simultaneous equation problems. The strongest impact of sales on advertising would occur in concurrent periods. The fact that the estimated coefficients on the depreciation coefficient go to zero and the advertising coefficient becomes stronger when a per capita measure is used in place of a relative one is consistent with a causal relation from firm sales to advertising. This issue is examined further in the next section.

The final dynamic structure examined here was the Comanor-Wilson variant of the Houthakker-Taylor model, as discussed in section II. Given the findings above and the fact that this third model involves estimating an even more complex nonlinear dynamic structure than equations 3 or 4, it did not seem reasonable to expect any definitive new results. However, mainly for comparative purposes, estimates were obtained employing this structure. In symbolic terms, it is given by

$$(6)\quad C_t = B_0 + B_1 \Delta Y_t + \lambda B_1 Y_{t-1} + B_2 \Delta P_t + \lambda B_2 P_{t-1} + B_3 \Delta A_t + \lambda B_3 A_{t-1} + B_4 C_{t-1} + u_t$$

This is the principal model used by Comanor and Wilson to generate estimates of the impacts of income, advertising, and prices. Comparable estimates on my data set are presented in Table 5.[28] To be consistent with their study, advertising is measured in relative terms in estimating equation 6.

It is clear from the estimated coefficients in Table 5 that the qualitative characteristics of this more complex dynamic model are quite similar to the Koyck models presented in Table 2 (i.e., the comparable estimates with the relative advertising measure). Income is once again the dominant explanatory variable. Industries that exhibit either strong advertising or price effects in Table 5 also tend to have the same characteristics in the earlier Koyck regressions. However, as one might also expect, there is more instability observed for these variables than in the models employing the simpler Koyck lag structure.

The major advantage of the Houthakker-Taylor dynamic model is, of course, its flexibility in allowing durables to take on qualitatively different dynamic response patterns from nondurables. Significantly, the estimates of Table 5 do indicate that three of the major durable classes (furniture, automobiles, and watches and jewelry) do have a negative stock effect and thus exhibit a different dynamic response pattern than predicted by the simple Koyck adjustment mechanism. However, it is also true that the main parameter differentiating the lag response in this model has a large standard error. At normal 5 percent confidence intervals, the hypothesis that a Koyck lag structure exists (i.e., that $\lambda \neq 1$) can be rejected in less than half the industry cases, and many industries for which the hypothesis is rejected involve nondurable categories with implausible lag structures.

If we compare the estimates of the advertising variable in Table 5 with the comparable estimates for the Koyck model in Table 2, significant positive improvement occurs for the H-T model for the durable categories of furniture, watches and jewelry, and appliances. On the other hand, the estimates for many of the nondurable classes significantly deteriorate. For example, the two advertising-intensive nondurable categories—toiletries and cleaning and polishing preparations—which exhibit highly significant coefficients in the Koyck estimates in Table 2 are insignificant in the more general H-T model.

The overall findings in tables 2 through 5 seem to suggest a clear strategy for further analysis. As noted above, the much poorer performance of the relative advertising variable vis-à-vis an absolute one (as well as the high estimated rates of depreciation for the latter variable in Table 4) suggests a high priority should be placed on investigating the nature of the causal relation between advertising and sales. At the same time, the least squares estimates show that it is difficult to make very fine discriminations between alternative lag structures. This is not surprising, given the few degrees of freedom and the general characteristics of annual time series data. Therefore, I decided to work with the simpler Koyck dynamic structure in the simultaneous equation estimation presented in the next section.

There are some compelling reasons for keeping the dynamic structures relatively simple in any simultaneous equation analysis. If complex nonlinear dynamic structures like the Houthakker-Taylor state adjustment model are used, then even the assumption of very simple linear feedback relations between advertising and sales results in complex nonlinear simultaneous equation models. These are difficult to estimate even if data samples with large numbers of observations are available.[29] In contrast, demand equations employing the simpler first-order lag structure of the Koyck model can be combined with well-known theoretical models of optimal advertising expenditures and estimated by standard linear simultaneous equation techniques. The analysis for doing so is developed in the next section.

Admittedly, the Koyck model may result in some misspecification of the dynamic response pattern, especially for the durable goods. However, its advantages of simplicity and tractability seem to override these disadvantages in any simultaneous equation work. Moreover, the above least squares estimates suggest that for nondurables, the simpler Koyck model has estimated coefficients more in conformance with theoretical predictions than those emerging from more complex dynamic models. This somewhat surprising result probably reflects the lesser demands which this model places on the relatively small samples available.

From a broader perspective, we are much more interested in the estimates of advertising on demand in the nondurable classes. This is

TABLE 5 Estimation of Demand Equation 6, Section IV, for 1956–1972: Advertising Measured in Relative Terms (figures in parentheses are t ratios)

Industry	b_0	ΔY_t	ΔP_t	ΔA_t	C_{t-1}	λ	R^2
Alcoholic beverages	.009 (1.58)	.015 (4.69)*	−.021 (2.10)*	−0.176 (2.29)*	0.835 (10.78)*	0.307 (4.01)*	.99
Food	.101 (1.68)	.112 (5.40)*	−.071 (1.40)	−0.092 (0.91)	0.713 (3.92)*	0.064 (0.70)	.98
Clothing	.013 (0.41)	.120 (5.19)*	−.011 (0.09)	0.640 (1.02)	0.319 (1.23)	0.357 (2.44)*	.99
Watches and jewelry	−.002 (0.32)	.016 (3.22)*	−.002 (0.20)	0.327 (1.21)	0.511 (1.22)	0.246 (1.17)	.99
Toiletries	.007 (1.21)	.009 (2.31)*	−.029 (2.58)*	0.028 (1.28)	0.710 (3.81)*	0.234 (1.50)	.99
Furniture	−.010 (0.81)	.097 (7.79)*	.014 (0.28)	1.24 (2.02)*	0.118 (0.59)	0.309 (4.87)*	.99
Appliances	−.039 (2.16)*	.037 (2.94)*	.026 (0.82)	0.244 (1.11)	0.508 (1.51)	0.530 (2.03)*	.98
Cleaning and polishing preparations	.022 (1.71)	.006 (1.97)*	−.033 (2.66)*	0.022 (0.65)	0.276 (1.26)	0.455 (2.30)*	.98
Drugs	−.001 (0.03)	.005 (1.71)	−.003 (0.18)	−0.018 (1.31)	0.781 (4.52)*	0.867 (1.47)	.99
Automobiles	−.418 (1.50)	.149 (3.74)*	.182 [illegible]	1.27 [illegible]	0.035 (0.08)	0.914 [illegible]	.9[illegible]

Tires and accessories	−.012	.003	.005	0.076	0.922	0.980	.99
	(2.35)*	(1.10)	(0.57)	(0.39)	(4.67)*	(0.95)	
Publishing	.005	.008	−.006	0.093	0.419	0.383	.93
	(1.69)	(2.08)*	(0.74)	(0.66)	(1.00)	(0.80)	
Sporting goods and toys	.049	.001	−.029	−0.219	1.00	1.64	.98
	(0.37)	(0.20)	(0.43)	(0.68)	(2.22)*	(0.99)	
Radio and TV	−.095	.052	.064	0.454	0.516	0.621	.99
	(1.29)	(4.41)*	(1.95)*	(1.95)*	(1.79)*	(1.55)	
Airline travel	−.007	.002	−.001	0.052	0.237	2.31	.99
	(2.86)*	(2.00)*	(1.16)	(1.57)	(1.11)	(1.41)	

* Statistically significant at 5 percent level or better.

because total media advertising expenditures are much more concentrated in nondurable goods. For the major media covered by our data, nondurables account for over 70 percent of total national advertising expenditures.[30] Thus, the basic question that is being investigated here—the effects of advertising relative to other factors in influencing demand across broad product categories—is much more important for nondurables simply because the size of advertising outlays is strongly weighted toward this class of goods. While the impacts of advertising on durable classes are also of interest, the procedures that I elected to use in my simultaneous equation work (for reasons discussed above) imply that the estimates on the durable classes should be treated with much more caution.

[V] ANALYSIS OF SIMULTANEOUS EQUATIONS

Theoretical Considerations

The determinants of advertising expenditures have been discussed extensively in both the institutional and theoretical literature. A frequent theme in the institutional literature is that advertising outlays for many firms are set as a constant percentage of sales, in effect a rule-of-thumb decision-making mechanism.[31] Such a rule is used primarily to describe short-run behavior. Over the long run, it is acknowledged, the relation of advertising to sales depends on a number of other factors.

Theoretical analysis of the relation of advertising to sales usually begins with the pioneering work of Rasmussen [1952] and Dorfman and Steiner [1954]. Rasmussen examined optimal advertising in terms of a static model in which a monopoly firm maximized its profit function expressed as

$$(1) \quad \Pi = PQ(A, P) - C[Q(A, P)] - AT$$

where

A = real advertising expenditures or the number of "viewer-messages"
T = advertising cost per viewer-message
P = product price
$Q(A, P)$ and $C(Q)$ = demand and production cost functions

When advertising expenditures are the only decision variable, Rasmussen showed that the optimality condition for this model can be formulated as

$$(2) \quad \frac{AT}{PQ} = \alpha \frac{P - C'(Q)}{P}$$

where

α = advertising elasticity of demand
$C'(Q)$ = marginal cost of a unit of production

This formula indicates that the advertising-to-sales ratio selected by the monopoly firm will vary directly with the advertising elasticity of demand α, and the profit margin on an additional unit of output, $[P - C'(Q)]/P$. The latter term is generally referred to in the literature as the Lerner index of monopoly.

Dorfman and Steiner generalized the foregoing simple static monopoly model to allow price and product quality to be endogenous variables along with advertising. Their analysis in turn has been generalized by a number of authors to include both dynamic and oligopolistic considerations. Among the authors are Nerlove and Arrow [1962], Gould [1970], Grabowski [1970], and Schmalensee [1972]. Since the last named has provided the most complete theoretical analysis to date, his work is used as a guideline for the analysis here.

In particular, Schmalensee has shown that the Rasmussen condition on the advertising-to-sales ratio can be generalized in a dynamic oligopolistic framework to the condition

$$(3) \quad \frac{AT}{PQ} = f(r)\,\frac{P - C'(Q)}{P}\,\alpha'$$

where

r = firm's discount rate
α' = firm's net advertising elasticity of demand (i.e., allowing for competitive reactions to its own advertising)

The model also assumes a demand function with a general first-order dynamic lag structure like that employed in the Koyck model of the previous section.

The main difference between equation 2 and equation 3 involves a nonlinear term, $f(r)$, which in effect states that the advertising-to-sales ratio is inversely related to the rate of discount. This arises from the dynamic character of the optimization problem. In addition, the elasticity coefficient also takes account of conjectural variation terms dealing with competitive reactions, rather than, as in the monopoly situation, with just the firm's own advertising elasticity of demand.

The dynamic oligopoly model can also be generalized to take account of interdependencies between advertising and other decision variables such as prices and product quality. Of course, this introduces another chain of complex conjectural variation terms into the analysis. In the current empirical work I abstract from these considerations and treat prices as an exogenous variable. In effect, i assume that oligopolists treat prices as externally determined and compete by "nonprice" means. This kind of model has received some attention in the literature. In any event, analysis of simultaneous equation interaction between prices and advertising would introduce far too many complexities for our current, limited data base, and hence such interactions are ignored in the current analysis.

Equation 3 can be used to structure the advertising-to-sales relationship in our empirical model. Specifically, the optimality condition may be viewed as denoting the firm's desired level of advertising in current dollars, AC_t^*, in any given period. Rearranging terms, the condition becomes

$$(3') \quad AC_t^* = f(r_t)\,\frac{P - C'(Q)}{P}\,\alpha' S_t$$

where S_t is firm sales in current dollars.

Since we have no direct data on either profit margins or elasticity of demand by consumption categories, it is not possible to include those terms explicitly in the empirical analysis. Since those factors may vary with either sales or the rate of discount or both, the following approximation to equation 3 is suggested:

$$(4) \quad AC_t^* = \beta_0 r_t^{\beta_1} S_t^{\beta_2}$$

with $\beta_1 < 0$ and $\beta_2 > 0$.

To complete this model of advertising outlays, an assumption on the dynamic lag structure relating AC_t^* to AC_t is necessary. There are a number of reasons why advertising expenditures can be expected to adjust only gradually toward desired levels. Contracts for many media must be signed before sales are definitely known, and there are various physical lags in implementing the decision to increase expenditures, especially if a change in content is also warranted. There is also some evidence from Schmalensee's [1972] study that a lag exists between aggregate advertising outlays and total consumption expenditures.

In accordance with the demand equation analysis developed above, a first-order partial adjustment lag structure is also assumed for advertising, or

$$(5) \quad AC_t / AC_{t-1} = (AC_t^* / AC_{t-1})^{\rho}$$

with $0 < \rho < 1$.

Combining equation 4 with equation 5 yields the dynamic model of advertising expenditures:

$$(6) \quad AC_t = \gamma_0 r_t^{\gamma_1} S_t^{\gamma_2} AC_{t-1}^{\gamma_3}$$

where

$\gamma_0 = \beta_0 \rho$
$\gamma_1 = \beta_1 \rho < 0$
$\gamma_2 = \beta_2 \rho > 0$
$\gamma_3 = 1 - \rho$

Equation 6 can be combined directly with the log version of the consumption function employing the Koyck dynamic structure used in the previous section to form a log-linear system of simultaneous equations. The only thing necessary to complete the system is a few identities reflecting the expression of advertising and sales in current terms in equation 6, and in either real per capita or relative terms in the demand equation.

When consumption and advertising are measured in per capita terms, the following system applies:

(7a) $\log C_1 = b_0 + b_1 \log Y_t + b_2 \log P_t + b_3 \log A_t + b_4 \log C_{t-1} + u_t$

(7b) $\log AC_t = c_0 + c_1 \log r_t + c_2 \log S_t + c_3 \log AC_{t-1} + v_t$

together with the identities

(7c) $C_t = S_t/(POP_t)(P_t)$

(7d) $A_t = AC_t/(POP_t)(PA_t)$

where POP_t is population and P_t and PA_t are the price index deflators for the particular product and advertising in period t.

Equations 7c and 7d can be expressed as log-linear identities. Together, the four equations form a log-linear simultaneous system that can be estimated by two-stage least squares and other simultaneous equation techniques. The endogenous variables are C_t, A_t, S_t, and AC_t; all other variables are treated as exogenous.

When advertising is measured in relative terms in equation 7a, the last identity is modified so that

(7d′) $A_t = AC_t/(PA_t)(NA_t)$

where NA_t is real national advertising expenditures in period t. The reduced form equation is then correspondingly modified to take account of the additional variable NA_t.

Empirical Results

In estimating equation system 7a through 7d an empirical estimate is needed for the interest or discount rate term in equation 7b. Moody's AAA bond rate was used here as a proxy variable. Although ideally there should be a separate measure for each industry group, reflecting its particular risk class, *time series* movements in the rate for specific industries and the

Moody's AAA rate should be significantly correlated if capital markets work properly.

Tables 6 through 9 contain two-stage least squares estimates of equations 7a and 7b. Tables 6 and 7 contain estimates with advertising in the demand equation measured in per capita terms, and tables 8 and 9 contain advertising measured in relative terms. The most dramatic finding is that the relation between sales and advertising is much stronger in the determinant equation than in the demand one. For the advertising equation (tables 7 and 9) sales are significant in ten of the fifteen consumption categories and have a *t* value greater than 1.0 in four of the other five industries. By contrast, the estimated coefficient on advertising in the demand equation, whether measured in per capita or relative terms, is significant in one-third or fewer of the consumption categories and has a *t* value less than 1.0 or the wrong sign in a majority of the industry classes. Thus, qualitatively different results are observed in the relation between sales and advertising for the two equations.

The estimated coefficients for the sales variable in the advertising equation take on a value between 0 and 1 in all cases. Since these coefficients are estimates of the short-run elasticities between sales and advertising, they indicate that the short-run adjustment of advertising is less than proportionate to a given change in sales. However, long-run elasticities generally exceed 1, given the estimated coefficient on lagged advertising. The latter variable is in the predicted range of 0 to 1 in all cases and is statistically significant for most industries. While some of the estimated coefficients on lagged advertising seem implausibly high (e.g., food, furniture, and airline services), this probably reflects omitted explanatory factors that influence advertising expenditures slowly over time and consequently are picked up in this first-order lag term.

The third variable in the advertising equation, the interest rate (*r*), takes on the predicted sign for most industries (twelve out of fifteen cases). Although the *t* values are usually greater than 1.0, they are in most cases not statistically significant at normal 5 percent confidence intervals. Given that this is a proxy variable, these results do not seem unreasonable. The estimates of the interest rate variable tend somewhat to be higher for durable goods than nondurable ones, although this is pronounced only in the case of furniture and automobiles.[32]

Turning to the two-stage estimates of the demand equation (tables 6 and 8), the results exhibit many similarities to least squares estimates of the previous section. As before, income is the dominant explanatory variable, and prices generally have the right sign but are statistically significant in only a minority of cases. However, as expected, the size and significance of the estimated advertising coefficients in the current simultaneous case show a general decline compared with corresponding estimates in Table 3.

This is particularly pronounced when the advertising variable is measured in per capita terms. In fact, although the relative advertising variable is statistically significant in two cases fewer, it has the predicted positive sign and t values greater than 1.0 in several industries for which the absolute variable does not. Thus, the relative measure exhibits greater stability and conformance to theoretical predictions when two-stage least squares estimation is used. This is in sharp contrast to OLSQ estimates. This result, together with the significant difference in the relation between sales and advertising in the demand and determinant equations suggest considerable simultaneous equation bias was indeed present in the OLSQ estimates for the per capita advertising case. Whether all such bias is completely removed by the current simultaneous equation approach is, of course, more conjectural.[33]

One very interesting pattern does emerge from the estimated coefficients on relative advertising in Table 8. Because the model is much more applicable to nondurable goods, attention is primarily focused on those results. Although most of the estimated advertising elasticities are quite small and statistically insignificant (even at 10 percent or higher intervals) three of the nondurable industries do have relatively high estimated elasticities and are statistically significant (or nearly so)—toiletries, cleaning and polishing preparations, and airlines. It is interesting to note that these categories also rank first, second, and third respectively in major media advertising-to-sales ratios for the fifteen industry groups studied here. This pattern suggests that for certain classes of goods advertising may have particularly significant demand effects, which are reflected in the high advertising levels in those sectors relative to sales.[34] In addition, in the estimation of depreciation rates in Table 4 for the capital stock model, those three industries exhibited the best results. They all reached maximum R^2 at the interior values of λ and had estimated depreciation rates that were plausible and consistent with past microeconomic work in this area. This lends support to the view that there is indeed a positive effect of advertising on total industry demand for those three advertising-intensive nondurable industries.

It is perhaps also significant that toiletries, cleaning and polishing, and airlines are fairly disaggregate industries compared to food, clothing, housing, etc. As I noted in my discussion of the Solow-Galbraith exchange in the Introduction, Solow [1968] conjectured that advertising would have little effect on consumer choice in the latter, more aggregate industries. On the other hand, as industries become more disaggregate, stronger advertising effects on sales might be achieved because of shifts of consumer demand among closely substitutable product groups. At what point this effect becomes empirically significant remains open to question. My results suggest that at the fairly high level of aggregation typically reflected by

TABLE 6 Two-Stage Least Squares Estimation of Demand Equation 7a, Section V, for 1956–1972: Advertising Measured in Real Per Capita Terms (figures in parentheses are t ratios)

Industry	b_0	Log Y_t	Log P_t	Log A_t	Log C_{t-1}	R^2
Alcoholic beverages	−1.65 (3.18)*	0.335 (4.82)*	−0.392 (2.58)*	−.008 (0.16)	.517 (6.29)*	.99
Food	−0.585 (2.15)*	0.187 (3.33)*	0.061 (0.31)	.063 (2.09)*	.118 (0.58)	.92
Clothing	−1.42 (2.33)*	0.927 (7.00)*	−0.578 (2.45)*	.166 (1.75)	−.091 (0.45)	.99
Watches and jewelry	−3.35 (1.80)*	0.735 (1.18)	−0.501 (0.97)	−.087 (0.94)	.534 (1.41)	.98
Toiletries	0.734 (0.98)	−0.067 (0.24)	−0.086 (0.14)	.286 (3.20)*	.715 (4.17)*	.99
Furniture	−3.14 (4.14)*	1.31 (3.51)*	−1.38 (2.80)*	.120 (1.21)	−.200 (0.53)	.98
Appliances	−7.42 (2.03)*	2.87 (2.35)*	0.907 (1.05)	−.153 (0.64)	−.226 (0.66)	.98

Appliances	−7.42	2.87	0.907	−.153	−.226	.98
	(2.03)*	(2.35)*	(1.05)	(0.64)	(0.66)	
Cleaning and polishing preparations	−2.21	0.280	−0.564	.295	−.008	.98
	(2.62)*	(1.92)	(0.85)	(1.95)*	(0.03)	
Drugs	−1.91	0.514	−0.336	.042	.520	.99
	(3.26)*	(3.11)*	(0.89)	(0.77)	(2.87)*	
Automobiles	−0.252	1.90	0.630	.561	−.179	.97
	(0.18)	(2.38)*	(0.29)	(3.23)*	(0.62)	
Tires and accessories	0.309	0.364	0.241	.176	.779	.99
	(0.13)	(1.08)	(0.84)	(0.62)	(5.17)*	
Publishing	−3.96	0.740	−0.339	.002	.119	.94
	(2.44)*	(1.51)*	(0.75)	(0.02)	(0.51)	
Sporting goods and toys	−2.75	0.387	−2.44	.095	.119	.99
	(1.82)*	(0.80)	(1.61)	(0.64)	(0.27)	
Radio and TV	−6.00	4.09	1.49	.051	.042	.99
	(1.61)	(6.52)*	(3.72)	(0.28)	(0.21)	
Airline travel	−2.00	1.48	−0.173	.338	.323	.99
	(1.99)*	(4.38)*	(1.35)	(3.94)*	(3.29)*	

* Statistically significant at 5 percent level or better.

TABLE 7 Two-Stage Least Squares Estimation of Advertising Determinant Equation 7b, Section V, for 1956–1972: Advertising Measured in Real Per Capita Terms (figures in parentheses are t ratios)

Industry	c_0	Log S_t	Log r_t	Log AC_{t-1}	R^2
Alcoholic beverages	−3.70 (1.41)	.389 (1.72)*	−.203 (1.36)	.760 (3.93)*	.96
Food	−2.59 (0.92)	.212 (1.01)	−.169 (1.40)	.887 (7.55)	.98
Clothing	−2.07 (0.71)	.599 (2.67)*	−.117 (0.60)	.213 (0.77)	.98
Watches and jewelry	−5.49 (1.36)	.623 (2.86)*	−.224 (0.67)	.602 (3.32)*	.93
Toiletries	−2.80 (1.61)	.451 (1.89)*	−.221 (1.62)	.646 (2.87)*	.97
Furniture	−8.13 (1.55)	.518 (2.53)*	−.563 (1.58)	.889 (3.75)*	.85
Appliances	−0.062 (0.02)	.483 (1.57)	−.207 (0.59)	.203 (1.18)	.55
Cleaning and polishing preparations	−4.33 (2.05)*	.614 (2.57)*	−.203 (1.80)*	.589 (3.53)*	.98
Drugs	−1.22 (0.40)	.393 (1.36)	−.094 (0.46)	.590 (3.37)*	.96
Automobiles	−4.74 (2.35)*	.778 (6.86)*	−.340 (2.23)*	.253 (1.94)*	.96
Tires and accessories	1.13 (0.36)	.558 (2.57)*	.099 (0.34)	.102 (0.36)	.95
Publishing	1.30 (0.43)	.533 (2.12)*	.404 (1.52)	.181 (0.71)	.95
Sporting goods and toys	−4.60 (1.23)	.613 (1.86)*	−.114 (0.40)	.570 (2.84)*	.97
Radio and TV	−4.54 (1.85)	.949 (4.82)*	.101 (0.34)	.120 (0.52)	.96
Airline travel	−1.51 (0.83)	.258 (0.87)	−.275 (1.13)	.748 (2.07)*	.98

*Statistically significant at 5 percent level or better.

most consumption categories in the national income accounts, there is little basis for maintaining the thesis that advertising has strong effects on demand.

Because the simultaneous equation model I used here incorporates the Koyck dynamic lag structure, my results for the durable categories are subject to much more qualification than those for nondurables. Although most of the durable classes did have highly insignificant advertising coefficients, one notable exception was the automobile industry. The estimated advertising elasticity for automobiles in Table 8 is larger than that for any other product class (durable or nondurable) and highly significant. Moreover, strong estimated effects of advertising on automobile demand were generally observed for all the alternative dynamic structures estimated in this study, including the Houthakker-Taylor dynamic structure of Table 5. Whether total industry advertising actually has the strong impact on the demand for new automobiles suggested by these estimates, however, is open to question. The estimated relation of advertising on sales in Table 9 also exhibits a large and statistically significant coefficient. Although the two-stage estimates of advertising elasticities are smaller than those for OLSQ, it is not obvious that my simultaneous equation model has accurately separated the causal flows in this major durable category.[35] Moreover, a more sophisticated dynamic model is clearly needed to analyze this industry, preferably one that directly includes the current stock of cars on the road as an explanatory variable. This type of analysis is obviously beyond the current study. However, given the relatively small number of firms involved, it may be more feasible than in other cases to obtain high-quality quarterly or even monthly advertising data to perform such an analysis.

[VI] CONCLUSIONS AND SUGGESTIONS FOR FUTURE WORK

The main result emerging from the empirical analysis performed here is the qualitatively different behavior of the advertising-consumption relationship in the determinant and demand equations. In almost all consumption categories considered, sales was a strong explanatory variable of advertising outlays. On the other hand, with the exception of a few advertising-intensive categories, advertising had an insignificant effect on consumer demand, after adjustments for external advertising and simultaneous equation effects were made.

Of course my findings do not imply that consumer choice decisions are completely insensitive to advertising. The main issue under investigation was whether advertising had significant effects on consumer allocations among fairly broad aggregate categories, where substitution possibilities are likely to be much weaker than, say, between alternative brands of a given product class or closely substitutable product categories. As one deals with more and more disaggregate consumption categories, much stronger effects of advertising on demand might be expected.

TABLE 8 Two-Stage Least Squares Estimation of Demand Equation 7a, Section V, for 1956–1972: Advertising Measure in Relative Terms (figures in parentheses are t ratios)

Industry	b_0	Log Y_t	Log P_t	Log A_t	Log C_{t-1}	R^2
Alcoholic beverages	−1.08 (2.90)*	0.383 (4.67)*	−0.516 (2.43)*	.082 (0.81)	.444 (3.45)*	.99
Food	−0.895 (3.01)*	0.234 (3.51)*	−0.099 (0.40)	.012 (0.16)	.189 (0.75)	.96
Clothing	−1.80 (3.55)*	1.11 (5.61)*	−1.03 (3.24)*	.244 (1.76)	−.016 (0.08)	.99
Watches and jewelry	−2.87 (1.67)	0.534 (0.93)	−0.584 (1.24)	−.151 (2.02)*	.609 (1.87)*	.98
Toiletries	0.021 (0.02)	0.033 (0.09)	−0.142 (0.18)	.340 (1.75)	.809 (3.75)*	.99
Furniture	−3.29 (3.54)*	1.26 (2.78)*	−1.41 (2.01)*	.092 (0.79)	−.047 (0.13)	.98
Appliances	−4.38 (3.50)*	1.84 (3.35)*	−0.002 (0.01)	.107 (1.03)	−.009 (0.05)	.99
Cleaning and polishing preparations	[illegible]					

Cleaning and polishing preparations	−2.92	0.292	−1.17	.221	.170	.98
	(3.49)*	(1.96)*	(2.23)*	(1.92)*	(0.77)	
Drugs	−2.28	0.654	−0.287	.069	.475	.99
	(2.96)*	(3.16)*	(0.86)	(0.87)	(2.27)*	
Automobiles	−2.45	2.50	0.775	.707	−.140	.97
	(3.22)*	(3.26)*	(0.36)*	(3.50)*	(0.49)	
Tires and accessories	−1.13	1.07	−0.667	.634	.306	.98
	(1.06)	(2.17)*	(0.88)	(1.46)	(0.76)	
Publishing	−4.13	0.830	−0.450	−.039	.138	.94
	(3.64)*	(2.21)*	(1.06)	(0.54)	(0.58)	
Sporting goods and toys	−3.67	0.587	−2.71	.292	−.202	.99
	(2.13)*	(1.52)	(1.72)	(1.11)	(0.34)	
Radio and TV	−5.78	4.12	1.59	.184	.004	.99
	(5.82)*	(8.48)*	(4.88)*	(1.26)	(.030)	
Airline travel	−3.80	2.06	−0.142	.517	.186	.99
	(4.26)*	(5.69)*	(0.96)	(3.28)*	(1.45)	

*Statistically significant at 5 percent level or better.

TABLE 9 Two-Stage Least Squares Estimation of Advertising Determinant Equation 7b, Section V, for 1956–1972: Advertising Measured in Relative Terms (figures in parentheses are t ratios)

Industry	c_0	Log S_t	Log r_t	Log AC_{t-1}	R^2
Alcoholic beverages	−3.78 (1.56)	.390 (1.73)	−.202 (1.36)	.762 (3.93)*	.96
Food	−2.71 (0.96)	.221 (1.06)	−.173 (1.44)	.883 (7.54)*	.98
Clothing	−2.25) (0.77)	.621 (2.78)*	−.128 (0.66)	.193 (0.70)	.93
Watches and jewelry	−5.37 (1.35)	.619 (2.84)*	−.219 (0.65)	.602 (3.32)*	.93
Toiletries	−2.82 (1.63)	.456 (1.91)*	−.222 (1.63)	.652 (2.85)*	.97
Furniture	−8.14 (1.55)	.519 (2.53)*	−.564 (1.58)	.889 (3.76)*	.85
Appliances	−0.790 (0.15)	.527 (1.72)	−.255 (0.73)	.203 (1.18)	.55
Cleaning and polishing preparations	−4.34 (2.06)*	.615 (2.58)*	−.203 (1.81)*	.588 (3.53)*	.98
Drugs	−1.10 (0.36)	.381 (1.32)	−.087 (0.43)	.596 (3.41)*	.96
Automobiles	−4.98 (2.48)*	.798 (7.11)*	−.357 (2.35)*	.242 (1.85)*	.96
Tires and accessories	1.04 (0.33)	.569 (2.62)*	.091 (0.31)	.094 (0.33)	.96
Publishing	1.31 (0.43)	.532 (2.12)*	.405 (1.53)	.181 (0.71)	.98
Sporting goods and toys	−4.70 (1.26)	.623 (1.90)*	−.118 (0.42)	.565 (2.82)*	.97
Radio and TV	−4.64 (1.89)*	.965 (4.91)*	.100 (0.34)	.106 (0.46)	.96
Airline travel	−1.52 (0.84)	.263 (0.89)	−.276 (1.14)	.742 (2.06)*	.98

*Statistically significant at 5 percent level or better.

As noted above, the few categories in which advertising continued to exhibit highly significant effects on demand, even after adjustments for simultaneous equation effects were made, were characterized by very high average advertising intensities in relation to the other categories. This suggests that certain types of goods may have product characteristics uniquely amenable to advertising. While this line of thought could not be pursued in any detail here because of data limitations, it is broadly consistent with the recent findings of Porter [1974] on the relation of advertising to profit rates.[36]

The results of my paper are quite different in spirit from the findings of Comanor and Wilson in the same area. It is therefore appropriate to discuss the possible reasons for these alternative findings. A major difference in design between my study and C&W's was, of course, in the nature of the data samples utilized: they used IRS data, and I used national income account and advertising trade media data. The strengths and problems associated with these alternative sources were discussed in detail above and need not be repeated here. In addition to data sample characteristics, other possible sources of the different findings include differences in the models utilized, the level of aggregation, and the time period covered in each analysis.

Although a different model formulation is utilized in this paper than in C&W's analysis, it would seem difficult to attribute the difference in findings to this fact. This is because their demand model was estimated on my sample, and advertising was still found to be a relatively poor determinant of consumption across product classes.

On the other hand, differences in the level of aggregation and in the time period covered may be significant. Considering the first point, many of C&W's categories are at a three-digit level of analysis (e.g., dairy products, meat packing, etc.) whereas many of the ones here are at a two-digit level (e.g., food). The importance of this factor could be tested by getting more disaggregate consumption data, since the trade media advertising data currently are available with a fine degree of detail. While more disaggregate consumption data are not publicly available, they might be obtainable from Department of Commerce worksheets. As a second-best approach, shipment data from the Annual Survey of Manufacturers might be used as an approximation of the consumption data. The latter course poses a number of additional problems of measurement error. I have done some preliminary work using the more disaggregate shipments data, and so far I have not obtained results indicating that advertising has strong effects, even at three-digit levels of industry classification.[37]

A final difference in the two studies concerns the time period investigated. C&W's study covers the early post–World War II period, 1946–1964, whereas this one is for the more recent one, 1956–1972. A major structural change in advertising that occurred over the earlier period was the development and rapid growth of TV as the most important of the mass communications media. This is significant for the issues at hand because the ability to exploit those new media may have varied considerably among product classes. The strong effects of advertising on demand observed by C&W over that earlier period in turn may have reflected a disequilibrium situation in which certain classes of products uniquely suited to TV advertising made strong initial gains vis-à-vis other classes. By the middle 1960s, the central point of my data series, this situation may have stabilized considerably, and the ability of advertising to strongly influence demand at the industry level may have become much more limited in character. In principle, this structural change hypothesis is directly testable by re-estimating the C&W demand equation on IRS data for the later period. These data are publicly available.[38]

Both studies are, of course, constrained by the nature of time series data. While demand functions estimated on time series data can provide insights into the significance of advertising effects on consumer choice, some controlled experiments could be much more informative in this area. In particular, from a social science perspective, it would be illuminating to be able to significantly vary the total level of advertising for specific industries in a controlled fashion vis-à-vis that for other industries. The only approximation of such an experiment in recent years was carried out for the cigarette industry. After the legislative ban on broadcast advertising took effect in 1971, the industry dramatically cut total advertising (on the order of 20 to 25 percent), while advertising in other classes was increasing. Although other events occurred that complicate the analysis of this situation,[39] the fact that per capita consumption of cigarettes has continued to grow despite that dramatic cutback in advertising would not appear to strengthen the case of those maintaining the hypothesis of strong industry effects of advertising.

In summary, the hypothesis that advertising has broad powerful effects on consumer choice does not gain much support from either observation of the unique situation of cigarette advertising or the more general demand function analysis performed in this paper. However, given the data problems encountered here and elsewhere, continued efforts to develop additional data sets for further examination of this question would seem highly desirable.

NOTES

1. See the discussion of this in Solow [1968, p. 48]. See also the comments in the same issue of *The Public Interest* on this subject by Marris [1968] and an earlier exchange between Galbraith and Solow in the fall 1967 issue of *The Public Interest*.
2. Among the pioneering works in this area are studies by Telser [1962], Palda [1964], and Peles [1971]. More recent studies that have incorporated simultaneous equation analyses include papers by Cowling [1972] and Lambin [1972]. A critical analysis of several of these studies is provided in Schmalensee [1972, Chap. 4].

3. See Schmalensee [1972, p. 113–116]. In one of the studies, Peles [1971] examined industry-level relations for the beer, cigarette, and automobile industries. He did find a significant relation for the automobile industry, but his regression analysis omitted several potential explanatory variables including the stock of cars on the road.
4. Schmalensee [1972, p. 213].
5. Comanor and Wilson [1974b, p. 65].
6. See for example Comanor and Wilson [1974a, Table 5.1, pp. 73–74].
7. For a more detailed discussion of the problems in using IRS data for time series analysis, see Backman [1967, App. A]. See also the discussion and examples provided in my own earlier critique of Comanor and Wilson's analysis [Grabowski 1974, p. 75].
8. See their discussion of the above effects and other measurement error problems resulting from deflating the dependent sales variable by their industry price measure [Comanor and Wilson 1974a, pp. 69–70].
9. While this study remains unpublished, a good summary discussion of it appears in Schmalensee [1972, p. 115].
10. Taylor's model and variable formulation differ in some respects from C&W's analysis. Hence, these factors may also explain some of the differences in the performance of the advertising variable. However, the advertising variable performed so poorly in all Taylor's relations that compositional error is likely to be the major source of differences in findings. This hypothesis could be checked by redoing Taylor's analysis using C&W's exact model formulation. Further analysis of measurement error produced by IRS data is provided by Schmalensee in the context of his cigarette industry study. See Schmalensee [1972, pp. 146–150].
11. In a recent paper, Wilder [1974] also attempted to deal with the simultaneous equation problem, using IRS data samples similar to C&W's. He concludes that the true causal relation is from sales to advertising rather than vice versa. However, he employs a static framework, and his analysis includes two advertising variables (a relative and an absolute measure) in all the estimated equations. Consequently, it is difficult to compare his findings with the dynamic models employed by C&W.
12. On the application of the Koyck transformation to models with more than one lagged distribution, such as equation 7, see, for example, Kmenta [1971, p. 49].
13. For example, the transformations described by Kmenta [1971] to put equation 7 in closed form produce a complex nonlinear functional relation involving second-order lag terms and autocorrelated residuals. By contrast, the iterative approach involves a relatively simple estimation problem; and autocorrelation is not introduced as a result of Koyck-type transformations.
14. See Comanor and Wilson [1974a, App. 5a, pp. 93–95] for a derivation of equation 13 using the basic Houthakker-Taylor methodology.
15. A number of alternative data sources were examined in addition to the media sources discussed in the text. First, traditional firm income statement data as reported on Securities and Exchange Commission Form 10K and in Moody's were considered. Here it was found that a majority of firms do not explicitly report advertising expenditures but, instead, aggregate them into more general administrative and selling cost categories. In addition, where advertising data were reported, they invariably were on a total firm basis rather than by individual industry categories. This leads to the same kind of problems for diversified firms that underlie objections to the use of IRS data.
16. The basic sources here include the Publishers Information Bureau (magazines), the Television Bureau of Advertising (network and spot TV), and Media Records, Inc. (newspapers). In recent years, issues of *Leading National Advertisers* provide data on three of these four media (all but newspapers) in one source.
17. Tobacco products showed a drastic change in allocation patterns toward outdoor and other unmeasured media in the late sixties and early seventies. This resulted in

considerable part from a 1971 legislative ban on cigarette advertising in the broadcast media, a major structural change for this category. The industry was also beset by a series of other structural changes throughout the sixties; those have been analyzed extensively elsewhere. See for example Schmalensee [1972], especially chapters 5 and 6, and Grabowski and Mueller [1971].

In the other industry that was excluded, gas and oil, allocations to radio and outdoor advertising varied extensively over the period 1966–1972 and actually exceeded 30 percent in some of those years.

18. In most cases the minor media account for only a few percentage points of the total. Even in the categories where minor media expenditures approach 10 percent, their allocation patterns over time would have to be substantially different from those of the major media to result in a measurement bias great enough to make significant coefficients become insignificant.

19. See Schmalensee [1972, pp. 173–174] and Comanor and Wilson [1974a, pp. 70–72].

20. A relative advertising variable has other advantages of a purely empirical nature. When absolute advertising measures are used, they must be transformed into real terms. It is questionable whether the advertising price indices available for doing so are accurate enough for that purpose. Relative advertising measures are affected by such considerations only in a second-order way, and hence they are not as sensitive to errors arising from deflating procedures. Similarly, it is easy to justify and approximate omissions from unmeasured media if a relative rather than absolute advertising variable is used.

21. It might be argued that because the audience for advertising messages in these media tends to grow with population, especially in the case of television, it is inappropriate to measure advertising in per capita terms. However, the price indices used to convert dollar advertising expenditures to real outlays are designed explicitly to take this phenomenon into account. In particular, the price deflator in each period measures cost per viewer-message. Real advertising is consequently measured in terms of the total number of viewer-messages. It is this variable, which is in effect quality adjusted for any increases in audience size, that is deflated by population in comparable fashion to income and consumption.

22. For a discussion of various studies of the issue, see Weiss [1969]. He concluded that the average rate of depreciation emerging from these studies was about 33 percent. Estimates for durable categories have been much higher in value.

23. See Houthakker and Taylor [1970, p. 305].

24. The equations in tables 2 and 3 were estimated in differenced form, which would be appropriate if serial correlation of the form $u_t = u_{t-1} + \epsilon_t$ were present. The qualitative characteristics of the results were not changed by this procedure. There was more instability in the parametric estimates, as one would expect when one eliminates a component of the variation in samples of short time series like that employed here.

25. For food, λ now takes on the implausible value of zero, but the asymptotic standard error for it is insignificant. The bizarre behavior exhibited by this industry indicates other statistical problems are present here, and a chief candidate in this regard, simultaneous equation bias, is discussed above.

26. See Peles [1971], who also found a 100 percent depreciation rate for automobiles.

27. Those studies are discussed by Weiss [1969] as mentioned in note 22, above.

28. While they also estimate a two-stage version of equation 3, they ultimately choose to accept the estimates from the single-equation analysis because the latter are more stable. See Comanor and Wilson [1974a, pp. 83–85].

29. See for example the difficulties encountered by Comanor and Wilson [1974a, App. 5c, pp. 102–103], who used a simple linear approximation to their highly nonlinear system. Another problem was that they had almost as many exogenous variables as degrees of

freedom. Consequently, they eliminated many variables from the reduced form on a priori grounds in order to have a sufficient number of degrees of freedom.

30. Table 1 further shows that one category, automobiles, accounts for more than a fourth of all durables advertising expenditures.
31. See for example the discussion in Schmalensee [1972, pp. 17–18], of various studies surveying firm practices in this regard.
32. A possible explanation of this phenomenon is that expected sales and profit margins are negatively influenced by interest rate increases for these products. Advertising-to-sales ratio would then be expected to move in an inverse relation, given the model underlying this estimated equation. Such a chain of events is particularly plausible for furniture, given its derivative relation to sales of new houses. Correspondingly, the coefficient on furniture is by far the largest in tables 7 and 9.
33. A possible identification problem arises if interest rates directly influence consumption levels as well as the advertising determinant equation. Fortunately for my purposes, interest rate measures like the one I used above generally have been highly insignificant explanatory variables of consumption except in some of the major durable classes. To check on this for my own sample, the residuals from the OLSQ estimates of the consumption function were correlated with the interest rate measure for all fifteen categories. A highly insignificant relation was observed for the majority of classes. However, a significant correlation at the 5 percent level did occur for furniture and watches and jewelry. In addition, autos was close to significant at the 10 percent level. The estimates for these durable classes should therefore be treated with particular caution.
34. In addition, the simple correlation between the advertising-to-sales ratios and the estimated advertising elasticities in Table 8 for the eight nondurable categories was equal to 0.81, which was statistically significant at the 1 percent level.
35. The questions raised above concerning identification have particular applicability for the auto industry (see note 33, above).
36. Porter found that a stratification of his sample based on product characteristics yielded vastly different results in the relation between advertising and profits. His stratification was based on the type of retail outlet for which the good was marketed—convenience or nonconvenience stores. Toiletries and cleaning and polishing would fall into his convenience class, in which much higher impacts of advertising on profit rates were observed.
37. The food and beverage industry in particular was examined using shipments data. The food group, for example, can be broken down into seven separate three-digit categories: soft drinks, coffee and tea, baking products, cereals, dairy products, meat and fish, and confections. For the Koyck log specification, advertising was significant only for cereals. On the other hand the relative price variable was significant in four categories and exhibited the expected negative sign with t values greater than 1.0 for all classes. These results are quite tentative in character, however, given some of the data problems associated with the shipments measure. Further analysis of the effects of advertising on sales at more disaggregate levels is currently in process and will be reported in future papers.
38. One curious and unexplained aspect of their analysis is that despite the degrees-of-freedom problem they encountered, they ignored IRS data available for several years after 1964.
39. Along with the legislative ban, the amount of antismoking advertising, previously mandated under the fairness doctrine, declined in amount. This undoubtedly had a positive effect on industry sales. However, given the subsequently strong sales performance in the face of drastically curtailed advertising, it seems difficult to conclude that

industry advertising expenditures were exerting strong effects on sales at the margin. For an analysis of this question, see Hamilton [1974, pp. 401–411] and also see Grabowski and Mueller [1971].

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