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The Advertising Capital Controversy

The interpretation of the positive cross-sectional relation between industry accounting rates of return and advertising intensity as evidence that advertising creates entry barriers rests on findings that advertising effects are short-lived. This paper argues that these findings have been biased by observations of marginal rather than average advertising depreciation rates. Then, from studies by Comanor and Wilson and Weiss, new evidence is adduced that advertising is in fact a long-lived investment and is unrelated to correctly measured rates of return. The results stand in opposition to the hypothesis of advertising-created entry barriers.

The ongoing debate over the competitive effects of advertising is in large measure a debate over the economic durability of advertising expenditures (see Telser 1968, 1969; Weiss 1969; Bloch 1974, 1980; Comanor and Wilson 1974, 1979, 1980; Ayanian 1975; and Demsetz 1979). Knowledge of this durability is crucial to interpretation of the well-known positive, cross-sectional relation between accounting rates of return and advertising intensity, as measured by advertising to sales ratios. Although other explanations are possible, the main contending hypotheses to explain this relation are barriers to entry and accounting bias. The barriers to entry hypothesis holds that heavy advertising expenditures create entry barriers that make possible persistently above-normal rates of return for firms in industries that advertise heavily. If advertising is a long-lived investment, however, as maintained by the accounting bias hypothesis, the possibility arises that the high accounting rates of return of heavy advertisers, which treat advertising as a current expense, merely reflect a bias arising from the expensing of advertising outlays. Thus, short-lived advertising is consistent with the barrier to entry hypothesis, while advertising which is a durable investment supports the accounting bias hypothesis.

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Attempts to estimate advertising depreciation rates and adjust accounting rates of return for the presence of advertising capital have yielded conflicting results. High depreciation rates and adjusted rates of return that preserve the accounting relation have been estimated by Comanor and Wilson (1974) in their influential study *Advertising and Market Power*. On the other side, low depreciation rates and adjusted rates of return unrelated to advertising intensity have been obtained by Bloch (1974) and Ayanian (1975).

In this comment the advertising depreciation rates estimated in Comanor and Wilson (1974) and in similar studies are viewed critically and an attempt is made to reconcile these estimates with those obtained by Bloch and Ayanian. Then, drawing on data reported by Comanor and Wilson and by Weiss (1969), new evidence is adduced in support of the accounting bias hypothesis.

I. Regression-estimated Sales Decay Rates

By far the most important support for the barriers to entry hypothesis comes from Comanor and Wilson (1974), who find rapid rates of decay of advertising-induced sales—decay rates so high that for 37 of their 39 industries the implied stocks of advertising capital are less than annual advertising outlays, and for 15 of these industries advertising capital stocks are zero, advertising being fully expensed.

As is typical in studies of the long-run effects of advertising, the sales decay rates are estimated by Comanor and Wilson from distributed lag equations in which current sales are related to advertising variables, 1-year lagged sales, and standardizing variables (1974, p. 181). This common approach, however, overlooks the fact that the regression estimation procedure will not relate these variables. Rather, it relates variations in sales to variations in advertising, lagged sales, and the standardizing variables. Thus the regression-estimated sales decay rates are marginal sales decay rates.

If one is interested in the long-run effects of a marginal advertising expenditure, these marginal sales decay rates are adequate.[1] But if one is interested in amortizing an industry's total advertising expenditures to obtain an advertising capital stock, these marginal sales decay rates

1. Inferences of marginal advertising depreciation rates from these marginal sales decay rates seem to be improper for the durable goods industries. Comanor and Wilson find many zero repeat-purchase probabilities for durable goods and infer from this that advertising has depreciated 100% in these industries. However, a zero repeat-purchase probability in their model is consistent with consumers' taking longer than 1 year to repeat purchase the durable good (e.g., an automobile). A 1-year lag structure is not designed to capture repeat purchases taking longer than a year to materialize. Thus marginal advertising depreciation rates cannot be inferred from repeat-purchase probabilities for these industries.

are of value only on the implausible assumption that the industry's total advertising expenditures depreciate at the same rate as its marginal advertising expenditures.

An increase in industry advertising expenditures can increase current sales by inducing marginal purchases by existing customers or new purchases by marginal noncustomers who do not normally purchase the product. The fact that these sales collapse relatively quickly when the marginal advertising is withdrawn tells us nothing about the repeat-purchase probability on "customary" purchases by the industry's inframarginal customers. The marginal sales decay rate seems likely to exceed the average sales decay rate for the industry. Yet it is the industry's average sales decay rate that must be used to amortize its total advertising expenditures in any study addressing the rate of return issue. Thus the regression-estimated sales decay rates are inappropriate unless it can be established that marginal and average advertising depreciation rates are equal. But intuition and the available evidence suggest that this is not the case.

There are two studies in this area that do not estimate advertising depreciation rates from sales decay rates: Bloch (1974) and Ayanian (1975). Each in effect infers advertising depreciation rates from firms' total advertising expenditures and independently estimated advertising capital stocks. The advertising depreciation rates estimated in this manner are average advertising depreciation rates. The fact that they are lower than most regression-estimated sales decay rates in the literature is consistent with the hypothesis that marginal advertising depreciation rates exceed average advertising depreciation rates, as suggested above.[2]

In this connection it should be noted that having significant portions of an industry's advertising expenditures depreciate rapidly is not inconsistent with having a low overall average advertising depreciation rate, as long as some significant portion of industry advertising is depreciating slowly. Consider a geometric advertising depreciation pattern as employed by Weiss (1969), Bloch (1974) and Ayanian (1975), and in modified form by Comanor and Wilson (1974). Let an industry have, for simplicity, an advertising history of a constant \$$A$ per year, made up of components a_1 and a_2. The components depreciate

2. Independent of this issue, Comanor and Wilson bias advertising capital stocks downward. They erroneously use, instead of the sales decay rate, a present valued sales decay rate as the advertising depreciation rate. To see the error in this, consider an advertising investment of \$$A$ which generate sales of \$$S$ per year forever. At Comanor and Wilson's interest rate of 6.35% the present value of sales is 15.75S. Since S of the 15.75S occurs this year, Comanor and Wilson would credit the industry with advertising capital of .937A. Yet clearly this is wrong, since by assumption of the example, A never depreciates.

geometrically at rates d_1 and d_2, respectively. Then the industry's advertising capital is

$$A/d = a_1/d_1 + a_2/d_2, \tag{1}$$

where d is the average advertising depreciation rate—the rate which must be used to amortize total advertising expenditures to obtain the advertising capital stock. Dividing equation (1) by A we find

$$1/d = (1/d_1)(a_1/A) + (1/d_2)(a_2/A) \tag{2}$$

and, thus,

$$d = [(1/d_1)(a_1/A) + (1/d_2)(a_2/A)]^{-1}. \tag{3}$$

The average periods of the advertising components, $1/d_i$, average to yield the average period of total advertising. The average advertising depreciation rate is in general less than the average of the advertising-weighted individual depreciation rates. For example, consider an industry conforming to our model with two equal-sized advertising components having separate depreciation rates of 100% and 10% per year. The average of these depreciation rates is 55% per year, but the industry average advertising depreciation rate, via equation (3), is only 18.2% per year. Thus, low average advertising depreciation rates are consistent with significant nondurable components in aggregate advertising expenditures, including relatively rapidly depreciating marginal advertising expenditures.

II. Average Advertising Durability

Neither the barriers to entry nor accounting bias hypothesis has gained general acceptance in the literature, and neither seems likely to in the absence of additional evidence on the durability of advertising expenditures. Comanor and Wilson (1979) have criticized the Bloch and Ayanian estimates and, in addition, have insisted that the competing hypotheses must be tested at the industry level rather than at the level of the firm, as was done by Bloch (1974) and Ayanian (1975). In an effort to move toward a resolution of this issue, I present in this section the results of an attempt to distinguish between these competing hypotheses and to estimate the average durability of advertising at the industry level. We begin with a reexamination of the 39 industries in Comanor and Wilson (1974).

Comanor and Wilson present the following basic equation relating industry accounting rates of return to advertising intensity and other variables (1974, p. 117, table 6.3, eq. [1]):[3]

3. Only 39 of the 41 industries in eq. (4) are included in Comanor and Wilson (1974) and in my advertising durability investigations. For two industries, they are unable to

$$R = 0.0390 + .337\,(A/S) + .00842\,(\log \text{Capital Requirements}) \atop \quad (4.85) \quad (2.32) \qquad\qquad (2.81)$$

$$+ .0311\,(\log \text{Growth of Demand}) \qquad R^2 = .50, \atop (2.42) \tag{4}$$

where R = the industry average accounting rate of return on stockholders' equity, 1954–57, and A/S = the corresponding advertising to sales ratio. At issue here, of course, is the interpretation of the advertising coefficient.

The contention of the accounting bias hypothesis is that advertising is a durable investment, so that the advertising to sales ratio is merely a proxy for the advertising capital intensity of the industry, to which biases in accounting rates of return are positively related. Any bias in accounting rate of return depends, of course, not only on advertising capital intensity but on other factors, including the rate of growth of past advertising expenditures (Weiss 1969; Ayanian 1975). Nonetheless, on the accounting bias hypothesis the conditions necessary for upward bias in the sample are present, and the advertising intensity variable is simply a proxy for industry advertising capital intensity.

On the other hand, the barriers to entry hypothesis holds that advertising expenditures are basically a current expense, so that there is little or no systematic bias in accounting rates of return caused by the expensing of advertising. Under the barriers to entry hypothesis the impact of heavy advertising on profit rates arises not from an accounting bias but from real profits attributable to product differentiation in conjunction with heavy advertising expenditures. This phenomenon is captured by the current advertising to sales ratio, which thus explains the systematic variation in accounting rates of return across industries. Thus, variation in accounting rates of return is a function of current advertising intensity under the barriers to entry hypothesis and is a function of advertising capital intensity, to which current advertising intensity is closely related, under the accounting bias hypothesis. This suggests the following test of the competing hypotheses.

Under the widely employed geometric depreciation pattern, with A representing annual advertising outlay, g the advertising growth rate, and d the average advertising depreciation rate, an industry's advertising capital at time t may be expressed as follows (Weiss 1969; Ayanian 1975):

$$C(t) = A(t)\left(\frac{1 + g}{d + g}\right). \tag{5}$$

estimate sales decay rates and thus do not report the data needed below. The remainder of table 6 lists results of including various combinations of additional standardizing variables. None proved statistically significant and none had an appreciable effect on the advertising coefficient.

Using equation (5) we can generalize the advertising to sales ratio, A/S, of regression equation (4) to C/S, the advertising capital to sales ratio:

$$(C/S) = (A/S)\left(\frac{1 + g}{d + g}\right) = (A/S)(ACF), \tag{6}$$

where ACF is the advertising capitalization factor. Notice that the A/S variable of regression equation (4) is just a special case of C/S, when $d = 1$, that is, when advertising is assumed to be a current expense.

Now consider reestimating regression equation (4) with the more general variable C/S replacing A/S at successively lower values of d (higher values of ACF). As ACF is increased C/S becomes an increasingly poor measure of current advertising intensity and an increasingly good measure of advertising capital intensity, if the successively lower d's are closer to the actual d's for the sample industries. For the successively reestimated equations, R^2 will be maximized by the C/S variable which is best able to explain variations in accounting rates of return across the industries. Under the barriers to entry hypothesis, this maximum R^2 should occur at a high value of d, since on this hypothesis profits depend on current advertising intensity. Under the accounting bias hypothesis, however, the maximum R^2 should occur at a low value of d (say, less than .33),[4] since on this hypothesis variation in accounting rates of return across the industries is a function of advertising capital intensity. Also, this same pattern should hold for the t-value of the advertising coefficient under the alternative hypotheses, since this is the variable which is capturing the barrier to entry or accounting bias effect.

The proposed substitution of C/S for A/S has implications also for the value of the advertising coefficient. Under the barriers to entry hypothesis the effect of multiplying A/S by a high ACF is to introduce into the advertising variable measurement error with a positive mean and variance. Since the regression line passes through the point of sample means we can measure the effect of the positive mean of ACF on the advertising coefficient as reducing its value to $1/\overline{ACF}$ of its former value. (If all industries had the same g, so that ACF was a constant across industries, this would be the only effect of scaling by ACF, and the above tests would be inoperable.) The remaining effect of scaling by ACF arises from the scattering of the measured advertising intensities because of the positive ACF variance. The effect of such measurement error, as is well known, is to bias the estimated advertising coefficient toward zero. Thus, on the barriers to entry hypothesis,

4. Bloch (1974), using a 3-year advertising life ($d = .33$), finds no relation between advertising intensity and adjusted rates of return, though earlier Weiss (1969), using the .33 geometric depreciation rate (but a short, 6-year, total advertising history), obtained the opposite result. Average advertising lives in excess of 3 years ($d < .33$) should unambiguously support the accounting bias hypothesis.

high values of ACF will yield an advertising coefficient which is less (closer to zero) than $\hat{\alpha}_1/\overline{ACF}$, where $\hat{\alpha}_1$ is the OLS coefficient of A/S. On the other hand, under the accounting bias hypothesis high values of ACF reduce measurement error in the advertising variable by converting it to a measure of advertising capital intensity. A reduction in measurement error will reduce the absolute downward bias in the advertising coefficient, thereby yielding a new estimated advertising coefficient greater than $\hat{\alpha}_1/\overline{ACF}$. Thus under the barriers to entry hypothesis the mean-adjusted advertising coefficient is expected to fall at low values of *d*, whereas under the accounting bias hypothesis it should rise.

Notice that a high correlation between A/S and successive values of C/S will make these effects small, but that this should not hinder discrimination between the competing hypotheses since their implications are qualitatively divergent. Before proceeding to the regression results, however, some additional discussion of the regression equations estimated is necessary.

Comanor and Wilson (1974) report all data necessary for the proposed regressions except data on the capital requirements variable. One avenue pursued below was simply to estimate regression equation (4) with this variable omitted. The R^2 for this equation at $ACF = 1$ turned out to be about .31, considerably below the .50 reported by Comanor and Wilson for the full equation. I therefore estimated a second regression equation in which the capital requirements variable was approximated by a dummy variable for the motor vehicles industry.[5] This variable performed strikingly like Comanor and Wilson's capital requirements variable, entering the regression with a positive and statistically significant coefficient and jumping the R^2 from .31 to .42 at $ACF = 1$.

In each of the regressions proposed above, ACF is based on the

5. Comanor and Wilson's measure of capital requirements is (MES) (total assets/gross sales) (1974, p. 113) where MES is an estimate of the minimum efficient plant size (in \$ million assets) for the industry. The MES is reported for 29 of our 39 industries (1974, p. 223). Inspection of those data revealed that the mean value of MES for 28 of the 29 industries was 15.76, with a standard deviation of 20.08. For one industry, motor vehicles, the MES was 375.0, almost 18 standard deviations above the 28-firm group mean! Related data for the 10 excluded industries (1974, p. 228) indicates that their MES values are similar to those of the 28-firm group. Further, variation in assets to sales across the industries seems likely to be relatively small with its value, probably ranging in the neighborhood of .5–1. The upshot of all this is that the capital requirements variable appears to have acted as a crude dummy variable for motor vehicles, taking on a "high" value for motor vehicles, and a "low" value otherwise. Indeed, Weiss (1969, p. 428), repeating Comanor and Wilson's (1974) regressions with 1963–64 profit rates, reports that capital requirements is statistically insignificant when the motor vehicle observation is deleted. These results recommend the direct dummy variable approach to motor vehicles, which has the highest profit rate and one of the lowest advertising intensities in Comanor and Wilson's sample.

customarily assumed geometric depreciation of advertising expenditures. As a test of the appropriateness of this assumption, these equations were also estimated using an advertising capitalization factor, ACF', based on an assumed "one-hoss-shay" or "sudden death" depreciation of advertising expenditures. The derivation of ACF', is as follows: with advertising growth at rate g, and having life N,

$$A(T - t) = A(T)/(1 + g)^t,$$

and

$$C(T) = A(T) + A(T - 1) + \ldots + A(T - N + 1).$$

Thus

$$\begin{aligned} C(T) &= A(T)\left[1 + \frac{1}{1+g} + \left(\frac{1}{1+g}\right)^2 + \ldots\right] \\ &\quad - A(T - N)\left[1 + \frac{1}{1+g} + \left(\frac{1}{1+g}\right)^2 + \ldots\right], \end{aligned} \tag{7}$$

$$C(T) = \Big(A(T) - A(T - N)\Big)\left(\frac{1+g}{g}\right), \tag{8}$$

$$C(T) = A(T)\left(1 - \frac{1}{(1+g)^N}\right)\left(\frac{1+g}{g}\right) = A(T)(ACF)'. \tag{9}$$

We are now ready to summarize the preceding discussion. Four regression equations will be estimated at successively higher advertising durabilities:

$$R = \alpha_0 + \alpha_1(A/S)(ACF) + \alpha_2 SGR, \tag{10a}$$

where SGR = sales growth rate (log demand growth);

$$R = \alpha_0 + \alpha_1(A/S)(ACF) + \alpha_2 SGR + \alpha_3 MVD, \tag{10b}$$

where MVD = 1 for motor vehicles, zero otherwise;

$$R = \alpha_0 + \alpha_1(A/S)(ACF)' + \alpha_2 SGR, \tag{10c}$$

and

$$R = \alpha_0 + \alpha_1(A/S)(ACF)' + \alpha_2 SGR + \alpha_3 MVD. \tag{10d}$$

The effects of doing so predicted by the alternative hypotheses are summarized in table 1.

The regression results are reported in tables 2 and 3. As can be seen there, accounting rate of return gives every indication of being a function of advertising capital intensity. Each R^2 increased continuously from its base value at $(ACF) = 1$ to the maximum R^2's (and associated maximum advertising t's) reported in table 2. The rise in the advertising coefficients reported in table 3 indicates that the rise in the R^2's and advertising t's of table 2 is due to the removal of measurement error

TABLE 1 Predicted Effects of Estimating Regression Equations with Successively Higher Advertising Durabilities

	Hypothesis	
Test Statistic	Barriers To Entry	Accounting Bias
R^2	Maximum at high d, low N	Maximum at low d, high N
Advertising t	Maximum at high d, low N	Maximum at low d, high N
Mean-adjusted advertising coefficient	Decrease (toward zero) at low d, high N	Increase (away from zero) at low d, high N

from the advertising variable, precisely as predicted by the accounting bias hypothesis.[6]

In terms of R^2, each of the sudden death *ACF*s performed better than the corresponding geometric *ACF*. There seem to be two possible explanations of this. The obvious explanation is that the rectangular depreciation pattern more closely captures the actual depreciation pattern of advertising expenditures, so that the *ACF* based on this is better able to explain profit rate variations across the industries. Note, however, that the advertising growth rates reported by Comanor and Wilson (1974) are based on industry advertising expenditures from 1948 to 1957. The geometric *ACF* implicitly assumes that the 1948–57 growth rate held for all prior periods—an assumption which seems certain not to be true. The sudden death *ACF*, in contrast, depends only on the advertising growth rate for the latest N periods. Prior advertising is irrelevant.[7] Thus the rectangular *ACF*, depending only on advertising

6. The temptation to dismiss these results because the R^2's and advertising coefficients are not statistically significantly different from their base values must be resisted. It is not the *amount* of increase but the *fact* of an increase rather than a decrease that supports the accounting bias hypothesis. These values are not expected to be statistically significantly different since *A/S* and *C/S* are closely related. Note also that our statistical tests on the *A/S* coefficients do not actually depend on a downward bias in these coefficients. The discussion of the text implicitly assumes that measurement error is limited to the advertising variable. As is well known, it is possible for a sufficiently large measurement error in *SGR* to upset a downward bias in the *A/S* coefficients. Maddala (1977, p. 294) presents the following expression (originally derived by Theil [1961]) for the measurement error bias in one coefficient estimator when a second variable in the regression is also subject to measurement error: $\hat{\beta}_1 - \beta_1 \doteq -(1/1-\rho^2)(\theta_1\beta_1 - \rho\theta_2\beta_2)$. Here ρ is the correlation coefficient between the true variables, and θ_1 (i = 1, 2) is the ratio of the measurement error variance to the true variable variance for variable i. Under the barriers to entry hypothesis scaling *A/S* by *ACF* increases θ_1. This must either create or increase a downward bias—as in the text—or reduce the bias if it is upward. In either case, however, the expected value of the (positive) advertising coefficient is reduced. Conversely, under the accounting bias hypothesis regressing on *C/S* reduces θ_1, thereby increasing the expected value of the positive advertising coefficient.

7. Formally, let *ER* be the error which arises in the expression

$$A(T)\left[1 + \frac{1}{1+g} + \left(\frac{1}{1+g}\right)^2 + \ . \ . \ .\right]$$

TABLE 2 **Accounting Rate of Return as a Function of Advertising Capital Intensity**

Equation	Estimated Coefficients				
	Constant	C/S	SGR	MVD	R^2
10a (d = 1)	5.09	.403	.330	. . .	.3120
10c (N = 1)	(5.75)	(2.31)	(2.61)		
10b (d = 1)	4.825	.481	.282	8.291	.4247
10d (N = 1)	(5.84)	(2.93)	(2.37)	(2.62)	
10a (d* = .24)	4.91	.122	.359	. . .	.3206
	(5.41)	(2.42)	(2.92)		
10b (d* = .28)	4.66	.162	.311	8.264	.4326
	(5.52)	(3.03)	(2.70)	(2.63)	
10c (N* = 7.9)	4.87	.067	.367	. . .	.3237
	(5.34)	(2.46)	(3.00)		
10d (N* = 6.8)	4.62	.089	.319	8.254	.4356
	(5.45)	(3.07)	(2.79)	(2.64)	

NOTE.—Dependent variable-industry average accounting rate of return, 1954–57, 39 industries. t-values in parentheses.
*Yielded maximum R^2 for eq.

during the sample period, may have been more accurate because all weight was given to advertising expenditures for which the advertising growth rate estimate was relatively accurate. In either of these cases, however, the advertising durability estimates based on the sudden death *ACF*s should be considered the more reliable estimates. This indicates, then, an average durability of advertising in the sample of 6.8 years with the motor vehicle industry dummied out and an average life of 7.9 years for the full sample, including motor vehicles.[8] Yet the precise average life of advertising in the sample is not at issue here. What is important is that all of the statistical results point unambiguously to advertising that is a long-lived durable investment.

It is of great interest to know whether or not these results prevail through time. For though the probability of obtaining all of the results of tables 2 and 3 purely by chance must be small, the emergence of similar findings in a different data set would virtually eliminate the

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because g deviates from the true g periods N and beyond. Then equation (7) of the text becomes:

$$C(T) = A(T)\left[1 + \frac{1}{1+g} + \left(\frac{1}{1+g}\right)^2 + \ . \ . \ . \ \right] - ER$$
$$- \left\{A(T-N)\left[1 + \frac{1}{1+g} + \left(\frac{1}{1+g}\right)^2 + \ . \ . \ . \ \right] - ER\right\}$$

from which we see the *ER*'s cancel, leaving eq. (7) of the text.

8. This, in turn, suggests very durable advertising in the motor vehicle industry. This is consistent with Ayanian's (1975) low depreciation rate estimate (5.1%) for automobiles but contradicts Comanor and Wilson's (1974) inference of 100% depreciation for motor vehicles based on a zero marginal 1-year repeat-purchase probability.

TABLE 3 Mean-adjusted Advertising Coefficients

Equation	$\hat{\alpha}_1$ at $(ACF) = 1/\overline{(ACF)}$*	Advertising Capital Intensity Coefficient at Maximum R^2
10a	.117	.122
10b	.158	.162
10c	.064	.067
10d	.086	.089

*At maximum R^2 for eq.

TABLE 4 Accounting Rate of Return as a Function of Advertising Capital Intensity

	Estimated Coefficients				
Equation	Constant	*C/S*	*SGR*	*MVD*	R^2
10a (d = 1)	6.898	.409	.234	. . .	
10c (N = 1)	(8.38)	(2.47)	(2.39)		.2998
10b (d = 1)	6.613	.498	.182	8.581	
10d (N = 1)	(9.01)	(3.34)	(2.06)	(3.18)	.4682
10a (d^* = .14)	6.697	.082	.253	. . .	
	(7.79)	(2.55)	(2.62)		.3069
10b (d^* = .24)	6.496	.146	.194	8.506	
	(8.66)	(3.38)	(2.22)	(3.17)	.4718
10c (N^* = 11.1)	6.710	.052	.252	. . .	
	(7.85)	(2.56)	(2.61)		.3077
10d (N^* = 7.0)	6.493	.087	.195	8.499	
	(8.66)	(3.39)	(2.24)	(3.17)	.4725

NOTE.—Dependent variable: industry average accounting rate of return, 1963–64, 36 industries. t-values in parentheses.

*Yielded maximum R^2 for eq.

possibility that the results above arose solely through random variation in the Comanor and Wilson data. Weiss (1969) reports data that permit reestimation of equations (10a)–(10d) for 36 IRS minor industries for the year 1963–64. Thirty-three of Weiss's industries also appeared in Comanor and Wilson (1974).[9]

Tables 4 and 5 report the results of applying our statistical tests to Weiss's data. As can be seen, the results are quantitatively similar and qualitatively identical to those obtained with Comanor and Wilson's data. Again, R^2 was maximized at high advertising durabilities; remov-

9. Weiss does not report sales data. These were obtained from published figures in *Statistics of Income* for the appropriate years. The Weiss data exclude firms with assets under $500,000, and the sales figures used here are industry totals for all firms reporting net income. The effect of this on *A/S* ratios across industries is probably trivial. Also, Weiss decomposes tobacco into cigarettes and other tobacco. These have been recombined here since only aggregate tobacco sales data are published. Finally, following Weiss, I deleted petroleum refining from the regressions because of the special tax laws applicable to that industry.

TABLE 5 Mean-adjusted Advertising Coefficients

Equation	$\hat{\alpha}_1$ at $(ACF) = 1/\overline{(ACF)}$*	Advertising Coefficient at Maximum R^2
10a	.072	.082
10b	.137	.146
10c	.046	.052
10d	.082	.087

*At maximum R^2 for eq.

ing motor vehicles again reduced the estimated average durability; the rectangular *ACF*s again performed better than the corresponding geometric *ACF*s; and the mean-adjusted advertising coefficients again rose.

The quantitative difference in the results suggests, if anything, advertising that is more durable than our previous estimates. The smaller rise in R^2 here reflects the fact that C/S^* was more highly correlated with A/S in this sample than in Comanor and Wilson's, so that A/S was here a better proxy for C/S^* than in their sample. Nonetheless, the rise in all of the test statistics again indicates unambiguously that A/S is a proxy for C/S^* and not the other way around.

The emergence of these results in a second data set provides strong support for the accounting bias hypothesis and further evidence against the barriers to entry hypothesis.

III. Adjusted Rates of Return

In this section, industry average accounting rates of return in Weiss's sample are adjusted for the presence of advertising capital, and the hypothesis of no relation between adjusted rates of return and advertising capital intensity is formally tested, using the rectangular depreciation pattern and 7-year advertising life estimated in equation (10d). The 7-year advertising life yields the highest R^2 for the Weiss sample, is not unduly influenced by the motor vehicle observation, does not entail projection of the advertising growth rate back beyond the 6-year advertising history from which it was estimated, and is strongly supported by the corresponding 6.8 year advertising life estimated from Comanor and Wilson's data.

As is well known, accounting rate of return is adjusted by replacing current advertising outlays with advertising depreciation in the numerator and adding advertising capital to assets in the denominator.

Let P = accounting profits; E = accounting equity; and $\Delta P = A(T) -$ (advertising depreciation). Then for adjusted rate of return, R', we have, in general,

$$R' = \frac{P + \Delta P}{E + C}. \tag{11}$$

We can gain insight by complicating the expression as follows:

$$\begin{aligned} R' &= \frac{P}{E + C} + \frac{\Delta P}{E + C} \\ R' &= \left(\frac{P}{E}\right)\left(\frac{E}{E + C}\right) + \left(\frac{\Delta P}{C}\right)\left(\frac{C}{E + C}\right). \end{aligned} \tag{12}$$

Thus adjusted rate of return is a weighted average of accounting rate of return, P/E, and an "adjustment ratio," $\Delta P/C$, the ratio of the change in profits to the change in equity.

Under sudden death depreciation, $\Delta P = A(T) - A(T - N)$. Recalling the derivation of equation (9) above, we see that

$$\frac{\Delta P}{C} = \left(\frac{g}{1 + g}\right), \tag{13}$$

and thus

$$R' = \left(\frac{P}{E}\right)\left(\frac{E}{E + C}\right) + \left(\frac{g}{1 + g}\right)\left(\frac{C}{E + C}\right). \tag{14}$$

So adjusted rate of return will equal, exceed, or fall short of accounting rate of return as $g/(1 + g)$ equals, exceeds, or falls short of accounting rate of return. This is the same bias condition derived by Weiss (1969) for the geometric depreciation pattern.

Table 6 reports industry advertising, accounting rates of return, and adjustment ratios drawn from Weiss (1969, p. 425, table 3) along with estimated advertising capital stocks and adjusted rates of return based on equations (9) and (11), with $N = 7$.

As is typical, the capitalization of advertising reduced the mean and variance of the sample rates of return. The mean of the rates of return fell from 9.39% to 8.01%, and their variance was reduced from 11.12 to 7.55. Taking the ratio of the reduction in variance to the accounting variance yields an estimated 32% of the variance in the accounting rates of return attributable to the failure to capitalize advertising expenditures.

The adjusted rates of return of table 6 are used below to test the hypothesis of no relation between adjusted rates of return and advertising capital intensity.[10] This is the expected relation if advertising is

10. There is no presumption that these adjusted rates of return are "true" rates of return. The adjustments are designed to remove only the systematic bias across industries arising from the expensing of advertising. In addition to the remaining effects of various accounting conventions, there is presumably a dispersion of industry advertising durabilities around the average advertising durability used for the adjustments. I hope however, that any remaining advertising-related biases are relatively small and randomly

TABLE 6 **Adjusted Rates of Return, 36 Industries**

Industry	\$Million A	Percentage R	Percentage $\Delta P/C$	\$Million C	Percentage R'
Soft drinks	165.3	13.4	8.6	898.1	11.1
Malt liquor	243.1	7.8	3.0	1,555.7	5.1
Wines and brandy	16.7	9.2	6.0	97.8	7.5
Distilled liquor	72.9	6.1	4.7	444.1	5.7
Meat	89.8	5.1	6.3	521.8	5.4
Dairy	134.8	7.2	3.2	857.8	6.0
Canning	136.3	7.5	1.6	910.2	5.4
Grain	231.4	8.6	8.2	1,272.5	8.4
Bakery	106.9	7.4	1.5	715.9	5.0
Sugar	4.8	10.4	− .5	34.1	10.0
Confectionary	73.0	12.1	7.4	410.5	10.3
Tobacco	316.7	12.1	3.4	2,004.3	8.3
Knit goods	29.5	8.0	4.5	180.7	7.3
Carpets	9.7	3.1	2.4	63.1	3.0
Mens' clothing	45.9	7.6	7.4	258.1	7.6
Womens' clothing	41.5	8.0	3.0	265.6	6.6
Furniture	34.8	8.0	2.2	228.4	6.8
Periodicals	42.4	7.5	27.6	137.6	11.5
Books	55.3	10.1	10.7	282.7	10.3
Drugs	385.9	13.9	5.0	2,326.0	9.7
Soaps and detergents	343.7	12.1	6.6	1,976.9	8.8
Paint	39.4	9.0	2.2	258.6	7.6
Cosmetics and perfumes	176.1	15.7	8.2	968.4	10.8
Tires	102.5	8.1	3.3	650.5	7.0
Footware	40.6	6.1	4.2	250.7	5.7
Hand tools	59.7	15.5	3.6	375.7	11.0
Electric appliances	86.8	8.4	5.0	523.2	7.5
Radio and TV	51.9	8.0	−5.8	433.3	4.0
Motor vehicles	161.5	17.2	− .8	1,158.2	15.7
Motor cycles, etc.	7.1	15.0	6.7	40.7	13.3
Optical and medical instruments	49.4	8.9	7.2	279.2	8.4
Photo equipment	54.2	14.0	5.4	323.2	12.2
Clocks and watches	23.2	8.5	3.6	146.0	6.2
Jewelry	11.6	7.5	1.9	76.8	6.0
Toys and sporting goods	47.8	5.4	15.4	214.1	8.2
Costume jewelry	2.3	5.4	3.7	14.4	4.9

simply a normal business investment and does not erect entry barriers. Table 7 reports the regression results, which are consistent with entry unimpeded by advertising.

The relation between advertising and rate of return is strongest in the equation including the motor vehicle dummy. To test the sensitivity of

distributed across the industries. My adjustments could disguise a systematic relation between true rates of return and advertising capital intensity only if the heavy advertisers had severely below average advertising durabilities—a counterintuitive proposition. Note also that the durabilities of the heavy advertisers seem likely to be weighted heavily in the R^2-maximizing average, since it is precisely these industries that are responsible for the positive relation.

TABLE 7 Adjusted Rate of Return as a Function of Advertising Capital Intensity

Constant	*C/S*	*SGR*	*MVD*	R^2
6.515	.007	.283		
(9.21)	(.29)	(3.46)		.2750
6.276	.019	.242	7.088	
(9.91)	(.88)	(3.28)	(3.13)	.4450

NOTE.—Dependent variable: industry adjusted rate of return, at N = 7.0, 36 industries. t-values in parentheses.

the finding of no statistically significant relation between adjusted rate of return and advertising capital intensity to the choice of N, this equation was reestimated at successively lower values of N until the advertising coefficient attained statistical significance at approximately the 5% level ($t > 1.96$, at 32 *df*). This did not occur until N was reduced below 2.5 years. This value is far below any of the average advertising durability estimates in either of our data sets. A positive relation between adjusted rate of return and advertising capital intensity cannot be supported by these results.

IV. Conclusion

The theory that heavy advertising expenditures create entry barriers is without foundation in fact. Measures of advertising capital intensity are consistently better able to explain variations in accounting rates of return across industries than is the simple advertising to sales ratio. This implies that the omission of advertising capital from firms' assets, rather than advertising-created entry barriers, is responsible for the high accounting rates of return of heavy advertisers.

Previous studies finding the effects of advertising to be short-lived, with concomitantly small advertising capital stocks, have erred in focusing on marginal, rather than average, advertising depreciation rates. Average advertising durabilities implied by advertising capital stocks best able to explain variations in accounting rates of return across industries are in the neighborhood of 7 years. Adjusted rates of return based on a 7-year advertising durability are unrelated to advertising capital intensity—as are those based on advertising durabilities of less than half this value. Thus, firms in industries with heavy advertising expenditures earn rates of return no greater than those in industries where advertising is light. Heavy advertising expenditures do not exempt firms from the forces and consequences of competition.

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