How Well Does Advertising Work?
Generalizations From A Meta-Analysis of Brand Advertising Elasticity

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ABSTRACT

This study conducts a meta-analysis of 751 short-term and 402 long-term direct-to-consumer brand advertising elasticities estimated in 56 studies published between 1960 and 2008. The study finds several new empirical generalizations about advertising elasticity. The most important generalizations are: The average short-term advertising elasticity is .12, which is substantially lower than the prior meta-analytic mean of .22 (Assmus, Farley, and Lehmann 1984); there has been a decline in the advertising elasticity over time; and advertising elasticity is higher a) for durable goods than nondurable goods, b) in the early stage of the life cycle than in the mature stage, c) for yearly data than for quarterly data, and d) when advertising is measured in Gross Rating Points than in monetary terms. The mean long-term advertising elasticity is .24, which is much lower than the implied mean in the prior meta-analysis (.41). Many of the results for short-term elasticity hold for long-term elasticity, with some notable exceptions. The authors discuss the implications of these findings.

Key Words: *Advertising Elasticity, Meta-analysis, Empirical generalization, Promotion, Marketing mix*

Advertising is one of the most important elements of the marketing mix. Controversy rages over whether firms are getting adequate returns on their advertising expenditures (Aaker and Carman 1982, Tellis 2004). One key element in this controversy is how effective advertising is in generating sales. The effectiveness of advertising is often measured in terms of advertising elasticity, i.e., the percentage increase in sales or market share for a one percent increase in advertising. Obtaining generalizable estimates of advertising elasticity and identifying factors that influence advertising elasticity can further our understanding of the effectiveness of advertising.

Assmus, Farley, and Lehmann (1984) provide the first empirical generalizations on advertising elasticity. In particular, these authors met analyze 128 estimates of advertising elasticity from 16 studies published between 1962 and 1981 and provide useful generalizations on the patterns of advertising elasticity. Over 25 years have passed since that publication. This period (1984-2008) has witnessed significant changes on many fronts that may have an impact on the measurement and effectiveness of advertising. First, the marketing environment has changed due to greater competition, globalization, the advent of the Internet, and the ability of the consumer to opt out of TV commercials through devices such as TiVo. Second, the data and methods for estimating advertising elasticity are increasing in sophistication with the use of disaggregate scanner data and the application of New Empirical Industrial Organization (NEIO) econometric models. It would therefore appear prudent to update the empirical generalizations on advertising elasticity by including data from studies published since 1981.

This study conducts a meta-analysis of 751 short-term brand-level direct-to-consumer advertising elasticities, as well as 402 long-term estimates of advertising elasticities, from 56 studies published between 1960 and 2008. Our study disconfirms a few findings from Assmus, Farley, and Lehmann (1984), validates some of the earlier findings, and uncovers several new empirical generalizations and insights.

In this regard, this research is similar in spirit to other follow-up meta-analytic studies in recent times. For example, Bijmolt, van Heerde, and Pieters (2005) update the meta-analysis of price elasticity conducted earlier by Tellis (1988). Hu, Lodish, and Krieger (2007) provide a partial update on the meta-analytic study of Lodish et al. (1995) related to TV advertising experiments. Our study can also be viewed as a meta-analytic complement to the broad review of advertising literature by Vakratsas and Ambler (1999). They develop a taxonomy, review 250 studies, and provide insights into *how* advertising works. Our study performs a meta-analysis of econometric estimates of advertising elasticity and provides insights into whether advertising works, the magnitude of the effect, and the factors which influence elasticity. In the process, the study adds to Hanssens' (2009) list of empirical generalizations about marketing's impact.

Our study complements the recent article by Fischer and Albers (2010). Both studies attempt to provide insights into the effect of marketing mix on sales. However, the foci of the two studies are quite different. Fischer and Albers provide an excellent analysis of the effect of marketing efforts (detailing, journal advertising, and consumer advertising) on primary demand (category expansion) in pharmaceutical product categories. Our analysis focuses on the effect of consumer advertising on selective demand (competitive brand sales) across a wide range of consumer products, including pharmaceuticals.

Consistent with the prior meta-analysis of Assmus, Farley, and Lehmann (1984), we find that advertising elasticity is higher in Europe than in the United States and higher when lagged sales is omitted from the model. However, the contribution of this research lies in the differences in results obtained and the additional insights revealed by our meta-analysis. First, the mean short-term advertising elasticity across the entire publication period (1960-2008) is .12, which is about half the mean advertising elasticity in the Assmus, Farley, and Lehmann meta-analysis. Relatedly, we find that advertising elasticity has declined over time. Second, we find strong product type and product life cycle effects that the Assmus, Farley, and Lehmann study does not detect, perhaps due to lack of sufficient observations. Third, we are able to include several variables that have become important in recent times (such as recessionary periods and omission of endogeneity) and obtain new insights about their role. For example, we find that contrary to general belief, short-term advertising elasticity is not lower in recession than in expansion; if anything, advertising elasticity is equal or higher during recession than in expansion. Our study also discusses some insights about interaction effects and long-term elasticity.

The remainder of the paper is organized as follows: The second section describes the data. The third section describes the meta-analysis procedure. The fourth section presents the empirical findings. The fifth section discusses the results and their implications. The final section summarizes the results in the form of empirical generalizations and provides some limitations and future research directions.

DATA

This section describes the compilation of the database used in the meta-analysis. The data consists of observations on advertising elasticity (dependent variable) and the potential influencing factors of advertising elasticity (independent variables).

Advertising Elasticity

For this meta-analysis, we select those studies that provide estimates of brand-level, short- or long-term consumer advertising elasticity, from econometric models using market data. Thus, our meta-analysis excludes (i) category advertising effects; (ii) effects based on experimental or other non-econometric designs; and (iii) business to business (B2B) advertising. We explain each of these choices.

First, category-level advertising elasticity measures the increase in category sales (primary demand) for one percent change in total category advertising. These effects have been generally of interest to economists and public policy makers who investigate whether advertising expands category demand in products such as milk, alcohol, and cigarettes (e.g., Gallet 2007). Fischer and Albers (2010) provide a recent comprehensive analysis of the primary demand effects of marketing efforts in the pharmaceutical industry. Our perspective is that of the brand managers, who are interested in the extent to which advertising of their brands impacts their own brand's sales (selective demand).

Second, following the scope of the prior meta-analysis by Assmus, Farley, and Lehmann (1984), we restrict our analysis to econometric estimates. Lodish and others conduct numerous TV advertising experiments and meta-analyze those results (Hu, Lodish, and Krieger 2007). However, their focus is mainly on whether advertising produces a significant impact on sales in controlled experiments and not in natural market scenarios, which is the purpose of our study.

Third, consistent with the prior Assmus, Farley, and Lehmann study, we focus on consumer advertising only. Studies that provide advertising elasticity in the B2B context are very few and generally pertain to journal advertising to doctors (B2B in the pharmaceutical industry). Fischer and Albers (2010) do a thorough job of analyzing this industry.

We adopt the following procedure for compiling the studies. We start our literature review with Assmus, Farley, and Lehmann (1984) as the base. We then use the Social Science Citation Index to identify 132 publications that reference the 1984 meta-analysis. We next use keyword searches (e.g., *advertising elasticity, advertising response, sales response*) in online search engines such as Google Scholar, ABI/Inform, and Lexis-Nexis to identify articles that discuss the subject area. We also review the reference lists in all of the above studies. We consider those studies that provide econometric estimates of advertising elasticity. While most studies directly report advertising elasticity, in some cases we have had to compute the elasticity based on available data or with inputs from the studies' authors. The process yields 751 short-term elasticities from 56 publications. Details of these studies are available in the Web Appendix (Table A1).

Advertising can impact sales both in the short term (current period) and in the long term (current and future periods). We define long-term or long-run advertising elasticity as the percent change in a brand's *current and future* period sales for one percent change in the brand's current advertising. Some studies directly provide estimates of long-term ad elasticity. Others provide estimates of short-term elasticity and carryover coefficient (coefficient of the lagged dependent variable) from the Koyck model. Long-run elasticity is [short-term ad elasticity/(1-carryover coefficient)] (Clarke 1976). A few researchers measure advertising as ad stock, defined as a weighted combination of current and past advertising based on an exponential smoothing coefficient. In this case, the estimate of advertising elasticity is the long-term elasticity. The short-term elasticity is [long-term elasticity * (1 – smoothing coefficient)] (Danaher, Bonfrer, and Dhar 2008). We obtain 402 long-term advertising elasticities from 38 studies listed in the Web Appendix (Table A1).

Influencing Factors

In addition to advertising elasticity, we collected data on 22 variables that can potentially influence elasticity and classified them into the six factors below.

1. <u>Time and Recession Factors</u>: Median year of data and duration of recession during the estimation period.
2. <u>Product and Geographic Factors</u>: Product type, product life cycle, and geographic area.
3. <u>Data Characteristics</u>: Temporal interval, data aggregation, dependent measure, advertising measure, and advertising type.

4. Omitted Variables: Omission of lag dependent variable, lag advertising, lag price, price, quality, promotion, and distribution.
5. Model Characteristics: Functional form, estimation method, incorporating endogeneity, and incorporating heterogeneity.
6. Other Characteristics: Published vs. unpublished work

Many of these variables correspond to those in the original meta-analysis on advertising elasticity by Assmus, Farley, and Lehmann (1984). However, availability of new data permits us to investigate several new variables, such as the time trend, presence of a recession, additional product types (service goods and pharmaceuticals), additional continents (Asia and Australia), and additional method factors (incorporation of endogeneity and heterogeneity).

Table 1 (Columns 3, 4) provides the levels of the independent variables and the sign of the expected relationship with advertising elasticity. Detailed description of the expected relationship and the operationalizations of the variables are in Table 2.

PROCEDURE

This section describes the univariate analysis, main meta-analytic model, alternate meta-analytic model for robustness, test of additional variables for insights, and the meta-analysis model for analyzing long-term advertising elasticity.

Univariate Analysis

First, we perform univariate analysis to obtain an estimate of the mean short-term advertising elasticity, which we then compare with the value in Assmus, Farley, and Lehmann (1984). We also analyze the median and distribution of advertising elasticity.

Meta-Analytic Model for Short-Term Elasticity

The purpose of this meta-analysis is to identify the potential influencing factors of advertising elasticity. Earlier meta-analytic studies (e.g., Assmus, Farley, and Lehmann 1984 and Tellis 1988) use Ordinary Least Squares (OLS) regression of the form:

$$A_{sj} = X_{sj}\beta + \varepsilon_{sj} \quad (1)$$

where A_{sj} is the j^{th} advertising elasticity from s^{th} study, X_{sj} are characteristics of the market, study design, and model that influence the elasticity (listed in Table 1), β's are the meta-analytic parameters of interest, and e_{sj} are the error terms, initially assumed to be independently and identically distributed $N(0,s^2)$. To account for within-study error correlations, Bijmolt and Pieters (2001) point out that unique study-specific characteristics not captured in the independent variables would appear in the error structure. This would result in non-zero correlations leading to non-zero error covariance (within-study), violating the assumptions of ordinary least squares regression. They, therefore, suggest the use of a hierarchical linear model (HLM) estimated with iterative generalized least squares (IGLS) to allow for within-study, block non-zero variance-covariance matrix. Specifically, they suggest a model of the form:

(2) $$A_{sj} = X_{sj}\beta + \zeta_s + \varepsilon_{sj}$$

where z_s is the unobserved study-specific effect and is assumed to be distributed with mean zero and standard deviation s^z. Following Bijmolt, van Heerde, and Pieters (2005), we use Model (2) in our analysis for identifying potential influencing factors.

Alternate Meta-Analytic Models to Test Robustness

We discuss many issues regarding the estimation of Model (2). First, the advertising elasticities themselves are not true parameters, but are estimated with error. This uncertainty surrounding the true advertising elasticity can be accounted for using the following procedure: (i) compile the estimated advertising elasticity A_{sj}, the j^{th} advertising elasticity from s^{th} study along with its standard error B_{sj}; (ii) assume the true parameters lie in the normal distribution $N(A_{sj}, B_{sj})$; (iii) draw $A^{\sim}_{sj}$ observation for each s, j from the corresponding normal distribution.; (iv) estimate Model 2 with $A^{\sim}_{sj}$ instead of A_{sj} to get $\boldsymbol{\beta}_k$, where $\boldsymbol{\beta}_k$ is the vector of regression parameters from the k^{th} iteration. Repeat steps (i) to (iv) for 500 iterations and average $\boldsymbol{\beta}_k$ across all 500 iterations to get an average estimate that takes into account the uncertainty surrounding the advertising elasticity.[1] Standard errors are available only for 437 A_{sj} observations, so we perform this analysis for only this subset of observations.

A second major issue is collinearity. A number of method variables are likely to be correlated. We assess the extent of multicollinearity through traditional measures such as bivariate correlation, variance inflation factor (VIF), condition index, and proportion of variance explained. However, since most of the method factors are discrete dummy variables, correlation measures often tend to be lower. Therefore, we use cross-tab analysis of pairs of variables and the corresponding chi-square measure to detect deviation from independence of two discrete variables. Based on these multiple measures, we identify pairs of variables with potential problems of collinearity. We exclude one of those variables from Model (2) and test for robustness by inspecting the significance of the other included variable.

Test of Additional Variables

We carry out several analyses to gain additional insights. First, we explore several interaction effects, which are listed below with a brief explanation for their choice: [2]

(i) Recession x product type: A recession may affect advertising elasticity of high-priced durable goods more than low-priced food products.

(ii) Product life cycle x product type: Advertising might be more important in the early stage of durable products because they are less easily known by trial.

(iii) Product life cycle x dependent measure: For growth products, advertising may have greater influence on sales than share due to higher potential for category sales growth while for mature products advertising may influence market share more than absolute sales since firms are competing for a share of fixed total market.

(iv) Data interval x omission of lagged sales: When data is more aggregate (yearly), omission of lagged sales (carryover effect) may not affect advertising elasticity as much as when data are less aggregate (weekly).

(v) Time period x nature of dependent variable:.

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[1] We thank the Area Editor for suggesting this method to account for uncertainty in elasticity estimates.

[2] Numerous interaction effects are possible. Incorporating many interactions would contribute to collinearity and compromise the stability of the model. We included those interactions for which we either had some priors based on theory or intuition (e.g., product life cycle x dependent measure), or which were otherwise of managerial interest (e.g., recession x product type).

Second, we investigate whether or not some brand characteristics influence advertising elasticity. We collect data on brand market share, brand advertising share, and relative price for 212 of 751 observations. However, Sethuraman, Srinivasan, and Kim (1999) state that the elasticity measure is related to brand share and advertising share by definition. For example, in the linear model, (absolute) advertising effect is measured as d(market share)/d(advertising). To convert into (percent) elasticity measure, we multiply the effect by mean brand advertising and divide by brand market share. Because market share is in the denominator and advertising is in the numerator, advertising elasticity, by definition, tends to be larger for brands with low market share and high advertising share. Therefore, we only test whether advertising elasticity is higher for high-priced brands by re-estimating Model (2) with brand relative price included.

Third, we use logistic regression to assess what factors influence the statistical significance of short-term advertising elasticity. Information on the statistical significance of advertising elasticity is available for 437 of 751 observations. The elasticity is significantly greater than zero ($p < .05$, one tailed test) in 57% of the observations. We estimate the following logit model to identify factors influencing the significance of advertising elasticity.

$$(3) \qquad P(A_{sj} \text{ is significantly} > 0) = \frac{\exp(V_{sj})}{1 + \exp(V_{sj})}, \text{ where } V_{sj} = X_{sj}\gamma + \varepsilon_{sj}$$

X_{sj} is the set of influencing variables listed in Table 1 and γ is the coefficient vector measuring the influence of the variable on the significance of advertising elasticity.

Analysis of Long-Term Advertising Elasticity

As with short-term elasticity, we first perform univariate analysis to obtain an estimate of the mean advertising elasticity and compare with the value in Assmus, Farley, and Lehmann (1984). We also obtain insights on the median and distribution of long-term advertising elasticity. Then, we estimate Model (2) to identify factors that influence long-term elasticity. We do not conduct robustness checks, due to lack of sufficient data and because standard errors are not available for long-term elasticity.

RESULTS

First, we present the results on short-term advertising elasticity in the following order: univariate analysis, overview of regression results, and results for individual influencing factors. Then, we present the results on long-term advertising elasticity.

Univariate Analysis

Figure 1 presents the distribution of short-run advertising elasticity. There are 751short-run brand-level advertising elasticities, with magnitudes ranging from -.35 to 1.80. Over 40% of the elasticities are between 0 and 0.05. About 7% of advertising elasticities are negative, though we generally expect advertising elasticity to be positive. In the spirit of meta-analysis, we retain the negative elasticities because the meta-analytic model will reveal whether any method or environmental variable is responsible for such negative estimates.

The mean short-term advertising elasticity across the 751 observations is .12, which is substantially lower than the mean of .22 from 128 observations in Assmus, Farley, and Lehmann (1984). The difference between the two results is attributable to: (i) reduction in advertising elasticities over time; (ii) inclusion of 32 product-level elasticities in Assmus et al., which are generally higher than the brand-level elasticities; and (iii) non-inclusion of estimates from Lambin (1976) in the Assmus study, which are generally below the prior mean of .22. Our estimate is closer to the mean advertising elasticity of .104 of Hu, Lodish, and Krieger (2007, Table 1) from 210 real-world TV advertising tests. Our estimate is also similar to Sethuraman and Tellis (1991), who find that the mean brand-level advertising elasticity across a wide range of categories is .11.

The median short-run advertising elasticity is even lower at .05, but closer to the uncorrected mean short-run elasticity of .04 in the recent comprehensive study on pharmaceuticals by Fischer and Albers (2010, Table W1). Primary authors report the standard errors (or t-values) of the estimates in 437 of the 751 observations. Advertising elasticities are significantly greater than zero at the 95% confidence level in 57% of the cases.

Overview of Meta-Analytic Results

Table 1 (Column 5) presents the results for the main meta-analytic model (2) for short-run ad elasticity. The model explains 37% of the variance in advertising elasticity, which is comparable to the prior meta-analysis of Assmus, Farley, and Lehmann (36%). Coefficients corresponding to twelve of the 22 independent variables are statistically significant at least at $p < .10$. They are: year of data, product type, product life cycle, region, temporal interval, level of data aggregation, measure of advertising, advertising type, omission of lag sales, omission of distribution, functional form, and omission of endogeneity.

We account for uncertainty in advertising elasticity by compiling 437 observations in which information on the extent of uncertainty, as measured by the standard error, is available. We then draw 500 random datasets using the method described in the procedure section, estimate Model (2), and compute the average of the estimates corresponding to each variable. These average estimates are in the Web Appendix (Table A2). All significant variables in the main regression model are also significant in this model, with the exception of the advertising measure. In addition, recession is positive and significant in this new model. Other significant variables are omission of lag price, quality, promotion, and estimation method.

We assess the extent of collinearity and find that the problem of collinearity exists but does not compromise the main results. All variance inflation factors are less than five, except one corresponding to estimation method, which is ten. All condition indices are less than 20. In the principal components analysis, no two variables explain more than 50% of the variance in one factor. However, bivariate correlation and cross-tabulation analysis reveals reasonably high levels of association between many pairs of variables. Therefore, we delete one variable at a time and inspect the robustness of other results. Almost all the original results are robust, except in two cases. The variable recession is positive and significant in a few alternate models (e.g., when year of data and data aggregation are excluded). Omission of endogeneity is not statistically significant in a few models. We also estimate stepwise regression, in which variables enter sequentially in order of incremental variance explained, so long as they are significant at $p < .10$. All 12 significant variables in the main regression model also enter the stepwise regression model. Details of these results are available from the authors.

We include each interaction effect mentioned in the procedure section one at a time, and we retain them if they are significant. Two effects -- product life cycle x product type and product life cycle x dependent variable -- are statistically significant. The percent of explained variance increases from 37% in the model with only main effects to 40% in the model incorporating interaction effects. The regression results are in Table 1 (Column 6).

To ascertain whether a brand's relative price impacts advertising elasticity, we use 212 observations in which information on price is available and estimate Model (2). Due to lack of sufficient observations, we can include only 13 of the 22 variables in the original model and cannot estimate interactions. The coefficient of relative price is positive (.03, std. error = .05), but not statistically significant.

Which factors influence the statistical significance of advertising elasticity? There are 437 observations in which information on statistical significance (t-values) are available. In 249 of the 437 observations (57%), advertising elasticity is significantly greater than zero. Results of logistic regression (3) are in the Web Appendix (Table A2). Due to lack of data, interaction effects are not included. The results reveal fewer significant coefficients than in the original model. Advertising elasticity is more likely to be significantly greater than zero in Europe than in the United States, for panel data than for aggregate firm data, and for television than print advertising. Some coefficients are marginally significant. One possible explanation for the lack of significance in this model is as follows: A significant advertising elasticity, whether .1 or .5, is taken as one. A non-significant coefficient, whether .001 or .05, is deemed as zero. This recoding absorbs meaningful variation in the data, which can result in fewer significant estimates than in the original model, with magnitude of advertising elasticity as the dependent variable.

We now present the results on short-run advertising elasticity for significant variables.

Time Trend and Recession

Median Year of Data. Given the increased competition in consumer products, the advent of the Internet as an alternate information source, and the ability of consumers to opt out of television commercials, we would expect consumers to be less responsive to advertising in more recent times than in the past. Consistent with our expectations, the corresponding regression coefficient of time (median year of data) is negative. This result is robust across models. (We also tested a quadratic effect of time; the coefficient was non-significant.)

Prior meta-analysis by Assmus, Farley, and Lehmann (1984) uses pre-1980 data, while our meta-analysis includes post-1980 data. Therefore, we compare advertising elasticity on pre-1980 data (1940-1979) with that on post-1980 data (1980-2004). Instead of treating year of data as a continuous variable, we include a dummy variable to indicate pre-and post-1980 periods. The regression coefficient for post-1980 is -.11 (std. error = .06), indicating a significant decline between the two time periods. The mean advertising elasticity is .13 pre-1980 (n = 463) and .10 post-1980 (n = 288).

Temporal differences in advertising elasticity may occur because of differences in consumer response to advertising over time, or because of differences in market characteristics and research methods. To explore the impact of market / method factors on the temporal differences in predicted advertising elasticity, we follow the approach in Bijmolt, van Heerde, and Pieters (2005, p.151) and compute the contribution of various factors to the difference. Table 3 presents the five key contributing factors that influence difference in the advertising elasticity between pre-1980 and post-1980 periods.[3]

1. Firm level aggregate data comprise the primary database pre-1980 (93% use), while the advent of scanner data increases use of panel data and reduces use of firm data post-1980 (47% use). This difference in database results in a .09 increase in ad elasticity post-1980 compared to pre-1980.
2. TV advertising is used more in the estimation post-1980 (60%) than pre-1980 (21%), resulting in an increase in ad elasticity of .07 post-1980.
3. Europe is grossly under-represented post-1980 (1%) compared to pre-1980 (48%). Because ad elasticity in Europe is higher than in the United States,, this difference causes a reduction in predicted ad elasticity by .04 post-1980.
4. Early researchers tend to use more temporally aggregate (yearly) data, while later researchers use less yearly and more weekly data. This difference causes ad elasticity to decrease by .03 post-1980 compared to pre-1980.
5. Because markets in general have matured over time, about 88% of products studied post-1980 are mature products, compared to 58% pre-1980. Because mature products have lower advertising elasticity, there is .03 reduction in ad elasticity post-1980.

In summary, changes in estimates of advertising elasticity over time can be attributed to changes in market and method characteristics. The observed negative regression coefficient for year of data suggests that the effect persists even after accounting for these factors.

Why might the advertising response be lower in recent times? Researchers point to advertising clutter and competitive advertising, both of which result in reduced recall and evaluation of the brand being advertised. For example, Kent (1995) documents that the average

[3] We thank one of the reviewers for suggesting this analysis.

number of network ads per hour tripled from six in the 1960's to 18 in the 1990's. Danaher, Bonfrer and Dhar (2008) report that advertising elasticity declines in the presence of high competitive clutter.

Recession. The current economic environment highlights the need to understand how marketing strategies should be modified in the face of recession. In particular, should advertising budgets be curtailed or increased during recession (see Tellis and Tellis 2009 for a recent survey of relevant literature)? If advertising elasticity is lower during recession, both the impact factor and budgetary considerations would suggest a reduction in advertising. However, if advertising elasticity is equal or higher during recession as during expansion, then the decision is not clear. Our meta-analysis reveals that advertising elasticity is not lower during recessionary times. On the contrary, advertising elasticity is higher during recession.

Product and Geographic Factors

Product Type: Availability of data permits us to test differences among many types of product categories – pharmaceutical, food, non-food, durable, and service goods (e.g., banks, movies). However, we do not have prior expectations for the relative magnitudes of these product categories.

Regression coefficients (Table 1) and comparison of means reveals that durable goods have the highest advertising elasticity, followed by pharmaceuticals and service goods. Frequently purchased food and non-food products have the lowest advertising elasticity. Non-food, nondurable products generally tend to be low-involvement items, such as household cleaners, whose purchase behavior may not be significantly influenced by advertising.

Product Life Cycle: Advertising either provides information or persuades consumers about the advertised brand. In either case, advertising is likely to be more relevant and useful in the early stage of the product life cycle, when consumers know little about the brand or have not formed preferences. Thus, advertising elasticity will be higher for products in the early stage of the life cycle than in the mature stage. Consistent with this expectation, products in the growth stage of the life cycle have a higher advertising elasticity (.16) than products in the mature stage (.11), and the coefficient is significant in the regression model (Table 1).

We also find an interaction between product life cycle and product type, as shown in Figure 2. Declining advertising elasticity from the growth stage to the mature stage of the life cycle appears to be more prominent in durable goods, moderate in food products, and is non-significant in non-durable, non-food products.

Geographic Region: Europe may under-advertise due to regulation, the short history of advertising in the region, or culture. The United States may have optimal or over-advertising because of the long history of advertising, intense competition, and advertising clutter. If this reasoning is right, then advertising elasticity is likely to be higher in Europe than in the U.S. We find that Europe has a significantly higher advertising elasticity (.17) than the U.S. (.11), and this effect holds in the regression model after accounting for other factors (Table 1).

Data Characteristics

Dependent Measure: Sales can be measured either in absolute terms (unit sales or dollar revenues or purchases), or in relative terms (market share). Absolute sales capture both competitive gains and gains due to primary market expansion. Relative sales capture only competitive gains. Because advertising can increase primary demand, we expect advertising elasticity to be higher when sales are recorded in absolute terms. Advertising elasticity is slightly higher for (absolute) sales elasticity (.13) than for relative (share) elasticity (.11), but the difference is not significant in the regression model.

However, we find a marginally significant ($p < .10$) interaction effect between product life cycle and dependent measure in the regression model (Table 1). The predicted means are represented in Figure 3. In growth products, advertising elasticity is higher when measured with sales as the dependent variable than when share is the dependent variable. This result is intuitive, because the potential for an increase in primary demand (which is better captured in the sales model) is higher in the growth stage of the life cycle.

Temporal Interval: Advertising generally has not only an instantaneous impact on sales but also a carryover impact. So, the greater the level of temporal aggregation, the more likely it is to capture the sales resulting from the carryover advertising. Also, the greater the level of aggregation, the larger the bias caused by wrongly capturing the carryover effect. Hence, we expect current period advertising elasticity to be larger when data are more aggregate (yearly or quarterly) rather than less aggregate (weekly or daily), if the model does not fully and correctly capture the carryover effect. Researchers typically estimate the carryover effect with the Koyck model. The use of aggregate data leads to a positive bias in the estimation of the carryover effect by this model (Tellis and Franses 2006).

Interestingly, we find a non-monotonic relationship between advertising and data interval; this effect holds both when lagged sale (carryover effect) is included or omitted. Ad elasticity is lowest with quarterly data and higher with weekly and yearly data.

Data Aggregation: Prior to the advent of scanner data, researchers estimated ad elasticity using predominantly firm-level aggregate data. Scanner data prompts the use of panel data and the estimation of advertising response at the individual level. Individual-level data appears to be a more appropriate unit of analysis for measuring response to advertising. While the univariate means are not different between the two groups (both about .12), after accounting for other factors, advertising elasticities estimated at the aggregate firm-level are significantly lower than those at the disaggregate consumer panel level. This result is consistent with the findings of Christen, et al. (1997).

A plausible explanation for this effect is that aggregate data are a linear aggregation of individual purchases, whereas panel data estimation uses non-linear aggregation of purchases. Gupta, et al. (1996, Tables 3 and 4) show that the price elasticity from a linear approximation to a logit model (without heterogeneity) are biased towards zero. Hence, linear approximations through the use of aggregate data may tend to downwardly bias advertising elasticity.

Advertising Measure: A brand's advertising may be measured in absolute terms (monetary value, gross rating points, etc.) or in relative terms (the brand's share of all advertising in the market). Depending on what competitors in the market are doing, changes in absolute advertising may not necessarily reflect the same changes in relative advertising. If competitors tend to match a target firm's advertising, then large changes in absolute advertising will translate into small changes in relative advertising. As a result, elasticities estimated with absolute advertising will be smaller than those estimated with relative advertising. The reverse holds if competitors do not match a target firm's advertising or if they react in the opposite direction. Thus, from the differences in elasticity between relative or absolute advertising measures, we may infer how competitors match a target firm's advertising strategy.

With respect to GRP and monetary (dollar) advertising measure, we provide a mathematical explanation as follows: Advertisers buy GRP's using dollars – one GRP being one percent of target audience (reach) given one exposure The impact of advertising (i.e., elasticity) can then be measured as the percent change in sales due to a 1% increase in GRPs, defined here as w. Let a 1% increase in advertising dollars increase GRPs by v%, then the impact of increasing advertising spending would be represented by vw. It follows that, other things equal, dollar elasticity is greater than GRP elasticity if $v > 1$ and GRP elasticity is greater than dollar elasticity if $v < 1$.

Comparison of elasticities for absolute vs. relative advertising reveal mixed results. Advertising elasticity with relative advertising is higher than advertising elasticity with dollar measure of absolute advertising but lower than with GRP measure of absolute advertising. However, within absolute advertising, elasticity measured with Gross Rating Point (GRP) is higher (.21) than advertising elasticity with monetary value (.09); this difference is significant in the regression model (Table 1). As stated above, this finding indicates the possibility of $v < 1$, on average. That is, firms may be operating in the region where a 1% increase in advertising dollars yields a less than 1% increase in GRP. Future research can assess if this inference holds. Another reason for the difference in elasticity may be due to its correlation with other model factors. For example, GRP elasticities may be highly represented in durable goods which generally have higher ad elasticities. Our analysis reveals that GRP elasticities were primarily in non durable goods and mature product life cycle. The results on advertising measure did not change when these variable were excluded from the model.

Advertising Type: Even though mean TV advertising elasticity (.12) is not significantly greater than print advertising elasticity (.11), after accounting for other factors, we find print advertising has a lower short-term ad elasticity than TV advertising in the regression analysis (Table 1). One reason for this effect may be because TV advertising, with its ability to arouse emotions, may be more effective than print advertising, which relies primarily on information appeals (Tellis, Chandy, and Thaivanich 2000). Another reason is provided by Rubinson (2009) where he shows that TV advertising effectiveness is increasing over time (versus other media), due to TV's ability to increase brand awareness more effectively.

Omitted Variables

Omission of Lagged Sales: The omission of a variable biases advertising elasticity, if that omitted variable is correlated with both the dependent variable (sales) and the included independent variable (advertising). The direction of the bias is the product of the signs of the correlations of the omitted variable with sales and advertising. Lagged sales are likely to be correlated positively with both current-period sales and current-period advertising (as current advertising is often set as a proportion of past sales). Therefore, we expect the omission of lagged sales to positively bias advertising elasticity. Consistent with this expectation, we find that, after accounting for other factors, the omission of lagged sales significantly increases advertising elasticity. Put another way, lagged sales picks up the carryover effect of advertising. The omission of lagged sales will ensure that the current advertising picks up some of this carryover effect.

Other Omitted Variables: Among other variables, we find that omission of distribution significantly increases advertising elasticity, perhaps because advertised brands are better distributed. Hence, distribution is both positively related to sales and to advertising, resulting in a positive omission bias. The effects of the exclusion of other variables are non-significant.

Model Characteristics

Functional Form and Estimation Method: Linear and double log models tend to produce higher advertising elasticity than share models. We find that functional form, overall, has greater influence on short-term advertising elasticity than estimation method.

Incorporating Endogeneity and Heterogeneity: A more recent trend in estimation of marketing mix is incorporating endogeneity. We do find that, in many models, omission of endogeneity induces a negative bias in the estimates, which is consistent with the belief that omitting endogeneity can bias the estimates towards zero (Villas-Boas and Winer 1999). That is, advertising elasticity is lower when endogeneity is not incorporated.

Recent modelers also incorporate heterogeneity by allowing for differences in advertising elasticity parameters across households in the sample, either through random effects or Bayesian models. However, we find that the effect of omission of heterogeneity on advertising elasticity is not significant, i.e., omission of heterogeneity does not significantly alter the advertising elasticity estimates.

Results on Long-Term Advertising Elasticity

Figure 1 presents the distribution of long-run advertising elasticities. There are 402 long-run brand-level advertising elasticities. Their magnitudes range from -1.2 to 4.5. Over 40% of the elasticities are between 0 and 0.1. About 5% of advertising elasticities are negative. The mean long-term advertising elasticity across the 402 observations is .24, which is much lower than the mean of .41 in Assmus, Farley, and Lehmann (1984).[4] The median long-term elasticity is even lower than the mean at .10.

The meta-analytic results for the long-run advertising elasticity are in Table 1 (Columns 7, 8). The variables in the main model explain 29% of the variance in long-run elasticity. The omission of lagged sales is not included as an independent variable because the coefficient of lagged sales is used to estimate long-run elasticity (dependent variable). Six variables that are statistically significant in the short-run elasticity models are also significant in the long-run model. They are: year of data, product type, region, measure of advertising, omission of distribution, and functional form.

Four variables that are significant in the short-run model are not significant in the long-run elasticity model: product life cycle, temporal interval, data aggregation, and omission of endogeneity. One reason for the lack of significance is as follows. Because long-term elasticity is computed using the formula: [short-term elasticity/(1-carryover effect)], the influence of a variable on long-term elasticity depends on its influence on both short-term elasticity and carryover effect. These two effects acting together may enhance or dampen the resultant

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[4] The short-term advertising elasticity in Assmus et al. (1984) is ,22 and the mean carryover is .468, leading to mean long-term advertising elasticity of .414 [=.22/(1-.468)].

coefficient. For example, mature products tend to have smaller short-term advertising elasticity but may have equal or smaller carryover effect compared to growth products. Hence, the effect of product life cycle on long-run elasticity may not be significant.

One surprising finding is that TV advertising has higher short-run elasticity but lower long-run elasticity than does print advertising. The higher long-run elasticity for print advertising may be because information in print (especially magazines) remains in memory for a longer period than TV advertising. Some variables that are not significant in the short-run model are significant in the long-run model: long-term ad elasticity is higher during recessions than in expansions; omission of lagged advertising and promotion are also significant in the long-run elasticity models.

IMPLICATIONS

The meta-analysis results have implications for managers and researchers.

Implications for Managers

The implications for managers relate to advertising budget determination and identification of conditions that favor or deter advertising.

Advertising Budgeting: We find the mean short-run advertising elasticity across all observations (1940-2004) is .12, the median elasticity is .05, and elasticity is declining over time. The finding that advertising elasticity is "small" seems to upset many practitioners, especially those in the agency business. This number seems even more troubling when one compares it to price elasticity, which meta-analyses suggest is over 20 times larger at -2.62 (Bijmolt, van Heerde, and Pieters 2005; Tellis 1988). However, a comparison of absolute elasticity may miss some pertinent issues. First and most importantly, price cuts affect revenues and profits immediately. So, while a small price cut can greatly enhance sales, it does not necessarily increase profits. Second, advertising has the potential to support a higher price. Third, price cuts can be selectively directed to only some consumers in order to minimize harm to the bottom line. Fourth, price cuts given to retailers may not be passed on to consumers.

Sethuraman and Tellis (1991) develop a model to integrate these factors and draw managerial implications about how advertising and price elasticities should affect managers' tradeoff between advertising and price discounting. In particular, they show that the advertising increase (ΔA) that would yield the same profits as a given price cut (Δp) in the short term can be computed from the equation:

$$\frac{\Delta A / A}{\Delta p / p} = \frac{k\varepsilon_p - f/g}{k\varepsilon_A - A/s} \tag{4}$$

where p is the price, A is advertising, k is contribution to price ratio, f is the fraction of consumer availing of the discount, g is retail pass-through of discount, S is dollar sales, and ε_p and ε_A are price and advertising elasticities, respectively. The optimum advertising-to-sales ratio is given by $(A/S)^* = (f/g)(\varepsilon_A / \varepsilon_p)$. Table 4 presents optimal results using the above formulas for different values of advertising elasticity, based on the following illustrative values: ε_p (absolute) = 2.6 (Bijmolt et al. 2005), f = .5, g = .5 and k = .5, A/S = .05 (all from Sethuraman and Tellis 1991).

Table 4 suggests a reduction in budgets allocated to conventional advertising in keeping with the declining trend in advertising elasticity. Alternately, a firm can take steps to increase advertising elasticity. Kent (1995) suggests the creation of unique messages, negotiating for non-compete coverage, and more precise targeting of advertising as some ways to overcome the harmful effects of advertising clutter and increase consumers' responsiveness to advertising.

<u>Advertising and Recession</u>: Conventional belief is that advertising should be reduced during recession because sales are lower or consumers are more price sensitive and less likely to be influenced by advertising in periods of recession than in periods of expansion. First, our results reveal that neither short-term nor long-term advertising elasticities are lower during

recession, measured as the percent of the estimation period under recession. So, at a minimum, managers need not reduce advertising in a recession because they falsely believe that the sales impact of advertising will be lower than in expansion periods.

Second, while the coefficient of recession for short-term advertising elasticity is positive, though not statistically significant, the coefficient for long-term elasticity is positive and significant suggesting that, in general, advertising elasticity is higher during recession. Possible reasons for this effect might be that during recession relative to expansion: (i) advertising clutter is lower due to cutbacks in advertising; (ii) consumers pay better attention to ad messages in order to be astute buyers; or (iii) ad budgets are supported by higher price and promotional incentives. One reason for the positive effect of long-term elasticity may be that the reduced clutter and increased attention to advertising during recession may not translate into immediate purchases (short-term), because of the tight economy at that time, but may translate into purchases at a later point in time (long-term) when the economy improves (see Tellis and Tellis 2009 for supporting evidence from other studies).

Conditions Favoring Advertising: Our finding of higher advertising elasticity suggests that, *other things equal*, advertising should be higher for durable goods over non-durable goods and for products in the early stage of the life cycle over mature products. The higher advertising elasticity in Europe than in the United States calls for a broader understanding of whether there is over-advertising in the U.S. (Aaker and Carman 1982) and under-advertising in Europe.

Implications for Researchers

The implications for researchers relate to methods for estimating advertising elasticity.

Temporal Interval: Advertising elasticity is significantly different depending on whether weekly, quarterly, or yearly data are used. These significant differences underscore the need for determining and using the “right” data interval for estimating advertising elasticity. The conventional view is that the best data interval matches the inter-purchase time for the product category. Recently, Tellis and Franses (2006) have shown that the optimal data interval that provides an unbiased estimate of advertising elasticity is the unit exposure time, defined as the largest calendar period such that advertising occurs at most once and at the same time in that period. This could be minutes or hours in some TV advertising, or days or weeks in print advertising. Furthermore, these authors show that more temporally disaggregate data does not bias the estimates. These findings would suggest that, if data are available, less aggregate daily or weekly data may be better than quarterly or yearly data for obtaining unbiased estimates of advertising elasticity.

Incorporating Endogeneity: We do find that, in many models, the omission of endogeneity induces a negative bias in advertising elasticity. One implication is that endogeneity should be taken into account when appropriate for the model and context; however, it should not be added as a "check-list" item to the research (Shugan 2004). For instance, there is some question as to whether price is truly endogenous for panel models estimated at the daily level, because retailers may not be able to determine optimal prices and may change them every day (Erdem et al. 2008). Similar arguments could be made for advertising response, as it is unlikely that brand manufacturers can detect and/or adjust their advertising levels quickly enough to adjust for weekly shifts in consumer demand. Clearly, they can detect and respond to shifts in demand over longer periods of time (quarterly or yearly).

Other Factors: We find that the omission of distribution has a positive effect on ad elasticity, while functional forms such as linear or double-log may produce different elasticities. Researchers should be cognizant of these differences and take the following steps: (i) include as many relevant covariates (e.g., price, promotion, quality) as are available; and (ii) understand the right econometric approach for the problem at hand or assess the sensitivity of their estimates of the elasticity to estimation procedures.

Non-Significant Variables: A number of variables are not significant in the regression model. Does this mean that these factors can be ignored while estimating advertising elasticity? We note that the absence of evidence of effects in the meta-analysis should not be taken as evidence of the absence of an effect. The lack of significance could be due to the lack of proper data, noise in the data, the aggregation effect, or other procedural reasons. Our view is that the "right" data and procedure must be used where possible. For example, the omission of heterogeneity does not significantly influence advertising elasticity in our meta-analysis. This does not mean researchers can safely ignore heterogeneity. It is generally appropriate to account for heterogeneity in advertising response, especially when estimating with panel data.

CONCLUSION

We meta-analyze 751 brand-level short-term advertising elasticities and 402 long-term advertising elasticities. Our objective is to update the earlier study by Assmus, Farley, and Lehmann (1984) and to add to the inventory of empirical generalizations by Hanssens (2009). We obtain several useful generalizations, which we list below. We then present the limitations and future research directions.

Key Empirical Generalizations

1. The average short-term advertising elasticity across the 751 observations is .12, which is substantially lower than the mean of .22 in Assmus, Farley, and Lehmann (1984), from 128 observations. The median advertising elasticity is even lower at .05.
2. The average long-run advertising elasticity across the 402 observations is .24, which is lower than the implied mean of .41 in Assmus, Farley, and Lehmann (1984), from 128 observations. The median long-term advertising elasticity is even lower at .10.

3. There is a decline in short-term advertising elasticity. There is a decline over time in long-term advertising elasticity. . These results suggest a reduction in conventional advertising if the firm was advertising optimally in the past.

4. On average, advertising elasticity does not decrease during recession. If anything, there is a positive relationship between months of recession in the dataset and advertising elasticity. This result suggests that a firm does not need to cut back on advertising in a recession because it believes customers will not be responsive to advertising.

5. Advertising elasticity is higher for durable goods than non-durable food and non-food products. The finding favors advertising for durable goods, other things being equal.

6. Short-run advertising elasticity is higher for products in the early stage of the life cycle than those in the mature stage. This effect is especially prominent in durable goods. This result supports focusing on advertising during the early stage and on price during later stages of the life cycle, especially for durable goods.

7. Advertising elasticity is generally higher in Europe than in North America, raising a question of whether there is under-advertising in Europe and over-advertising in the U.S.

8. There is a non-monotonic relationship between advertising elasticity and data interval. The elasticities estimated from both weekly and yearly data are higher than those from quarterly data. This result reinforces the need for using the appropriate data interval as derived by Tellis and Franses (2006).

9. TV advertising elasticity is generally higher than print advertising elasticity in the short term, but print advertising elasticity is higher than TV advertising elasticity in the long term . This finding calls for a careful consideration of cost and effectiveness when allocating budgets between the two media.

10. Advertising elasticity is lower when endogeneity in advertising is not incorporated in the model. When appropriate, researchers should attempt to incorporate endogeneity using recently developed New Empirical Industrial Organization (NEIO) models, or acknowledge that the estimate may be lower because of the omission.

Limitations and Future Research

Our study has some limitations that are typical of most meta-analytic research. First, while we have tried to be exhaustive in our literature review, we may have overlooked some publications that estimate advertising elasticity. Second, in identifying the factors that influence advertising elasticity, we are limited by the variables that are available in the original studies. For example, we could not collect data on all four stages of the life cycle or individual country of origin, so we could not estimate influences of these variables on advertising elasticity.

These limitations provide potential directions for future research. On a more substantive level, future research must try to analyze more growth products, durable goods, industrial goods, and service goods. Future research can also measure the effects of online advertising and incorporate them in meta-analyses as well as perform a meta-analysis of the duration of advertising – the period during which the effect of advertising lasts.

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Table 1
Meta-Analysis Model (2) Regression Coefficients (Standard Errors)

No	Variable	Level	Exp. Sign	Short-Term Ad Elasticity		Long-Term Ad Elasticity	
				Main effect only	Main + Interaction effect	Main effect only	Main + Interaction effect
0	Intercept	All obs.		.07(.12)	-.08(.17)	.06(.2)	-.26(.21)
Time Trend and recession							
1	Time Trend	Year of data	-	-.004(.002)**	-.004(.001)***	-.005(.002)**	-.007(.003)***
2	Recession	Months of recession	-	.01(.06)	.02(.06)	.42(.10)***	.34(.09)***
Product and Geographic Factors							
3	Product type	Drug	?	.19(.09)**	.16(.14)	.14(.11)	.29(.13)***
		Durable	?	.29(.09)***	.26(.06)***	.27(.08)***	.48(.1)***
		food	?	.03(.03)	-.15(.06)**	.08(.05)	-.13(.1)
		service	?	.10(.07)	-.04(.11)	-.10(.08)	-.08(.08)
		Non Food	base	0	0	0	0
4	Product life cycle	Mature	-	-.08(.05)**	-.08(.06)*	.08(.06)	.15(.12)
		Growth	base	0	0	0	0
5	Region (continent)	Europe	+	.09(.05)**	.16(.06)***	.16(.05)***	.34(.08)***
		Other	?	.05(.05)	.06(.05)	.09(.06)	.08(.05)
		America	base	0	0	0	0
Data Characteristics							
6	Dependent measure	Absolute	+	-.03(.02)	.08(.07)	-.12(.04)***	.20(.10)**
		Relative	base	0	0	0	0
7	Temporal Interval	Weekly	-	.04(.03)	.05(.03)	.05(.06)	.04(.07)
		Yearly	+	.08(.04)**	.09(.03)***	.10(.11)	-.03(.18)
		Quarterly	base	0	0	0	0
8	Data aggregation	Firm	?	-.20(.05)***	-.24(.06)***	.07(.08)	-.03(.06)
		Panel	Base	0	0	0	0
9	Advertising measure	Relative	?	.07(.03)**	.07(.03)***	-.11(.07)*	-.10(.07)
		GRP	?	.16(.08)**	.16(.09)**	.16(.06)***	.30(.09)***
		Monetary	base	0	0	0	0
10	Advertising type	TV	?	.19(.09)**	.21(.09)**	-.17(.05)***	-.18(.05)***
		Aggregate	?	.11(.06)*	.14(.05)**	-.03(.05)	-.01(.05)
		Print	base	0	0	0	0
Omitted Variables							
11	Lag dependent variable	Omitted	+	.10(.07)*	.09(.06)*	--	--
		Included	base	0	0	--	--
12	Lag advertising	Omitted	+	.002(.03)	.01(.03)	.14(.04)***	.13(.03)***
		Included	base	0	0	0	0
13	Lag price	Omitted	-	.01(.05)	.03(.05)	.04(.08)	.17(.12)
		Included	base	0	0	0	0

14	Price	Omitted	-	-.01(.03)	-.01 (.03)	.03(.05)	.02(.07)
		Included	base	0	0	0	--
15	Quality	Omitted	?	-.02(.07)	-.04(.06)	-.15(.08)*	-.11(.07)
		Included	base	0	0	0	0
16	Promotion	Omitted	?	-.03(.08)	-.01(.08)	.13(.08)*	.14(.07)**
		Included	base	0	0	0	0
17	Distribution	Omitted	+	.11(.04)***	.11(.04)***	.10(.05)**	.11(.06)**
		Included	base	0	0	0	0
Model Characteristics							
18	Functional form	Double log	?	.14(.07)**	.14(.08)*	.16(.07)***	-.07(.09)
		Linear	?	.26(.10)***	.24(.09)***	.07(.10)	.12(.10)
		other	?	.23(.09)***	.22(.08)***	-.28(.09)***	-.13(.10)
		share	base	0	0	0	0
19	Estimation Method	GLS	?	-.02(.03)	-.04(.03)	-.17(.05)***	-.18(.04)***
		MLE	?	.05(.05)	.02(.05)	.12(.08)	.18(.09)**
		OLS	?	.004(.02)	-.01(.02)	-.10(.06)*	-.12(.07)*
		Other	base	0	0	0	0
20	Endogeneity	Omitted	-	-.16(.08)**	-.16(.08)**	-.01(.07)	.04(.07)
		Included	base	0	0	0	0
21	Heterogeneity	Omitted	?	-.06(.06)	-.04(.07)	.07(.09)	.09(.10)
		Included	base	0	0	0	0
Other Characteristics							
22	Study type	Published	-	.09(.10)	.07(.12)	-.02(.17)	-.16 (.16)
		Working	base	0	0	0	0
Interaction Effects							
1	Mature life cycle*durable		?	--	-.34 (.13)***	--	-.39(.11)***
2	Mature life cycle*food		?	--	-.10(.18)	--	.21(.14)
3	Mature life cycle*nonfood		?	--	.12(.12)	--	--
4	Life cycle*abs		-	--	-.13(.09)*	--	-.40(.14)***

Note

Expected (Exp.) sign: + = positive relationship (compared to base level); - = negative relationship; ? = ambiguous relationship

***p < .01, **p < .05, * p < .10;

One –tailed test used if expected sign is unambiguous (+ or -)
Two-tailed test used if expected sign is ambiguous (?)

-- = coefficient not included or not estimable.

Table 2

Potential Influencing Factors of Advertising Elasticity

#	Variable/ Level	Expected relationship with advertising elasticity (a.e.)	Operationalization / how data obtained
Time Trend and Recessionary Factors			
1	Median year of data	Advertising elasticity would decrease over time because of increased competition, ad clutter, the advent of the Internet as an alternate information source, and the ability of the consumer to opt out of television commercials through devices such as TiVo.	Median year of the estimation period is used to detect time trend. For example, if the study used data from 1982-1990 to estimate advertising elasticity (a.e.), then that a.e. observation is said to come from its median year 1986.
2	Recession	During recessionary times, consumers would become more price conscious and tend to ignore generally image-based advertising. So a.e. would be smaller during recessionary times.	Recession is defined as two quarters of negative GDP growth. Data for U.S. and other countries obtained from NBER and OECD web sites. Where recession data is not identified, U.S. data is substituted. Recession variable is measured as the number of months that the economy is in recession as a proportion of total months in the estimation period.
Product and Geographic Factors			
3	Product type Pharmaceutical Durable Food Non Food Service	No prior expectations.	Category type information is directly obtained from the individual studies.
4	Product life cycle Growth Mature	Advertising either provides information or persuades consumers about the advertised brand, which are more relevant in the early stage of the life cycle, when consumers know little about the brand or have not formed preferences. Thus advertising elasticity will be higher for products in the early stage of the life cycle than in mature stage.	Product life cycle information is directly obtained from the individual studies. Where the authors indicated, the product is an established product, it is classified as a mature product.
5	Region America Europe Other	Europe may have under advertising due to regulation, short history of advertising , or culture, while the US may have optimal or over-advertising because of the long history of advertising, intense competition, and advertising wars. If this reasoning is right, then advertising elasticity is likely to be higher in Europe than in the US.	Region information is based on the continent in which the data for estimation of a.e. is obtained. Most data in the American continent are from the U.S. Many studies which estimate data from Europe state the country of the data (e.g., France, Germany). However, we cannot analyze at the country level because there are inadequate observations at the country level to obtain credible regression estimates.

Data Characteristics			
6	<u>Temporal Interval</u> Weekly Quarterly Yearly	Advertising generally has a carryover impact. So, the greater the level of temporal aggregation, the more likely it is to capture the sales resulting from the carryover advertising. Hence, we expect current period advertising elasticity to be larger when data are more aggregated (Yearly or Quarterly) than less aggregated (weekly or daily), if the model does not capture the carryover effect.	Data interval information is directly obtained from the individual studies. Some levels are combined due to paucity of data: Weekly – Daily, weekly, monthly Quarterly – Bimonthly, quarterly Yearly -- annual
7	<u>Data aggregation</u> Firm Panel	Estimation of a.e. using firm level data implicitly aggregates consumer level information in a linear fashion. Estimation of a.e. with panel data uses maximum likelihood estimation that combines information in a non-linear fashion. So, the results may be different but the direction of change is unknown	Most of the data are aggregated across consumers at the brand level. These aggregated data are called firm-level data. The panel data type consists of individual consumer level choice data with corresponding individual advertising data (exposures).
8	<u>Dependent measure</u> Absolute (sales) Relative (share)	Absolute sales capture both competitive gains and gains due to primary market expansion. Relative sales capture only competitive gains. Because advertising can increase primary demand, we expect advertising elasticity to be higher when sales are recorded in absolute terms.	Data on dependent measure is directly obtained from the estimation model that produced the elasticity. If the model has unit or dollar sales as dependent variable, then type is absolute. If the dependent variable is market share, it is classified as relative.
9	<u>Advertising measure</u> Monetary GRP Relative	Depending on what competitors in the market are doing, changes in absolute advertising may not necessarily reflect the same changes in relative advertising. If competitors tend to match a target firm's advertising, then large changes in absolute advertising will translate into small changes in relative advertising. As a result, elasticity estimated with absolute advertising will be smaller than those estimated with relative advertising. The reverse holds if competitors do not match the advertising.	A brand's advertising may be measured in absolute terms – monetary values or gross rating points or in relative terms (the brand's share of advertising in the market). Data on advertising measure directly obtained from the individual studies. Where the researchers used absolute advertising, information is provided as to whether advertising is measured in monetary units or gross-rating points.
10	<u>Advertising type</u> Print TV Aggregate	It is not clear whether consumers are more responsive to print advertising or TV advertising. However, because aggregate advertising is a combination of print and TV ads, we expect a.e. from aggregate advertising to be between print and TV advertising.	Directly obtained from the type of advertising described in individual studies. Advertising is aggregate if the advertising is a combination of more than one type of advertising (print / TV/billboards etc.). Where nothing is mentioned, deemed as aggregate advertising.
Omitted Variables			
11	<u>Lag dependent variable</u> Omitted Included	Lagged sales are likely to be correlated positively with current period sales and current period advertising (as current advertising is often set as a proportion of past sales). Therefore, we expect omission of lagged sales to positively bias advertising elasticity.	Directly obtained from the model from which the advertising elasticity is estimated.

12	Lag advertising Omitted Included	Lagged advertising is likely to be correlated positively with current period sales and current period advertising. Therefore, we expect omission of lagged advertising to positively bias the advertising elasticity measure.	Directly obtained from the model from which the advertising elasticity is estimated.
13	Lag price Omitted Included	Lagged price is likely to be correlated negatively with current period sales and positively with current period advertising. Therefore, omission of lagged price will negatively bias the advertising elasticity.	As above
14	Price Omitted Included	Price is likely to be correlated negatively with current period sales and positively with current period advertising. Therefore, we expect omission of price to negatively bias the advertising elasticity measure.	As above
15	Quality Omitted Included	Unable to predict the sign of correlation between quality and sales and hence the direction of the effect	As above
16	Promotion Omitted Included	Unable to predict the sign of correlation between promotion and advertising.	As above
17	Distribution Omitted Included	Distribution is likely to be correlated positively with current period sales and positively with current period advertising. Therefore, we expect omission of distribution to positively bias the advertising elasticity measure.	As above
Model Characteristics			
18	Functional form Double log Linear, Share Other	No prior expectations	Directly obtained from the model from which the advertising elasticity is estimated.
19	Estimation method GLS, OLS Other, MLE	No prior expectations	Directly obtained from the model from which the advertising elasticity is estimated.
20	Endogeneity Omitted Included	No theoretical reasoning but Vilas Boas and Winer (1999) find that omitting endogeneity in price elasticity estimation biases the estimate toward zero.	A model incorporates endogeneity if it treats advertising as a dependent variable endogenously determined within the model structure.
21	Heterogeneity Omitted Included	No prior expectations	A model that allows for differences in advertising response parameters across households or segments in the sample is deemed to incorporate heterogeneity.
Other Factors			
22	Study type Published Unpublished	Because of the general bias toward publishing articles that product significant effects, a.e. in published articles should be higher than a.e. from unpublished works.	Directly obtained from the studies.

Table 3

Key Contributors to changes in Short-Run Advertising Elasticity – Pre and Post 1980

Variable	Level	Model (2) Main Effect Coefficient	% in group Post-1980	% in group Pre-1980	Contribution to advertising elasticity
Aggregation	Firm	-0.195	46.5	93.3	0.09
Ad type	TV	0.193	59.7	21.4	0.07
Region	Europe	0.086	1.1	48.4	-0.04
Data interval	Yearly	0.083	3.8	36.3	-0.03
Life cycle	Mature	-0.083	87.9	57.5	-0.03

<u>Sample Interpretation and Illustration for Aggregation</u>

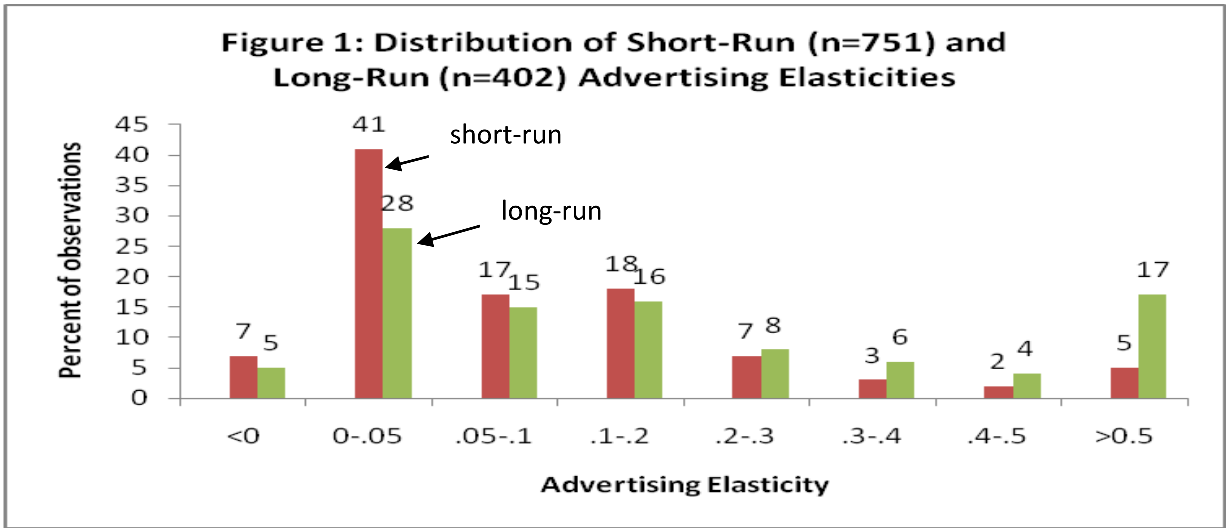
The regression coefficient from main effects Model (2) for data aggregation (firm vs. panel) is -.195; that is ad elasticity estimated from firm data is .195 lower than that from panel data. Panel data s rarely used and firm level data s predominantly used pre-1980 -- about 93% of short-run ad elasticity observations pre-1980 are from firm data, whereas 47% of the observations Post-1980 use firm data. This difference in data representation results in an increase in mean predicted advertising elasticity of .09 post-1980 compared to pre-1980 period [computed as -.195*(46.5-93.3)/100 = .09, rounded to two decimals]

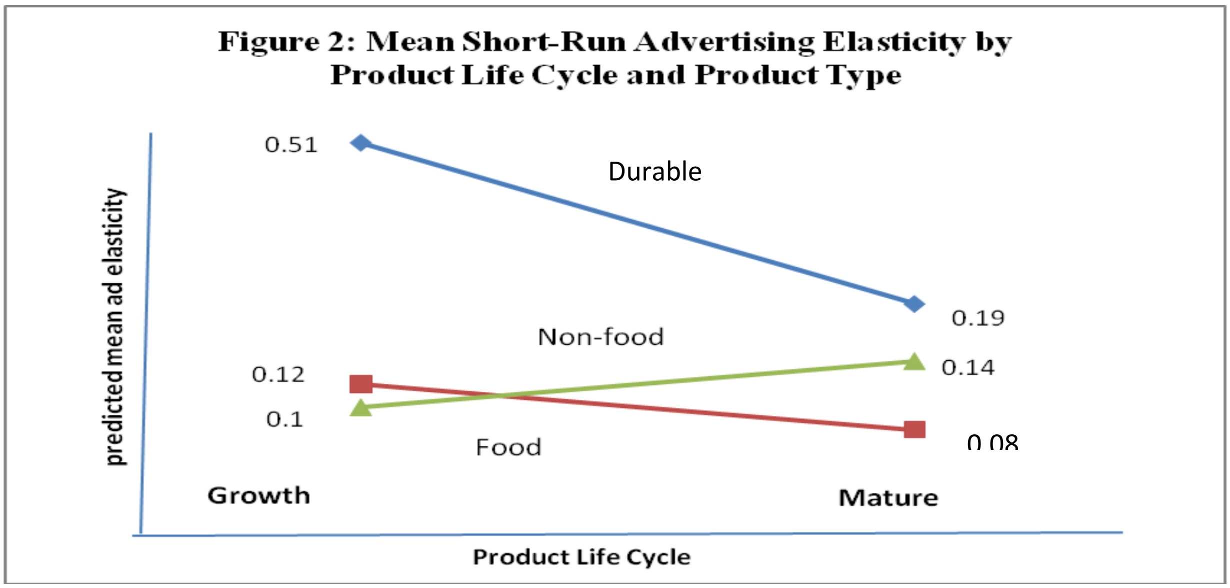
Table 4

Optimal Advertising for Different Values of Advertising Elasticity

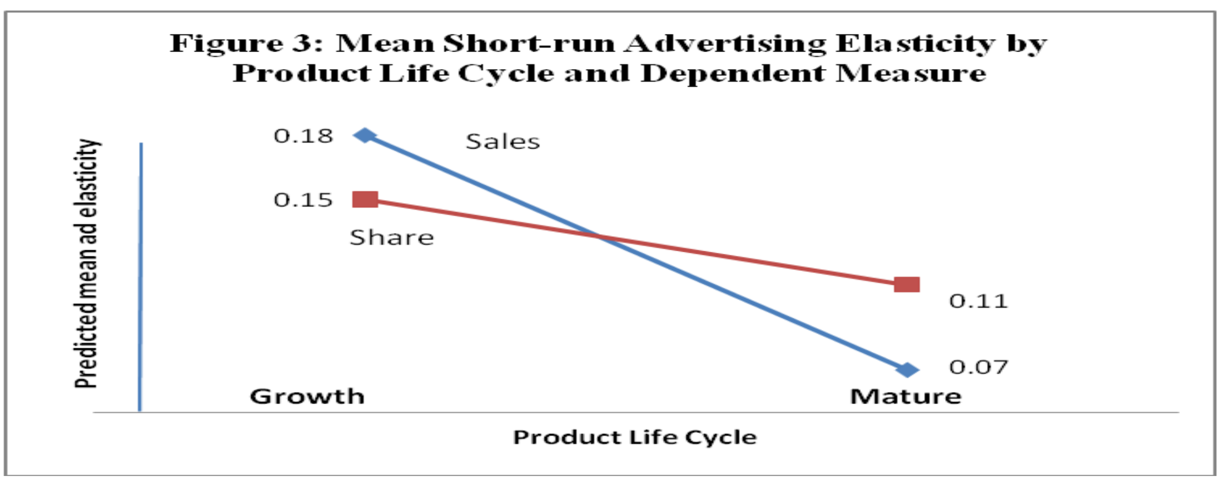
Basis for advertising elasticity	Ad elasticity	Optimal advertising as % of sales	Percent advertising increase needed to match 1% price cut
Prior meta-analysis - 1984			
Mean short-run	.22	8.5	5
This meta-analysis - 2010			
Mean short-run	.12	4.6	30
Median short-run	.05	1.9	---*

*Not computable since denominator in Equation (4) is zero or negative. The denominator being negative implies that the incremental profits from an advertising increase are negative. Therefore, the firm should reduce its advertising and not increase advertising.





Note: Pharmaceutical and service goods not reported due to small sample sizes (< 10).



WEB APPENDIX – Table A1

Studies in the Meta Analysis

#	Authors	Year	Publication	Volume & Pages	Title	# of STAE	# of LTAE
1	Aribarg and Arora	2008	Journal of Marketing Research	45 (Aug), 391-402	Brand Portfolio Promotions	10	10
2	Baidya and Basu	2007	Journal of Targeting, Measurement and Analysis for Marketing	16 (3), 181-188	Effectiveness of Marketing Expenditures: A Brand Level Case Study	1	0
3	Balachander and Ghose	2003	Journal of Marketing	67 (4), 4-13	Reciprocal Spillover Effects: A Strategic Benefit of Brand Extensions	15	9
4	Bemmaor	1984	Journal of Marketing Research	21 (Aug) 298-308	Testing Alternative Econometric Models on the Existence of Advertising Threshold Effect	20	0
5	Bird	2002	Applied Economics Letters	9, 763-767	Advertise or Die: Advertising and Market Share Dynamics Revisited	7	7
6	Bridges, Briesch and Shu	2009	Working Paper		Do Target Markets Respond Differentially to Advertising, and If So, How?	43	0
7	Brodie and Kluyver	1984	Journal of Marketing Research	21(May) 194-201	Attraction Versus Linear and Multiplicative Market Share Models: An Empirical Evaluation	22	22
8	Capps, Seo and Nichols	1997	Journal of Agricultural and Applied Economics	29 (2), 291-302	On the Estimation of Advertising Effects for Branded Products: An Application to Spaghetti Sauces	3	0
9	Carpenter, Cooper, Hanssens & Midgley	1988	Marketing Science	7(4), 393-412	Modeling Asymmetric Competition	10	0
10	Chintagunta, Kadiyali and Vilcassim	2006	Journal of Business	79 (6), 2761-87	Endogeneity and Simultaneity in Competitive Pricing and Advertising: A Logit Demand Analysis	27	27
11	Clarke	1973	Journal of Marketing Research	10 (Aug), 250-261	Sales Advertising Cross-Elasticities and Advertising Competition	18	18
12	Cowling and Cubbin	1971	Econometrica	38 (Nov), 378-394	An Econometric Investigation of the United Kingdom Car Market	30	12
13	Crespi and Marette	2002	Journal of Agricultural Economics	84 (3), 691-701	Generic Advertising and Product Differentiation	2	0

14	Danaher, Bonfrer and Dhar	2008	Journal of Marketing Research	45 (Apr), 211-225	The Effect of Competitive Advertising Interference on Sales for Packaged Goods	15	15
15	Deighton, Henderson and Neslin	1994	Journal of Marketing Research	31 (Feb), 28-43	The Effects of Advertising on Brand Switching and Repeat Purchasing	12	12
16	Doganoglu and Klapper	2006	Quantitative Marketing & Economics	4, 5-29	Goodwill and Dynamic Advertising Strategies	3	3
17	Dube and Manchanda	2005	Marketing Science	24 (1), 81-95	Differences in Dynamic Brand Competition Across Markets: An Empirical Analysis	9	8
18	Dube, Hitsch and Manchanda	2005	Quantitative Marketing and Economics	3, 107-144	An Empirical Model of Advertising Dynamics	2	2
19	Erdem and Sun	2002	Journal of Marketing Research	39 (Nov.) 408-420	An Empirical Investigation of the Spillover Effects of Advertising and Sales Promotions in Umbrella Branding	4	0
20	Erickson	1977	American Marketing Association	125-129	The Time Varying Effectiveness of Advertising	3	3
21	Ghosh, Neslin and Shoemaker	1984	Journal of Marketing Research	21(May) 202-210	A Comparison of Market Share Models and Estimation Procedures	8	8
22	Goeree	2004	Working Paper	WP 2004-09	Advertising in the U.S. Personal Computer Industry	8	0
23	Holak and Reddy	1986	Journal of Marketing	50 (4), 219-227	Effects of a Television and Radio Advertising Ban: A Study of the Cigarette Industry	20	20
24	Houston and Weiss	1974	Journal of Marketing Research	11 (Mar), 151-155	An Analysis of Competitive Market Behavior	5	4
25	Hsu and Liu	2004	Journal of International Food and Agri Marketing	16 (1), 7-18	Evaluating Branded Advertising of Fluid Milk Products in Taiwan	5	0
26	Jedidi, Mela and Gupta	1999	Marketing Science	18 (1), 1-22	Managing Advertising and Promotion for Long-Run Profitability	4	4
27	Jeuland	1979	Marketing Science Institute Proceedings	310-326	Empirical Investigation of Price and Advertising Competition Using a Market Share Model	10	0
28	Johansson	1973	Journal of American Statistical Association	63 (Dec), 824-827	A Generalized Logistic Function With an Application to the Effect of Advertising	2	0
29	Iizuka and Jin	2005	Social Sciences Research Network	Working Paper	Direct to Consumer Advertising and Prescription Choice	3	3

30	Kuehn, McGuire and Weiss	1966	Chicago: American Marketing Association		Measuring the Effectiveness of Advertising in Science, Technology and Marketing	1	0
31	Lambin	1969	Journal of Industrial Economics	17 (Apr), 86-103	Measuring the Profitability of Advertising: An Empirical Study	3	3
32	Lambin	1970	Journal of Business	43 (Oct), 468-484	Optimal Allocation of Competitive Marketing Efforts: An Empirical Study	3	3
33	Lambin	1972	Journal of Marketing Research	9 (May), 119-126	A Computer On-line Marketing Mix Model	2	2
34	Lambin	1976	Amsterdam: North Holland Publishing Company	Book	Advertising, Competition and Market Conduct in Oligopoly Over Time	176	48
35	Leach and Reekie	1996	Applied Economics	28: 1081-91	A Natural Experiment of the Effect of Advertising on Sales: The SASOL Case	6	6
36	Lee, Fairchild and Behr	1988	Agribusiness	4 (6), 579-589	Commodity and Brand Advertising in the US Orange Juice Market	4	4
37	Lyman	1994	Journal of Regulatory Economics	6: 41-58	Advertising and Sales Promotion in Electricity	4	20
38	Metwally	1974	The Review of Economics and Statistics	57 (Nov) 417-27	Advertising and Competitive Behavior of Selected Australian Firms	24	0
39	Metwally	1980	Journal of Advertising Research	20 (Oct), 59-64	Sales Response to Advertising of Eight Australian Products	8	8
40	Moriarty	1975	Journal of Marketing Research	12(May) 142-150	Cross-Sectional, Time-Series Issues in the Analysis of Marketing Decision Variables	34	34
41	Narayanan, Desiraju and Chintagunta	2004	Journal of Marketing	68 (Oct), 90-105	Return on Investment Implications for Pharmaceutical Promotional Expenditures: The Role of Marketing-Mix Interactions	3	3
42	Palda	1964	Englewood Cliffs, NJ: Prentice-Hall, Inc.	Book	The Measurement of Cumulative Advertising Effects	9	4
43	Parker and Gatignon	1996	Marketing Letters	7 (1), 95-109	Order of Entry, Trial Diffusion, and Elasticity Dynamics: An Empirical Case	3	0
44	Parsons	1975	Journal of Marketing Research	12 (Nov), 476-480	The Product Life Cycle and Time Varying Advertising Elasticities	6	5
45	Parsons	1976	Journal of Marketing Research	13 (Feb), 76-79	A Ratchet Model of Advertising Carryover Effects	5	3

46	Picconi and Olson	1978	Journal of Marketing Research	15 (Feb), 82-92	Advertising Decision Rules in a Multibrand Environment: Optimal Control Theory and Evidence	6	6
47	Rennhoff and Wilber	2008	Social Sciences Research Network	Working Paper	The Effectiveness of Post-Release Movie Advertising	15	15
48	Rojas, Peterson	2008	International Journal of Industrial Organization	26, 288-307	Demand for Differentiated Products: Price and Advertising from the US Beer Market	17	17
49	Sexton	1970	Journal of Marketing Research	7 (Aug), 338-347	Estimating Marketing Policy Effects on Sales of a Frequently Purchased Product	12	0
50	Shankar and Bayus	2003	Strategic Management Journal	24, 375-384	Network Effects and Competition: An Empirical Analysis of the Home Video Game Industry	2	0
51	Shum	2004	Journal of Economics and Management Strategy	13 (2), 241-272	Does Advertising Overcome Brand Loyalty? Evidence from the Breakfast-Cereals Market	48	0
52	Vilcassim, Kadiyali and Chintagunta	1999	Management Science	45 (4), 499-518	Investigating Dynamic Multifirm Market Interactions in Price and Advertising	3	3
53	Weiss	1968	Journal of Marketing Research	5 (Aug), 290-295	Determinants of Market Share	3	0
54	Wildt	1974	Journal of Marketing Research	11 (Feb), 50-62	Multifirm Analysis of Competitive Decision Variables	3	3
55	Wittink	1977	Journal of Advertising Research	17 (Apr), 38-42	Advertising Increases Sensitivity to Price	26	24
56	Wosinska	2002	Harvard Business School	Working Paper No. 03-058	Just What the Patient Ordered? Direct-to-Consumer Advertising and the Demand for Pharmaceutical Products	4	4

Note: STAE = Short-Term Advertising Elasticity; LTAE = Long-Term Advertising Elasticity.

Table A2

Regression Results – Alternate Models: Coefficient (Standard Error)

		Level	Exp. Sign	Model with uncertainty	Logit Model (3)
0	Aggregate/Intercept	All obs.		.153(.09)	-7.21(99.8)
Time Trend and recession					
1	Time Trend	continuous	-	-.002(.001)**	.02(.02)
2	Recession	continuous	-	.11(.04)***	.57(1.15)
Product and Geographic Factors					
3	Product type	Drug	?	.24(.03)***	-9.03(198.3)
		Durable	?	.09(.04)**	1.15(49.6)
		food	?	-.002(.02)	2.56(49.6)
		service	?	.14(.06)**	-.01(.27)
		Non Food	base	0	0
4	Product life cycle	Mature	-	-.07(.02)***	-.01(.27)
		Growth	base	0	0
5	Region (continent)	Europe	+	.12(.04)***	1.52(.55)***
		Other	?	-.08(.02)***	-1.74(.58)***
		America	base	0	0
Data Characteristics					
6	Dependent measure	Absolute	+	.04(.03)*	.05(.22)
		Relative	base	0	0
7	Temporal Interval	Weekly	-	-.01(.04)	.58(.45)
		Yearly	+	.07(.02)***	-.42(.41)
		Quarterly	base	0	0
8	Data aggregation	Firm	?	-.23(.04)***	-.88(.5)*
		Panel	Base	0	0
9	Advertising measure	Monetary	?	-.01(.02)	.68(.47)*
		GRP	?	.17(.09)**	1.41(.88)
		Relative	base	0	0
10	Advertising type	TV	?	.15(.06)**	.97(.52)*
		Aggregate	?	.02(.04)	-.73(.35)**
		Print	base	0	0
Omitted Variables					
11	Lag dependent variable	Omitted	+	.05(.02)**	.09(.19)
		Included	base	0	0
12	Lag advertising	Omitted	+	.02(.01)**	.26(.25)
		Included	base	0	0
13	Lag price	Omitted	-	.1(.04)***	-.63(.5)
		Included	base	0	0
14	Price	Omitted	-	-.01(.02)	.36(.2)*
		Included	base	0	0

15	Quality	Omitted	?	.07(.02)***	.4(.35)
		Included	base	0	0
16	Promotion	Omitted	?	-.13(.05)**	.52(.53)
		Included	base	0	0
17	Distribution	Omitted	+	.005(.01)	.19(.25)
		Included	base	0	0
Model Characteristics					
18	Functional form	Double log	?	.14(.04)***	3.29(86.7)
		Linear	?	.33(.05)***	3.65(86.7)
		other	?	.3(.06)***	4.65(86.7)
		share	base	0	0
19	Estimation Method	GLS	?	-.001(.03)	-1.16(.68)*
		MLE	?	-.13(.05)**	.87(1.25)
		OLS	?	.06(.01)***	.15(.46)
		Other	base	0	0
20	Endogeneity	Omitted	?	-.2(.03)***	-.18(.44)
		Included	base	0	0
21	Heterogeneity[1]	Omitted	?	--	--
		Included	base	--	--
Other Characteristics					
22	Study type	Published	-	--	--
		Working	base	--	--

Notes: -- = coefficient not estimable due to lack of data.

1. Both discrete and continuous heterogeneity are included in this measure as there is only one study (Balanchander, et al) using discrete heterogeneity out of nine that accounted for heterogeneity. Given the few observations (9), this effect is not able to be reliably estimated.