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# The effect of advertising on brand awareness and perceived quality: An empirical investigation using panel data

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**Abstract** We use a panel data set that combines annual brand-level advertising expenditures for over three hundred brands with measures of brand awareness and perceived quality from a large-scale consumer survey to study the effect of advertising. Advertising is modeled as a dynamic investment in a brand's stocks of awareness and perceived quality and we ask how such an investment changes brand awareness and quality perceptions. Our panel data allow us to control for unobserved heterogeneity across brands and to identify the effect of advertising from the time-series variation within brands. They also allow us to account for the endogeneity of advertising through recently developed dynamic panel data estimation techniques. We find that advertising has consistently a significant positive effect on brand awareness but no significant effect on perceived quality.

**Keywords** Advertising · Brand awareness · Perceived quality · Dynamic panel data methods

**JEL Classification** L15 · C23 · H37

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## 1 Introduction

In 2006 more than $280 billion were spent on advertising in the U.S., well above 2% of GDP. By investing in advertising, marketers aim to encourage consumers to choose their brand. For a consumer to choose a brand, two conditions must be satisfied: First, the brand must be in her choice set. Second, the brand must be preferred over all the other brands in her choice set. Advertising may facilitate one or both of these conditions.

In this research we empirically investigate how advertising affects these two conditions. To disentangle the impact on choice set from that on preferences, we use actual measures of the level of information possessed by consumers about a large number of brands and of their quality perceptions. We compile a panel data set that combines annual brand-level advertising expenditures with data from a large-scale consumer survey, in which respondents were asked to indicate whether they were aware of different brands and, if so, to rate them in terms of quality. These data offer the unique opportunity to study the role of advertising for a wide range of brands across a number of different product categories.

The awareness score measures how well consumers are informed about the existence and the availability of a brand and hence captures directly the extent to which the brand is part of consumers' choice sets. The quality rating measures the degree of subjective vertical product differentiation in the sense that consumers are led to perceive the advertised brand as being better. Hence, our data allow us to investigate the relationship between advertising and two important dimensions of consumer knowledge. The behavioral literature in marketing has highlighted the same two dimensions in the form of the size of the consideration set and the relative strength of preferences (Nedungadi 1990; Mitra and Lynch 1995). It is, of course, possible that advertising also affects other aspects of consumer knowledge. For example, advertising may generate some form of subjective horizontal product differentiation that is unlikely to be reflected in either brand awareness or perceived quality. In a recent paper Erdem et al. (2008), however, report that advertising focuses on horizontal attributes only for one out of the 19 brands examined.

Understanding the channel through which advertising affects consumer choice is important for researchers and practitioners alike for several reasons. For example, Sutton's (1991) bounds on industry concentration in large markets implicitly assume that advertising increases consumers' willingness to pay by altering quality perceptions. While profits increase in perceived quality, they may decrease in brand awareness (Fershtman and Muller 1993; Boyer and Moreaux 1999), thereby stalling the competitive escalation in advertising at the heart of the endogenous sunk cost theory. Moreover, Doraszelski and Markovich (2007) show that even in small markets industry dynamics can be very different depending on the nature of advertising. From an empirical perspective, when estimating a demand model, advertising could be modeled as affecting the choice set or as affecting the utility that the consumer derives from a brand. If the role of advertising is mistakenly specified as affecting quality perceptions (i.e., preferences) rather than brand awareness as it often is, then the estimated parameters may be biased. In her study of the U.S. personal computer industry, Sovinsky Goeree (2008) finds that traditional demand models overstate price elasticities because they assume that consumers are aware of—and hence choose among—all brands in the market when in actuality most consumers are aware of only a small fraction of brands.

For our empirical analysis we develop a dynamic estimation framework. Brand awareness and perceived quality are naturally viewed as stocks that are built up over time in response to advertising (Nerlove and Arrow 1962). At the same time, these stocks depreciate as consumers forget past advertising campaigns or as an old campaign is superseded by a new campaign. Advertising can thus be thought of as an investment in brand awareness and perceived quality. The dynamic nature of advertising leads us to a dynamic panel data model. In estimating this model we confront two important problems, namely unobserved heterogeneity across brands and the potential endogeneity of advertising. We discuss these below.

When estimating the effect of advertising across brands we need to keep in mind that they are different in many respects. Unobserved factors that affect both advertising expenditures and the stocks of perceived quality and awareness may lead to spurious positive estimates of the effect of advertising. Put differently, if we detect an effect of advertising, then we cannot be sure if this effect is causal in the sense that higher advertising expenditures lead to higher brand awareness and perceived quality or if it is spurious in the sense that different brands have different stocks of perceived quality and awareness as well as advertising expenditures. For example, although in our data the brands in the fast food category on average have high advertising and high awareness and the brands in the cosmetics and fragrances category have low advertising and low awareness, we cannot infer that advertising boosts awareness. We can only conclude that the relationship between advertising expenditures, perceived quality, and brand awareness differs from category to category or even from brand to brand.

Much of the existing literature uses cross-sectional data to discern a relationship between advertising expenditures and perceived quality (e.g., Kirmani and Wright 1989; Kirmani 1990; Moorthy and Zhao 2000; Moorthy and Hawkins 2005) in an attempt to test the idea that consumers draw inferences about the brand's quality from the amount that is spent on advertising it (Nelson 1974; Milgrom and Roberts 1986; Tellis and Fornell 1988). With cross-sectional data it is difficult to account for unobserved heterogeneity across brands. Indeed, if we neglect permanent differences between brands, then we find that both brand awareness and perceived quality are positively correlated with advertising expenditures, thereby replicating the earlier studies. Once we make full use of our panel data and account for unobserved heterogeneity, however, the effect of advertising expenditures on perceived quality disappears.[1]

Our estimation equations are dynamic relationships between a brand's current stocks of perceived quality and awareness on the left-hand side and the brand's previous stocks of perceived quality and awareness as well as its own and its rivals' advertising expenditures on the right-hand side. In this context, endogeneity arises for two reasons. First, the lagged dependent variables are by construction correlated with all past error terms and therefore endogenous. As a consequence, traditional fixed-effect methods are necessarily inconsistent.[2] Second, advertising expenditures may also be endogenous for economic reasons. For instance, media coverage such as news reports may affect brand awareness and perceived quality beyond the amount spent on advertising. To the extent that these shocks to the stocks of perceived quality and awareness of a brand feed back into decisions about advertising, say because the brand manager opts to advertise less if a news report has generated sufficient awareness, they give rise to an endogeneity problem.

To resolve the endogeneity problem we use the dynamic panel data methods developed by Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998). The key advantage is that these methods do not rely on the availability of strictly exogenous explanatory variables or instruments. This is an appealing methodology that has been widely applied (e.g., Acemoglu and Robinson 2001; Durlauf et al. 2005; Zhang and Li 2007) because valid instruments are often hard to come by. Further, since these methods involve first differencing, they allow us to control for unobserved factors that affect both advertising expenditures and the stocks of perceived quality and awareness and may lead to spurious positive estimates of the effect of advertising. In addition, our approach allows for factors other than advertising to affect a brand's stock of perceived quality and awareness to the extent that these factors are constant over time.

Our main finding is that advertising expenditures have a significant positive effect on brand awareness but no significant effect on perceived quality. These results appear to be robust across a wide range of specifications. Since awareness is the most basic kind of information a consumer can have for a brand, we conclude that an important role of advertising is information provision. On the other hand, our results indicate that advertising is not likely to alter consumers' quality perceptions. This conclusion calls for a reexamination of the implicit assumption underlying Sutton's (1991) endogenous sunk cost theory. It also suggests that advertising should be modeled as affecting the choice set and not just utility when estimating demand. Finally, our findings lend empirical

[1] Another way to get around this issue is to take an experimental approach, as in Mitra and Lynch (1995).

[2] This source of endogeneity is not tied to advertising in particular; rather it always arises in estimating dynamic relationships in the presence of unobserved heterogeneity. An exception is the (rather unusual) panel-data setting where one has $T \to \infty$ instead of $N \to \infty$. In this case the within estimator is consistent (Bond 2002, p. 5).

support to the view that advertising is generally procompetitive because it disseminates information about the existence, the price, and the attributes of products more widely among consumers (Stigler 1961; Telser 1964; Nelson 1970, 1974).

The remainder of the paper proceeds as follows. In Sections 2 and 3 we explain the dynamic investment model and the corresponding empirical strategy. In Section 4 we describe the data and in Section 5 we present the results of the empirical analysis. Section 6 concludes.

## 2 Model specification

We develop an empirical model based on the classic advertising-as-investment model of Nerlove and Arrow (1962). Related empirical models are the basis of current research on advertising (e.g., Naik et al. 1998; Dube et al. 2005; Doganoglu and Klapper 2006; Bass et al. 2007). Naik et al. (1998), in particular, find that the Nerlove and Arrow (1962) model provides a better fit than other models that have been proposed in the literature such as Vidale and Wolfe (1957), Brandaid (Little 1975), Tracker (Blattberg and Golanty 1978), and Litmus (Blackburn and Clancy 1982).

We extend the Nerlove and Arrow (1962) framework in two respects. First, we allow a brand's stocks of awareness and perceived quality to be affected by the advertising of its competitors. This approach captures the idea that advertising takes place in a competitive environment where brands vie for the attention of consumers. The advertising of competitors may also be beneficial to a brand if it draws attention to the entire category and thus expands the relevant market for the brand (e.g., Nedungadi 1990; Kadiyali 1996). Second, we allow for a stochastic component in the effect of advertising on the stocks of awareness and perceived quality to reflect the success or failure of an advertising campaign and other unobserved influences such as the creative quality of the advertising copy, media selection, or scheduling.

More formally, we let $Q_{it}$ be the stock of perceived quality of brand $i$ at the start of period $t$ and $A_{it}$ the stock of its awareness. We further let $E_{it-1}$ denote the advertising expenditures of brand $i$ over the course of period $t-1$ and $E_{-it-1} = (E_{1t-1}, \ldots, E_{i-1t-1}, E_{i+1t-1}, \ldots, E_{nt-1})$ the advertising expenditures of its competitors. Then, at the most general level, the stocks of perceived quality and awareness of brand $i$ evolve over time according to the laws of motion

$$Q_{it} = g_{it}(Q_{it-1}, E_{it-1}, E_{-it-1}, \varepsilon_{it}),$$
$$A_{it} = h_{it}(A_{it-1}, E_{it-1}, E_{-it-1}, \varepsilon_{it}),$$

where $g_{it}(\cdot)$ and $h_{it}(\cdot)$ are brand- and time-specific functions. The idiosyncratic error $\varepsilon_{it}$ captures the success or failure of an advertising campaign along with all other omitted factors. For example, the quality of the advertising campaign may matter just as much as the amount spent on it. By recursively substituting for the lagged stocks of perceived quality and awareness we can write the current stocks as functions of all past advertising expenditures and the current and all past error terms. This shows that these shocks to brand awareness and perceived quality are persistent over time. For example, the effect of a particularly good (or bad) advertising campaign may linger and be felt for some time to come.

We model the effect of competitors' advertising on brand awareness and perceived quality in two ways. First, we consider a brand's "share of voice." We use its advertising expenditures, $E_{it-1}$, relative to the average amount spent on advertising by rival brands in the brand's subcategory or category, $\overline{E}_{-it-1}$.[3] To the extent that brands compete with each other for the attention of consumers, a brand may have to outspend its rivals to cut through the clutter. If so, then what is important may not be the absolute amount spent on advertising but the amount relative to rival brands. Second, we consider the amount of advertising in the entire market by including the average amount spent on advertising by rival brands in the brand's subcategory or category. Advertising is market expanding if it attracts consumers to the entire category but not necessarily to a particular brand. In this way, competitors' advertising may have a positive influence on, say, brand awareness.

Taken together, our estimation equations are

$$Q_{it} = \mu_i + \lambda_t + \gamma Q_{it-1} + f(E_{it-1}, \overline{E}_{-it-1}) + \varepsilon_{it}, \tag{1}$$

$$A_{it} = \mu_i + \lambda_t + \gamma A_{it-1} + f(E_{it-1}, \overline{E}_{-it-1}) + \varepsilon_{it}. \tag{2}$$

Here $\mu_i$ is a brand effect that captures unobserved heterogeneity across brands and $\lambda_t$ is a time effect to control for possible systematic changes over time. The time effect may capture, for example, that consumers are systematically informed about a larger number of brands due to the advent of the internet and other alternative media channels. Through the brand effect we allow for factors other than advertising to affect a brand's stocks of perceived quality and awareness to the extent that these factors are constant over time. For example, consumers may hear about a brand and their quality perceptions may be affected by word of mouth. Similarly, it may well be the case that consumers in the process of purchasing a brand become more informed about it and that their quality perceptions change, especially for high-involvement brands. Prior to purchasing a car, say, many consumers engage in research about the set of available cars and their respective characteristics, including quality ratings from sources such as car magazines and Consumer Reports. If these effects do not vary over time, then we fully account for them in our estimation because the dynamic panel data methods we employ involve first differencing.

The parameter $\gamma$ measures how much of last period's stocks of perceived quality and awareness are carried forward into this period's stocks; $1 - \gamma$ can

[3]The Brandweek Superbrands survey reports on only the top brands (in terms of sales) in each subcategory or category. The number of brands varies from 3 for some subcategories to 10 for others. We therefore use the average, rather than the sum, of competitors' advertising.

therefore be interpreted as the rate of depreciation of these stocks. Note that in the estimation we allow all parameters to be different across our estimation equations. For example, we do not presume that the carryover rates for perceived quality and brand awareness are the same.

The function $f(\cdot)$ represents the response of brand awareness and perceived quality to the advertising expenditures of the brand and potentially also those of its rivals. In the simplest case absent competition we specify this function as

$$f(E_{it-1}) = \beta_1 E_{it-1} + \beta_2 E_{it-1}^2.$$

This functional form is flexible in that it allows for a nonlinear effect of advertising expenditures but does not impose one. Later on in Section 5.6 we demonstrate the robustness of our results by considering a number of additional functional forms. To account for competition in the share-of-voice specification, we set

$$f\left(E_{it-1}, \overline{E}_{-it-1}\right) = \beta_1 \left(\frac{E_{it-1}}{\overline{E}_{-it-1}}\right) + \beta_2 \left(\frac{E_{it-1}}{\overline{E}_{-it-1}}\right)^2$$

and in the total-advertising specification, we set

$$f\left(E_{it-1}, \overline{E}_{-it-1}\right) = \beta_1 E_{it-1} + \beta_2 E_{it-1}^2 + \beta_3 \overline{E}_{-it-1}.$$

## 3 Estimation strategy

Equations 1 and 2 are dynamic relationships that feature lagged dependent variables on the right-hand side. When estimating, we confront the problems of unobserved heterogeneity across brands and the endogeneity of advertising.

In our panel-data setting, ignoring unobserved heterogeneity is akin to dropping the brand effect $\mu_i$ from Eqs. 1 and 2 and then estimating them by ordinary least squares. Since this approach relies on both cross-sectional and time-series variation to identify the effect of advertising, we refer to it as "pooled OLS" (POLS) in what follows.

To account for unobserved heterogeneity we include a brand effect $\mu_i$ and use the within estimator that treats $\mu_i$ as a fixed effect. We follow the usual convention in microeconomic applications that the term "fixed effect" does not necessarily mean that the effect is being treated as nonrandom; rather it means that we are allowing for arbitrary correlation between the unobserved brand effect and the observed explanatory variables (Wooldridge 2002, p. 251). The within estimator eliminates the brand effect by subtracting the within-brand mean from Eqs. 1 and 2. Hence, the identification of the slope parameters that determine the effect of advertising relies solely on variation over time within brands; the information in the between-brand cross-sectional relationship is not used. We refer to this approach as "fixed effects" (FE).

While FE accounts for unobserved heterogeneity, it suffers from an endogeneity problem. In our panel-data setting, endogeneity arises for two reasons. First, since Eqs. 1 and 2 are inherently dynamic, the lagged stocks of perceived quality and awareness may be endogenous. More formally, $Q_{it-1}$ and $A_{it-1}$ are by construction correlated with $\varepsilon_{is}$ for $s < t$. The within estimator subtracts the within-brand mean from Eqs. 1 and 2. The resulting regressor, say $Q_{it-1} - \overline{Q}_i$ in the case of perceived quality, is correlated with the error term $\varepsilon_{it} - \overline{\varepsilon}_i$ since $\overline{\varepsilon}_i$ contains $\varepsilon_{it-1}$ along with all higher-order lags. Hence, FE is necessarily inconsistent. Second, advertising expenditures may also be endogenous for economic reasons. For instance, media coverage such as news reports may directly affect brand awareness and perceived quality. Our model treats media coverage other than advertising as shocks to the stocks of perceived quality and awareness. To the extent that these shocks feed back into decisions about advertising, say because the brand manager opts to advertise less if a news report has generated sufficient awareness, they give rise to an endogeneity problem. More formally, it is reasonable to assume that $E_{it-1}$, the advertising expenditures of brand $i$ over the course of period $t-1$, are chosen at the beginning of period $t-1$ with knowledge of $\varepsilon_{it-1}$ and higher-order lags and that therefore $E_{it-1}$ is correlated with $\varepsilon_{is}$ for $s < t$.

We apply the dynamic panel-data method proposed by Arellano and Bond (1991) to deal with both unobserved heterogeneity and endogeneity. This methodology has the advantage that it does not rely on the availability of strictly exogenous explanatory variables or instruments. This is welcome because instruments are often hard to come by, especially in panel-data settings: The problem is finding a variable that is a good predictor of advertising expenditures and is uncorrelated with shocks to brand awareness and perceived quality; finding a variable that is a good predictor of lagged brand awareness and perceived quality and uncorrelated with current shocks to brand awareness and perceived quality is even less obvious. The key idea of Arellano and Bond (1991) is that if the error terms are serially uncorrelated, then lagged values of the dependent variable and lagged values of the endogenous right-hand-side variables represent valid instruments.

To see this, take first differences of Eq. 1 to obtain

$$\begin{aligned} Q_{it} - Q_{it-1} = {} & (\lambda_t - \lambda_{t-1}) + \gamma(Q_{it-1} - Q_{it-2}) \\ & + \big(f(E_{it-1}) - f(E_{it-2})\big) + (\varepsilon_{it} - \varepsilon_{it-1}), \end{aligned} \tag{3}$$

where we abstract from competition to simplify the notation. Eliminating the brand effect $\mu_i$ accounts for unobserved heterogeneity between brands. The remaining problem with estimating Eq. 3 by least-squares is that $Q_{it-1} - Q_{it-2}$ is by construction correlated with $\varepsilon_{it} - \varepsilon_{it-1}$ since $Q_{it-1}$ is correlated with $\varepsilon_{it-1}$ by virtue of Eq. 1. Moreover, as we have discussed above, $E_{it-1}$ may also be correlated with $\varepsilon_{it-1}$ for economic reasons.

We take advantage of the fact that we have observations on a number of periods in order to come up with instruments for the endogenous variables. In particular, this is possible starting in the third period where Eq. 3 becomes

$$Q_{i3} - Q_{i2} = (\lambda_3 - \lambda_2) + \gamma(Q_{i2} - Q_{i1}) + \big(f(E_{i2}) - f(E_{i1})\big) + (\varepsilon_{i3} - \varepsilon_{i2}).$$

In this case $Q_{i1}$ is a valid instrument for $(Q_{i2} - Q_{i1})$ since it is correlated with $(Q_{i2} - Q_{i1})$ but uncorrelated with $(\varepsilon_{i3} - \varepsilon_{i2})$ and, similarly, $E_{i1}$ is a valid instrument for $(f(E_{i2}) - f(E_{i1}))$. In the fourth period $Q_{i1}$ and $Q_{i2}$ are both valid instruments since neither is correlated with $(\varepsilon_{i4} - \varepsilon_{i3})$ and, similarly, $E_{i1}$ and $E_{i2}$ are both valid instruments. In general, for lagged dependent variables and for endogenous right-hand-side variables, levels of these variables that are lagged two or more periods are valid instruments. This allows us to generate more instruments for later periods. The resulting estimator is referred to as "difference GMM" (DGMM).

A potential difficulty with the DGMM estimator is that lagged levels may be poor instruments for first differences when the underlying variables are highly persistent over time. Arellano and Bover (1995) and Blundell and Bond (1998) propose an augmented estimator in which the original equations in levels are added to the system. The idea is to create a stacked data set containing differences and levels and then to instrument differences with levels and levels with differences. The required assumption is that brand effects are uncorrelated with changes in advertising expenditures. This estimator is commonly referred to as "system GMM" (SGMM). In Section 5 we report and compare results for DGMM and SGMM.

It is important to test the validity of the instruments proposed above. Following Arellano and Bond (1991) we report a Hansen $J$ test for over-identifying restrictions. This test examines whether the instruments are jointly exogenous. We also report the so-called difference-in-Hansen $J$ test to examine specifically whether the additional instruments for the level equations used in SGMM (but not in DGMM) are valid.

Arellano and Bond (1991) further develop a test for second-order serial correlation in the first differences of the error terms. As described above, both GMM estimators require that the levels of the error terms be serially uncorrelated, implying that the first differences are serially correlated of at most first order. We caution the reader that the test for second-order serial correlation is formally only defined if the number of periods in the sample is greater than or equal to 5 whereas we observe a brand on average for just 4.2 periods in our application.

Our preliminary estimates suggest that the error terms are unlikely to be serially uncorrelated as required by Arellano and Bond (1991). The $AR(2)$ test described above indicates first-order serial correlation in the error terms. An $AR(3)$ test for third-order serial correlation in the first differences of the error terms, however, indicates the absence of second-order serial correlation in the error terms.[4] In this case, $Q_{it-2}$ and $E_{it-2}$ are no longer valid instruments for Eq. 3. Intuitively, because $Q_{it-2}$ is correlated with $\varepsilon_{it-2}$ by virtue of Eq. 1 and $\varepsilon_{it-2}$ is correlated with $\varepsilon_{it-1}$ by first-order serial correlation, $Q_{it-2}$ is correlated

[4] Of course, the $AR(3)$ test uses less observations than the $AR(2)$ test and is therefore also less powerful.

with $\varepsilon_{it-1}$ in Eq. 3, and similarly for $E_{it-2}$. Fortunately, however, $Q_{it-3}$ and $E_{it-3}$ remain valid instruments because $\varepsilon_{it-3}$ is uncorrelated with $\varepsilon_{it-1}$.

We carry out the DGMM and SGMM estimation using STATA's xtabond2 routine (Roodman 2007). We enter third and higher lags of either brand awareness or perceived quality, together with third and higher lags of advertising expenditures as instruments. In addition to these "GMM-style" instruments, for the difference equations we enter the time dummies as "IV-style" instruments. We also apply the finite-sample correction proposed by Windmeijer (2005) which corrects for the two-step covariance matrix and substantially increases the efficiency of both GMM estimators. Finally, we compute standard errors that are robust to heteroskedasticity and arbitrary patterns of serial correlation within brands.

## 4 Data

Our data are derived from the Brandweek Superbrands surveys from 2000 to 2005. Each year's survey lists the top brands in terms of sales during the past year from 25 broad categories. Inside these categories are often a number of more narrowly defined subcategories. Table 1 lists the categories along with their subcategories. The surveys report perceived quality and awareness scores for the current year and the advertising expenditures for the previous year by brand.

Perceived quality and awareness scores are calculated by Harris Interactive in their Equitrend brand-equity study. Each year Harris Interactive surveys online between $20,000$ and $45,000$ consumers aged 15 years and older in order to determine their perceptions of a brand's quality and its level of awareness for approximately $1,000$ brands.[5] To ensure that the respondents accurately reflect the general population their responses are propensity weighted. Each respondent rates around 80 of these brands. Perceived quality is measured on a 0–10 scale, with 0 meaning unacceptable/poor and 10 meaning outstanding/extraordinary. Awareness scores vary between 0 and 100 and equal the percentage of respondents that can rate the brand's quality. The quality rating is therefore conditional on the respondent being aware of the brand.[6]

[5]The exact wording of the question is: "We will display for you a list of brands and we are asking you to rate the overall quality of each brand using a 0 to 10 scale, where '0' means 'Unacceptable/Poor Quality', '5' means 'Quite Acceptable Quality' and '10' means 'Outstanding/Extraordinary Quality'. You may use any number from 0 to 10 to rate the brands, or use 99 for 'No Opinion' option if you have absolutely no opinion about the brand." Panelists are being incentivized through sweepstakes on a periodic basis but are not paid for a particular survey.

[6]The 2000 Superbrands survey does not separately report perceived quality and salience scores. We received these scores directly from Harris Interactive. 2000 is the first year for which we have been able to obtain perceived quality and salience scores for a large number of brands. Starting with the 2004 and 2005 Superbrands surveys, salience is replaced by a new measure called "familiarity." For these two years we received salience scores directly from Harris Interactive. The contemporaneous correlation between salience and familiarity is 0.98 and significant with a $p$-value of 0.000.

**Table 1** Categories and subcategories

1. *Apparel*
2. Appliances
3. Automobiles
   - a. *general automobiles*
   - b. luxury
   - c. subcompact
   - d. sedan/wagon
   - e. trucks/suvs/vans
4. Beer, wine, liquor
   - a. beer
   - b. *wine*
   - c. malternatives
   - d. liquor
5. Beverages
   - a. general
   - b. new age/sports/water
6. Computers
   - a. software
   - b. hardware
7. Consumer electronics
8. Cosmetics and fragrances
   - a. color cosmetics
   - b. *eye color*
   - c. *lip color*
   - d. women's fragrances
   - e. men's fragrances
9. Credit cards
10. *Entertainment*
11. Fast food
12. *Financial services*
13. Food
    - a. ready to eat cereal
    - b. cereal bars
    - c. cookies
    - d. *cheese*
    - e. crackers
    - f. salted snacks
    - g. frozen dinners and entrées
    - h. frozen pizza
    - i. *spaghetti sauce*
    - j. coffee
    - k. ice cream
    - l. refrigerated orange juice
    - m. refrigerated yogurt
    - n. soy drinks
    - o. luncheon meats
    - p. *meat alternatives*
    - q. *baby formula/electrolyte solutions*
    - r. *pourable salad dressing*
14. Footwear
15. Health and beauty
    - a. bar soap
    - b. toothpaste
    - c. *shampoo*
    - d. *hair color*
16. Household
    - a. cleaner
    - b. laundry detergents
    - c. diapers
    - d. facial tissue
    - e. toilet tissue
    - f. automatic dishwater detergent
17. Petrol
    - a. oil companies
    - b. automotive aftercare/lube
18. Pharmaceutical OTC
    - a. allergy/cold medicine
    - b. stomach/antacids
    - c. analgesics
19. Pharmaceutical prescription
20. *Retail*
21. Telecommunications
22. *Tobacco*
23. Toys
24. Travel
25. *World Wide Web*

Items in italics have been removed

We supplement the awareness and quality measures with advertising expenditures that are taken from TNS Media Intelligence and Competitive Media Reporting. These advertising expenditures encompass spending in a wide range of media: Magazines (consumer magazines, Sunday magazines, local magazines, and business-to-business magazines), newspaper (local and national newspapers), television (network TV, spot TV, syndicated TV, and network cable TV), radio (network, national spot, and local), Spanish-language media (magazines, newspapers, and TV networks), internet, and outdoor.

After eliminating categories and subcategories where observations are not at the brand level (apparel, entertainment, financial services, retail, world wide web) or where the data are suspect (tobacco), we are left with 19 categories (see again Table 1). We then drop all private labels and all brands for which we do not have perceived quality and awareness scores as well as advertising expenditures for at least two years running. This leaves us with 348 brands.

Table 2 contains descriptive statistics for the overall sample and also by category. In the overall sample the average awareness score is 69.35 and the average perceived quality score is 6.36. The average amount spent on advertising is around $66 million per year. There is substantial variation in these measures across categories. The variation in perceived quality (coefficient of variation is 0.11 overall, ranging from 0.04 for appliances to 0.13 for computers) tends to be lower than the variation in brand awareness (coefficient of variation is 0.28 overall, ranging from 0.05 for appliances to 0.46 for telecommunications), in line with the fact the quality rating is conditional on the respondent being aware of the brand. The contemporaneous correlation between brand awareness and perceived quality is 0.60 and significant with a $p$-value of 0.000.

The contemporaneous correlation between advertising expenditures and the change in brand awareness is 0.0488 and significant with a $p$-value of 0.0985 and the contemporaneous correlation between advertising expenditures and the change in perceived quality is 0.0718 and significant with a $p$-value of 0.0150. These correlations anticipate the spurious correlation between both brand awareness and perceived quality and advertising expenditures if permanent differences between brands are neglected (POLS estimator). We will see though that the effect of advertising expenditures on perceived quality

**Table 2** Descriptive statistics

| | # obs | # brands | Brand awareness (0–100) | | Perceived quality (0–10) | | Advertising ($1,000,000) | |
|---|---|---|---|---|---|---|---|---|
| | | | Mean | Std. dev. | Mean | Std. dev. | Mean | Std. dev. |
| Overall | 1,478 | 348 | 69.35 | 19.43 | 6.36 | 0.70 | 66.21 | 118.52 |
| Appliances | 21 | 4 | 85.09 | 4.54 | 7.35 | 0.32 | 41.87 | 33.19 |
| Automobiles | 137 | 30 | 67.81 | 6.72 | 6.51 | 0.59 | 99.85 | 64.62 |
| Beer, wine, liquor | 98 | 24 | 62.23 | 10.13 | 5.68 | 0.72 | 36.78 | 45.11 |
| Beverages | 95 | 22 | 84.57 | 13.84 | 6.51 | 0.58 | 41.33 | 42.19 |
| Computers | 79 | 17 | 59.80 | 23.05 | 6.41 | 0.81 | 130.43 | 130.07 |
| Consumer electronics | 29 | 7 | 67.83 | 18.68 | 6.60 | 0.73 | 104.83 | 160.66 |
| Cosmetics and fragrances | 70 | 19 | 49.37 | 15.75 | 5.83 | 0.52 | 38.02 | 47.48 |
| Credit cards | 29 | 6 | 70.97 | 18.08 | 6.24 | 0.73 | 174.54 | 109.77 |
| Fast food | 60 | 12 | 93.83 | 5.32 | 6.28 | 0.42 | 214.80 | 156.23 |
| Food | 247 | 65 | 80.18 | 14.94 | 6.66 | 0.65 | 13.93 | 13.81 |
| Footwear | 38 | 8 | 64.95 | 18.98 | 6.39 | 0.42 | 40.27 | 46.89 |
| Health and beauty | 54 | 11 | 82.50 | 9.80 | 6.67 | 0.41 | 27.28 | 33.44 |
| Household | 128 | 31 | 73.83 | 16.03 | 6.66 | 0.56 | 21.80 | 25.43 |
| Petrol | 48 | 13 | 60.52 | 17.19 | 5.95 | 0.30 | 33.54 | 34.65 |
| Pharmaceutical OTC | 56 | 15 | 76.96 | 13.89 | 6.79 | 0.37 | 38.71 | 18.13 |
| Pharmaceutical prescription | 31 | 10 | 29.97 | 9.69 | 5.54 | 0.67 | 76.23 | 36.40 |
| Telecommunications | 52 | 11 | 49.33 | 22.86 | 5.28 | 0.52 | 367.93 | 360.54 |
| Toys | 25 | 5 | 72.12 | 9.74 | 6.95 | 0.32 | 108.55 | 54.36 |
| Travel | 181 | 38 | 59.48 | 15.43 | 6.26 | 0.52 | 25.41 | 25.88 |

disappears once unobserved heterogeneity is accounted for (FE and GMM estimators).

The intertemporal correlation is 0.98 for brand awareness, 0.95 for perceived quality, and 0.93 for advertising expenditures. This limited amount of intertemporal variation warrants preferring the SGMM over the DGMM estimator. At the same time, however, it constrains how finely we can "slice" the data, e.g., by isolating a brand-specific effect of advertising expenditures on brand awareness and perceived quality.

Since the FE, DGMM, and SGMM estimators rely on within-brand across-time variation, it is important to ensure that there is a sufficient amount of within-brand variation in brand awareness, perceived quality, and advertising expenditures. Table 3 presents a decomposition of the standard deviation in these variables into an across-brands and a within-brand component for the overall sample and also by category. The across-brands standard deviation is a measure of the cross-sectional variation and the within-brand standard deviation is a measure of the time-series variation. The across-brands standard deviation of brand awareness is about six times larger than the within-brand standard deviation. This ratio varies across categories and ranges from 2 for automobiles, beer, wine, liquor, and pharmaceutical prescription to 6 for health and beauty and pharmaceutical OTC. In case of perceived quality the ratio is about 4 (ranging from 1 for telecommunications to 5 for consumer electronics, credit cards, and household). Hence, while there is more cross-sectional than time-series variation in our sample, the time-series variation is substantial for both brand awareness and perceived quality. Figure 1 illustrates

**Table 3** Variance decomposition

| | Brand awareness (0–100) | | Perceived quality (0–10) | | Advertising ($1,000,000) | |
|---|---|---|---|---|---|---|
| | Across | Within | Across | Within | Across | Within |
| Overall | 20.117 | 3.415 | 0.726 | 0.176 | 100.823 | 43.625 |
| Appliances | 5.282 | 1.334 | 0.323 | 0.148 | 28.965 | 21.316 |
| Automobiles | 6.209 | 3.281 | 0.561 | 0.141 | 54.680 | 32.552 |
| Beer, wine, liquor | 10.181 | 4.105 | 0.705 | 0.186 | 41.713 | 12.406 |
| Beverages | 13.435 | 2.915 | 0.582 | 0.190 | 37.505 | 13.372 |
| Computers | 23.094 | 3.843 | 0.850 | 0.313 | 110.362 | 65.909 |
| Consumer electronics | 19.952 | 5.611 | 0.800 | 0.167 | 105.249 | 114.381 |
| Cosmetics and fragrances | 18.054 | 3.684 | 0.563 | 0.208 | 38.446 | 20.053 |
| Credit cards | 19.568 | 3.903 | 0.788 | 0.159 | 118.059 | 43.415 |
| Fast food | 6.132 | 1.660 | 0.361 | 0.202 | 159.306 | 33.527 |
| Food | 16.241 | 2.255 | 0.702 | 0.134 | 15.655 | 7.998 |
| Footwear | 20.417 | 4.267 | 0.388 | 0.167 | 45.791 | 7.640 |
| Health and beauty | 10.536 | 1.772 | 0.397 | 0.136 | 27.054 | 19.075 |
| Household | 16.719 | 3.896 | 0.561 | 0.113 | 18.789 | 16.672 |
| Petrol | 20.179 | 3.669 | 0.415 | 0.116 | 27.227 | 20.496 |
| Pharmaceutical OTC | 13.339 | 2.363 | 0.336 | 0.129 | 16.325 | 9.080 |
| Pharmaceutical prescription | 9.393 | 5.772 | 0.753 | 0.230 | 38.648 | 27.919 |
| Telecommunications | 21.659 | 5.604 | 0.452 | 0.334 | 317.434 | 178.406 |
| Toys | 11.217 | 3.589 | 0.360 | 0.127 | 61.419 | 18.584 |
| Travel | 16.063 | 3.216 | 0.516 | 0.153 | 22.136 | 10.909 |

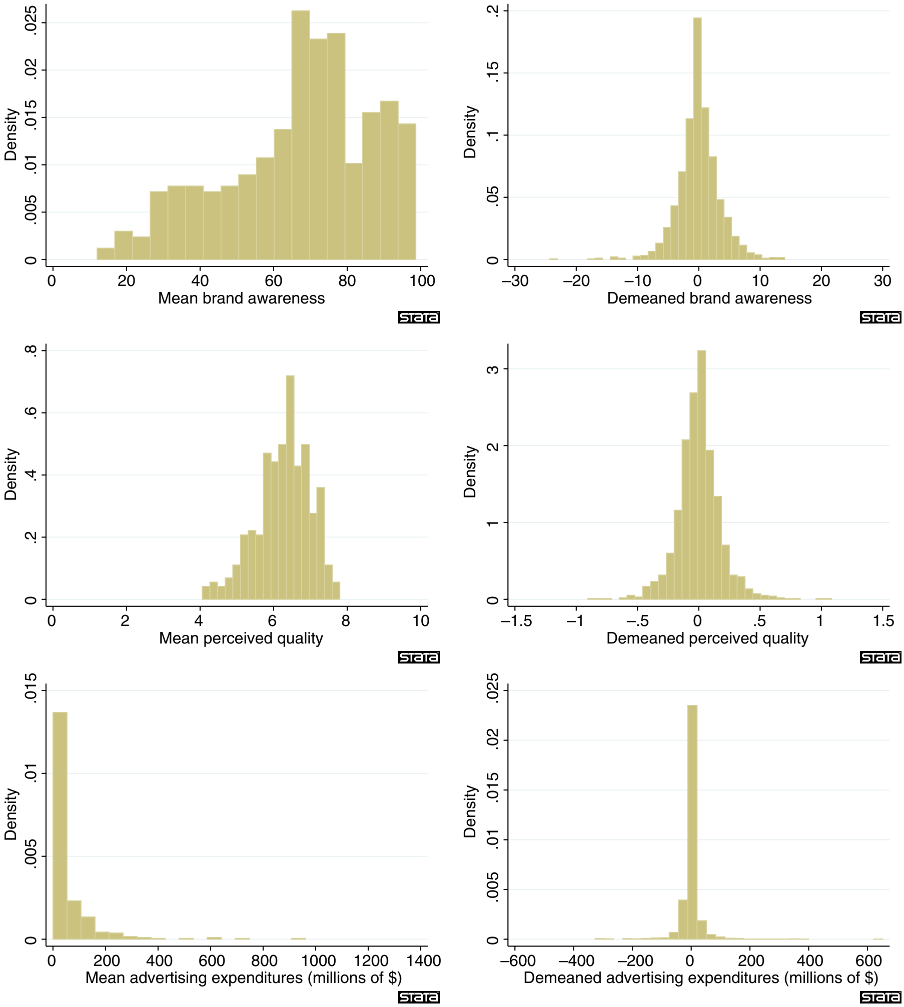


**Fig. 1** Variance decomposition. Histogram of brand-mean of brand awareness, perceived quality, and advertising expenditures (*left panels*) and histogram of de-meaned brand awareness, perceived quality, and advertising expenditures (*right panels*)

the decomposition for the overall sample. The left panels show histograms of the brand-mean of brand awareness, perceived quality, and advertising expenditures and the right panels show histograms of the de-meaned variables. Again it is evident that the time-series variation is substantial for both brand awareness and perceived quality.

## 5 Empirical results

In Tables 4 and 5 we present a number of different estimates for the effect of advertising expenditures on brand awareness and perceived quality,

**Table 4** Brand awareness

| | POLS | FE | DGMM | SGMM |
|---|---|---|---|---|
| Lagged brand awareness | 0.942*** | 0.223*** | 0.679*** | 0.837*** |
| | (0.00602) | (0.0479) | (0.109) | (0.0266) |
| Advertising | 0.00535*** | 0.00687 | 0.0152 | 0.00627** |
| | (0.00117) | (0.00443) | (0.0139) | (0.00300) |
| Advertising$^2$ | −0.00000409*** | −0.00000139 | −0.0000105 | −0.00000524** |
| | (0.000000979) | (0.00000332) | (0.00000745) | (0.00000239) |
| Marginal effect of advertising at: | | | | |
| Mean | 0.00481*** | 0.00668 | 0.0138 | 0.00558** |
| | (0.00107) | (0.00412) | (0.0129) | (0.00269) |
| 25th pctl. | 0.00527*** | 0.00684 | 0.0150 | 0.00617** |
| | (0.00116) | (0.00438) | (0.0138) | (0.00296) |
| 50th pctl. | 0.00514*** | 0.00679 | 0.0147 | 0.00600** |
| | (0.00113) | (0.00430) | (0.0135) | (0.00288) |
| 75th pctl. | 0.00470*** | 0.00664 | 0.0136 | 0.00544** |
| | (0.00105) | (0.00405) | (0.00127) | (0.00263) |
| Advertising test: | | | | |
| $\beta_1 = \beta_2 = 0$ | Reject*** | Do not reject | Do not reject | Reject* |
| Specification tests: | | | | |
| Hansen $J$ | | | Reject*** | Do not reject |
| Difference-in-Hansen $J$ | | | | Do not reject |
| Arellano & Bond $AR(2)$ | | | Reject** | Reject** |
| Arellano & Bond $AR(3)$ | | | Do not reject | Do not reject |
| Goodness of fit measures: | | | | |
| $R^2$-within | | 0.494 | | |
| $R^2$-between | | 0.940 | | |
| $R^2$ | 0.969 | 0.851 | | |
| # obs | 1,148 | 1,148 | 819 | 1,148 |
| # brands | 317 | 317 | 274 | 317 |

Standard errors in parenthesis
$^*p = 0.10$; $^{**}p = 0.05$; $^{***}p = 0.01$

respectively. Starting with the simplest case absent competition, we present estimates of $\gamma$, $\beta_1$, and $\beta_2$ (the coefficients on $Q_{it-1}$ or $A_{it-1}$ and $E_{it-1}$ and $E^2_{it-1}$) along with the marginal effect $\beta_1 + 2\beta_2 E_{it-1}$ calculated at the mean and the 25th, 50th, and 75th percentiles of advertising expenditures.

The POLS estimates in the first column of Tables 4 and 5 suggest a significant positive effect of advertising expenditures on both brand awareness and perceived quality. In both cases we also reject the null hypothesis that advertising plays no role in determining brand awareness and perceived quality ($\beta_1 = \beta_2 = 0$). Of course, as mentioned above, POLS accounts for neither unobserved heterogeneity nor endogeneity. In the next columns of Tables 4 and 5 we present FE, DGMM, and SGMM estimates that attend to these issues.[7]

[7]The estimates use at most 317 out of 348 brands because we restrict the sample to brands with data for two years running but use third and higher lags of brand awareness respectively perceived quality and advertising expenditures as instruments. Different sample sizes are reported for the DGMM and SGMM estimators. Sample size is not a well-defined concept in SGMM since this estimator essentially runs on two different samples simultaneously. The xtabond2 routine in STATA reports the size of the transformed sample for DGMM and of the untransformed sample for SGMM.

**Table 5** Perceived quality

| | POLS | FE | DGMM | SGMM | Objective quality | Brand awareness |
|---|---|---|---|---|---|---|
| Lagged perceived quality | 0.970*** | 0.391*** | 0.659*** | 1.047*** | 0.981*** | 0.937*** |
| | (0.0110) | (0.0611) | (0.204) | (0.0459) | (0.0431) | (0.0413) |
| Brand awareness | | | | | | 0.00596*** |
| | | | | | | (0.00165) |
| Advertising | 0.000218** | 0.0000822 | −0.0000195 | 0.0000219 | 0.0000649 | −0.000298 |
| | (0.0000952) | (0.000198) | (0.000969) | (0.000205) | (0.000944) | (0.000256) |
| Advertising$^2$ | −0.000000133 | 0.0000000408 | 0.000000108 | 0.0000000571 | 0.0000000807 | 0.000000319 |
| | (0.000000107) | (0.000000162) | (0.000000945) | (0.000000231) | (0.00000308) | (0.000000267) |
| Marginal effect of advertising at: | | | | | | |
| Mean | 0.0002** | 0.0000877 | −5.13e−06 | 0.0000295 | 0.0000594 | −0.000256 |
| | (0.0000819) | (0.000180) | (0.000848) | (0.000176) | (0.000740) | (0.000222) |
| 25th pctl. | 0.000215** | 0.000083 | −0.0000174 | 0.0000230 | 0.0000642 | −0.000292 |
| | (0.0000933) | (0.000195) | (0.000952) | (0.000201) | (0.000917) | (0.000251) |
| 50th pctl. | 0.000211** | 0.0000844 | −0.0000139 | 0.0000249 | 0.0000623 | −0.000282 |
| | (0.00009) | (0.000191) | (0.000922) | (0.000194) | (0.000847) | (0.000242) |
| 75th pctl. | 0.0001965** | 0.0000887 | −2.32e−06 | 0.0000310 | 0.0000588 | −0.000248 |
| | (0.0000793) | (0.000177) | (0.000825) | (0.000170) | (0.000714) | (0.000215) |
| Advertising test: | | | | | | |
| $\beta_1 = \beta_2 = 0$ | Reject** | Do not reject | Do not reject | Do not reject | Do not reject | Do not reject |
| Specification tests: | | | | | | |
| Hansen $J$ | | | Do not reject | Reject** | Do not reject | Reject** |
| Difference-in-Hansen $J$ | | | | Reject** | Do not reject | Do not reject |
| Arellano & Bond $AR(2)$ | | | Reject*** | Reject*** | Reject*** | Reject*** |
| Arellano & Bond $AR(3)$ | | | Do not reject | Do not reject | Do not reject | Do not reject |
| Goodness of fit measures: | | | | | | |
| $R^2$-within | | 0.180 | | | | |
| $R^2$-between | | 0.952 | | | | |
| $R^2$ | 0.914 | 0.909 | | | | |
| # obs | 1,148 | 1,148 | 819 | 1,148 | 604 | 1,148 |
| # brands | 317 | 317 | 274 | 317 | 178 | 317 |

Standard errors in parenthesis. SGMM estimates in columns labeled “Objective quality” and “Brand awareness”
$*p = 0.10$; $**p = 0.05$; $***p = 0.01$

Regardless of the class of estimator we find a significant positive effect of advertising expenditures on brand awareness. With the FE estimator we find that the marginal effect of advertising on awareness at the mean is 0.00668. It is borderline significant with a $p$-value of 0.105 and implies an elasticity of 0.00638 (with a standard error of 0.00392). A one-standard-deviation increase of advertising expenditures increase brand awareness by 0.0408 standard deviations (with a standard error of 0.0251). The rate of depreciation of a brand's stock of awareness is estimated to be 1–0.223 or 78% per year. The FE estimator identifies the effect of advertising expenditures on brand awareness solely from the within-brand across-time variation. The problem with this estimator is that it does not deal with the endogeneity of the lagged dependent variable on the right-hand side of Eq. 2 and the potential endogeneity of advertising expenditures. We thus turn to the GMM estimators described in Section 3.

We focus on the more efficient SGMM estimator. The coefficient on the linear term in advertising expenditures is estimated to be 0.00627 ($p$-value 0.037) and the coefficient on the quadratic term is estimated to be $-0.00000524$ ($p$-value 0.028). These estimates support the hypothesis that the relationship between advertising and awareness is nonlinear. The marginal effect of advertising on awareness is estimated to be 0.00558 ($p$-value 0.038) at the mean and implies an elasticity of 0.00533 (with a standard error of 0.00257). A one-standard-deviation increase of advertising expenditures increases brand awareness by 0.0340 standard deviations (with a standard error of 0.0164). The rate of depreciation decreases substantially after correcting for endogeneity and is estimated to be $1-0.828$ or 17% per year, thus indicating that an increase in a brand's stock of awareness due to an increase in advertising expenditures persists for years to come.

The Hansen $J$ test for overidentifying restrictions indicates that the instruments taken together as a group are valid. Recall from Section 3 that we must assume that an extra condition holds in order for the SGMM estimator to be appropriate. The difference-in-Hansen $J$ test confirms that it does, as we cannot reject the null hypothesis that the additional instruments for the level equations are valid. While we reject the hypothesis of no second-order serial correlation in the error terms, we cannot reject the hypothesis of no third-order serial correlation. This result further validates our instrumenting strategy. However, one may still be worried about the SGMM estimates because DGMM uses a strict subset of the orthogonality conditions of SGMM and we reject the Hansen $J$ test for the DGMM estimates (see Table 4). From a formal statistical point of view, rejecting the smaller set of orthogonality conditions in DGMM is not conclusive evidence that the larger set of orthogonality conditions in SGMM are invalid (Hayashi 2000, pp. 218–221).

In Fig. 2 we plot the marginal effect of advertising expenditures on brand awareness over the entire range of advertising expenditures for our SGMM estimates along with a histogram of advertising expenditures. For advertising expenditures between \$400 million and \$800 million per year the marginal effect of advertising on awareness is no longer significantly different from zero

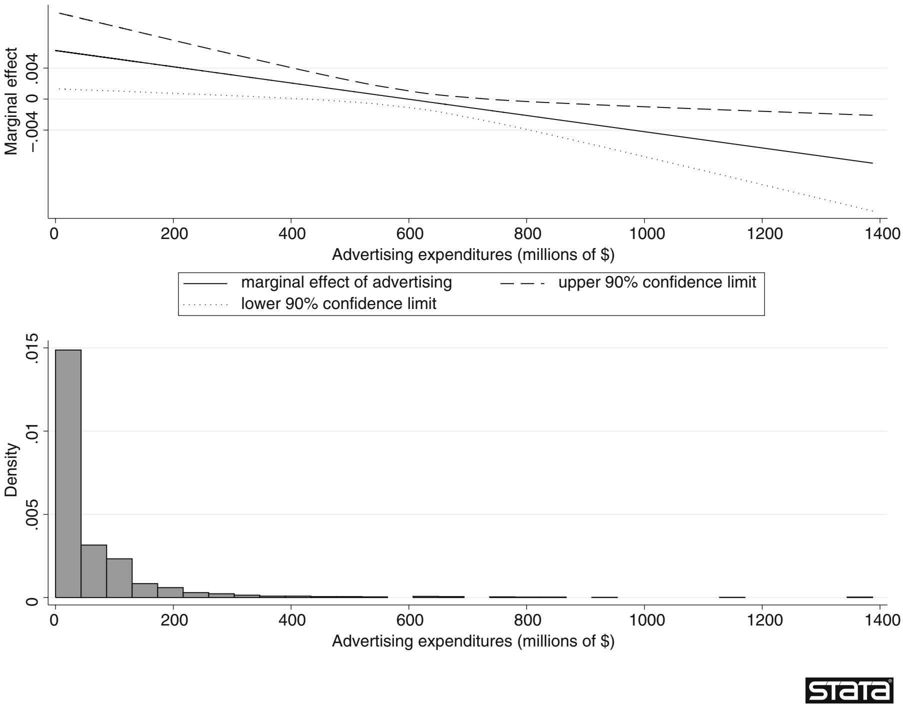


**Fig. 2** Pointwise confidence interval for the marginal effect of advertising expenditures on brand awareness (*upper panel*) and histogram of advertising expenditures (*lower panel*). SGMM estimates

and, statistically, it is actually negative for very high advertising expenditures over $800 million per year. The former case covers around 1.9% of observations and the latter less than 0.5%. One possible interpretation is that brands with very high current advertising expenditures are those that are already well-known (perhaps because they have been heavily advertised over the years), so that advertising cannot further boost their awareness. Indeed, average awareness for observations with over $400 million in advertising expenditures is 74.94 as compared to 69.35 for the entire sample.

Turning from brand awareness in Table 4 to perceived quality in Table 5, we see that the positive effect of advertising expenditures on perceived quality found by the POLS estimator disappears once unobserved heterogeneity is accounted by the FE, DGMM, and SGMM estimators. In fact, we cannot reject the null hypothesis that advertising plays no role in determining perceived quality. Figure 3 graphically illustrates the absence of an effect of advertising expenditures on perceived quality at the margin for our DGMM estimates. While the effect of advertising expenditures on perceived quality is very imprecisely estimated, it appears to be economically insignificant: The implied elasticity is −0.0000534 (with a standard error of 0.00883) and a one-standard-deviation increase of advertising expenditures decrease perceived quality by

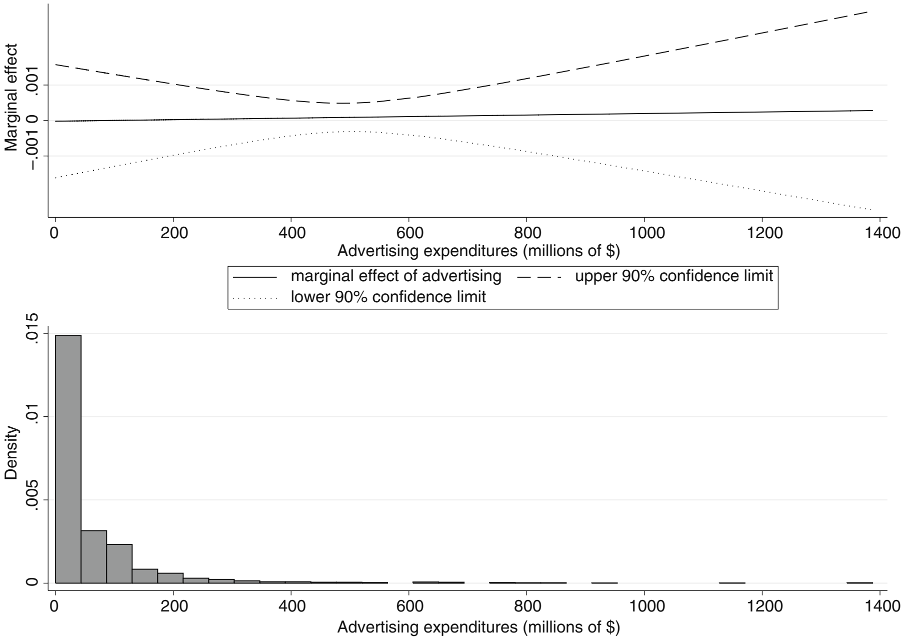


**Fig. 3** Pointwise confidence interval for the marginal effect of advertising expenditures on perceived quality (*upper panel*) and histogram of advertising expenditures (*lower panel*). DGMM estimates

0.000869 standard deviations (with a standard error of 0.144). Note that the comparable effects for brand awareness are two orders of magnitude larger. Much of the remainder of this paper is concerned with demonstrating the robustness of this negative result.

Before proceeding we note that whenever possible we focus on the more efficient SGMM estimator. Unfortunately, for perceived quality in many cases, including that in the fourth column of Table 5, the difference-in-Hansen $J$ test rejects the null hypothesis that the extra moments in the SGMM estimator are valid. In these cases we focus on the DGMM estimator.

## 5.1 Objective and perceived quality

An important component of a brand's perceived quality is its objective quality. To the extent that objective quality remains constant, it is absorbed into the brand effects. But, even though the time frame of our sample is not very long, it is certainly possible that the objective quality of some brands has changed over the course of our sample. If so, then the lack of an effect of advertising expenditures on perceived quality may be explained if brand managers increase advertising expenditures to compensate for decreases in objective quality. To the extent that increased advertising expenditures and decreased objective quality cancel each other out, their net effect on perceived quality may be zero.

The difficulty with testing this alternative explanation is that we do not have data on objective quality. We therefore exclude from the analysis those categories with brands that are likely to undergo changes in objective quality (appliances, automobiles, computers, consumer electronics, fast food, footwear, pharmaceutical OTC, telecommunications, toys, and travel). The resulting estimates are reported in Table 5 under the heading "Objective quality." We still find no effect of advertising expenditures on perceived quality.[8]

## 5.2 Variation in perceived quality

Another possible reason for the lack of an effect of advertising expenditures on perceived quality is that perceived quality may not vary much over time. This is not the case in our data. Indeed, the standard deviation of the year-to-year changes in perceived quality is 0.2154.

Even for those products whose objective quality does not change over time there are important changes in perceived quality (standard deviation 0.2130). For example, consider bottled water where we expect little change in objective quality over time, both within and across brands. Nonetheless, there is considerable variation in perceived quality. The perceived quality of Aquafina Water ranges across years from 6.33 to 6.90 and that of Poland Spring Water from 5.91 to 6.43, so the equivalent of over two standard deviations. Across the brands of bottled water the range is from 5.88 to 6.90, or the equivalent of over four standard deviations.

Further evidence of variation in perceived quality is provided by the automobiles category. Here we have obtained measures of objective quality from Consumer Reports that rate vehicles based on their performance, comfort, convenience, safety, and fuel economy. We can find examples of brands whose objective quality does not change at least for a number of years while their perceived quality fluctuates considerably. For example, Chevy Silverado's objective quality does not change between 2000 and 2002, but its perceived quality increases from 6.08 to 6.71 over these three years. Similarly, GMC Sierra's objective quality does not change between 2001 and 2003, but its perceived quality decreases from 6.72 to 6.26.

The final piece of evidence that we have to offer is the variance decomposition from Section 4 (see again Table 3 and Fig. 1). Recall that the across-brands standard deviation of brand awareness is about six times larger than the within-brand standard deviation. In case of perceived quality the ratio is about 4. Hence, while there is more cross-sectional than time-series variation in our sample, the time-series variation is substantial for both brand aware-

[8]The marginal effects are calculated at the mean, 25th, 50th, and 75th percentile for advertising for the brands in the categories judged to be stable in terms of objective quality over time.

ness and perceived quality. Also recall from Section 4 that perceived quality with an intertemporal correlation of 0.95 is somewhat less persistent than brand awareness with an intertemporal correlation of 0.98. Given that we are able to detect an effect of advertising expenditures on brand awareness, it seems unlikely that insufficient variation within brands can explain the lack of an effect of advertising expenditures on perceived quality; instead, our results suggest that the variation in perceived quality is unrelated to advertising expenditures.

The question then becomes what besides advertising may drive these changes in perceived quality. There are numerous possibilities, including consumer learning and word-of-mouth effects. Unfortunately, given the data available to us, we cannot further explore these possibilities.

### 5.3 Brand awareness and perceived quality

Another concern is that consumers may confound awareness and preference. That is, consumers may simply prefer more familiar brands over less familiar ones (see Zajonc 1968). To address this issue we proxy for consumers' familiarity by adding brand awareness to the regression for perceived quality. The resulting estimates are reported in Table 5 under the heading "Brand awareness." While there is a significant positive relationship between brand awareness and perceived quality, there is still no evidence of a significant positive effect of advertising expenditures on perceived quality.

### 5.4 Competitive effects

Advertising takes place in a competitive environment. Most of the industries being studied here are indeed oligopolies, which suggests that strategic considerations may influence advertising decisions. We next allow a brand's stocks of awareness and perceived quality to be affected by the advertising of its competitors as discussed in Section 2.[9] Competitors' advertising, in turn, can enter our estimation Eqs. 1 and 2 either relative in the share-of-voice specification or absolute in the total-advertising specification. We report the resulting estimates in Table 6.

Somewhat surprisingly, the share-of-voice specification yields an insignificant effect of own advertising. We conclude that the share-of-voice specification is simply not an appropriate functional form in our application. The total-advertising specification readily confirms our main findings presented above that own advertising affects brand awareness but not perceived quality. This is true even if we allow competitors' advertising to enter quadratically in

[9]For this analysis we take the subcategory rather than the category as the relevant competitive environment. Consider for instance the beer, wine, liquor category. There is no reason to expect the advertising expenditures of beer brands to affect the perceived quality or awareness of liquor brands. We drop any subcategory in any year where there is just one brand due to the lack of competitors.

**Table 6** Competitive effects

| | Share of voice | | Total advertising | |
|---|---|---|---|---|
| | Brand awareness | Perceived quality | Brand awareness | Perceived quality |
| Lagged awareness/quality | 0.872*** | 1.068*** | 0.845*** | 0.356** |
| | (0.0348) | (0.0406) | (0.0217) | (0.145) |
| Relative advertising | 0.236 | 0.0168 | | |
| | (0.170) | (0.0164) | | |
| (Relative advertising)$^2$ | −0.00912 | −0.00102 | | |
| | (0.0104) | (0.00132) | | |
| Advertising | | | 0.00892** | −0.0000180 |
| | | | (0.00387) | (0.000592) |
| Advertising$^2$ | | | −0.00000602** | −0.0000000303 |
| | | | (0.00000248) | (0.000000535) |
| Competitors' advertising | | | −0.00609* | 0.00128** |
| | | | (0.00363) | (0.000515) |
| Marginal effect of advertising at: | | | | |
| Mean | 0.00333 | 0.000225 | 0.00812** | −0.000140 |
| | (0.00239) | (0.000218) | (0.00355) | (0.000524) |
| 25th pctl. | 0.0164 | 0.00113 | 0.00881** | −0.0000174 |
| | (0.01218) | (0.00110) | (0.00382) | (0.000582) |
| 50th pctl. | 0.00624 | 0.00429 | 0.00861** | −0.0000164 |
| | (0.00448) | (0.000416) | (0.00375) | (0.000565) |
| 75th pctl. | 0.00264 | 0.000179 | 0.00797** | −0.0000132 |
| | (0.00190) | (0.000173) | (0.00349) | (0.000510) |
| Advertising test: | | | | |
| $\beta_1 = \beta_2 = 0$ | Do not reject | Do not reject | Reject** | Do not reject |
| Specification tests: | | | | |
| Hansen $J$ | Do not reject | Reject* | Do not reject | Do not reject |
| Difference-in-Hansen $J$ | Do not reject | Do not reject | Do not reject | |
| Arellano & Bond $AR(2)$ | Reject** | Reject*** | Reject** | Reject*** |
| Arellano & Bond $AR(3)$ | Do not reject | Do not reject | Do not reject | Do not reject |
| # obs | 1,147 | 1,147 | 1,147 | 1,147 |
| # brands | 317 | 317 | 317 | 317 |

Standard errors in parenthesis. DGMM estimates in column labeled "Total advertising/perceived quality" and SGMM estimates otherwise
$^{*}p = 0.10$; $^{**}p = 0.05$; $^{***}p = 0.01$

addition to linearly. Competitors' advertising has a significant negative effect on brand awareness and a significant positive effect on perceived quality.

Repeating the analysis using the sum instead of the average of competitors' advertising yields largely similar results except that the share-of-voice specification yields a significant negative effect of advertising on brand awareness, thereby reinforcing our conclusion that this is not an appropriate functional form.[10]

Overall, the inclusion of competitors' advertising does not seem to influence our results about the role of own advertising on brand awareness and perceived quality. This justifies our focus on the simple model without competition. Moreover, it suggests that the following alternative explanation for our main findings presented above is unlikely. Suppose awareness depended positively on the total amount of advertising in the brand's subcategory or category while perceived quality depended positively on the brand's own advertising but negatively on competitors' advertising. Then the results from the simple model without competition could be driven by an omitted variables problem: If the brand's own advertising is highly correlated with competitors' advertising, then we would overstate the impact of advertising on awareness and understate the impact on perceived quality. In fact, we might find no impact of advertising on perceived quality at all if the brand's own advertising and competitors' advertising cancel each other out.

### 5.5 Category-specific effects

Perhaps the ideal data for analyzing the effect of advertising are time series of advertising expenditures, brand awareness, and perceived quality for the brands being studied. With long enough time series we could then try to identify for each brand in isolation the effect of advertising expenditures on brand awareness and perceived quality. Since such time series are unfortunately not available, we have focused so far on the aggregate effect of advertising expenditures on brand awareness and perceived quality, i.e., we have constrained the slope parameters in Eqs. 1 and 2 that determine the effect of advertising to be the same across brands. Similarly, we have constrained the carryover parameters in Eqs. 1 and 2 that determine the effect of lagged perceived quality and brand awareness respectively to be the same across brands.

As a compromise between the two extremes of brands in isolation versus all brands aggregated, we first examine the effect of advertising in different categories. This adds some cross-sectional variation across the brands within a

[10]We caution the reader against reading too much into these results: The number and identity of the brands within a subcategory or category varies sometimes widely from year to year in the Brandweek Superbrands surveys. Thus, the sum of competitors' advertising is an extremely volatile measure of the competitive environment. Moreover, the number of brands varies from 3 for some subcategories to 10 for others, thus making the sum of competitors' advertising difficult to compare across subcategories.

**Table 7** Category-specific effects

| | Brand awareness | | Perceived quality | |
|---|---|---|---|---|
| | Marginal effect | Carryover rate | Marginal effect | Carryover rate |
| Appliances | 0.0233 | 0.838*** | 0.00374 | 0.880*** |
| | (0.0167) | (0.0730) | (0.00315) | (0.0413) |
| Automobiles | 0.00526 | 0.840*** | 0.000172 | 0.854*** |
| | (0.0154) | (0.0402) | (0.000864) | (0.0476) |
| Beer, wine, liquor | −0.0264 | 0.839*** | −0.000988 | 0.811*** |
| | (0.0423) | (0.0408) | (0.00535) | (0.0553) |
| Beverages | −0.0245 | 0.869*** | −0.000564 | 0.877*** |
| | (0.0554) | (0.0265) | (0.00567) | (0.0463) |
| Computers | 0.0193** | 0.799*** | 0.000722 | 0.826*** |
| | (0.00777) | (0.0370) | (0.000470) | (0.0488) |
| Consumer electronics | 0.0210** | 0.810*** | 0.00189*** | 0.849*** |
| | (0.00931) | (0.0361) | (0.000518) | (0.0445) |
| Cosmetics and fragrances | −0.104* | 0.766*** | 0.000874 | 0.862*** |
| | (0.557) | (0.0521) | (0.00141) | (0.0545) |
| Credit cards | 0.00983* | 0.834*** | 0.000231 | 0.853*** |
| | (0.00527) | (0.0371) | (0.000222) | (0.0514) |
| Fast food | 0.0144*** | 0.859*** | 0.000727*** | 0.849*** |
| | (0.00543) | (0.0262) | (0.000207) | (0.0530) |
| Food | 0.0296 | 0.869*** | 0.00287 | 0.873*** |
| | (0.0371) | (0.0301) | (0.00390) | (0.0432) |
| Footwear | −0.0120 | 0.830*** | 0.00390*** | 0.878*** |
| | (0.0248) | (0.0622) | (0.00139) | (0.0498) |
| Health and beauty | 0.0841*** | 0.875*** | 0.00665*** | 0.879*** |
| | (0.0319) | (0.0278) | (0.00188) | (0.0441) |
| Household | 0.0743 | 0.862*** | 0.00914*** | 0.876*** |
| | (0.0670) | (0.0317) | (0.00296) | (0.0434) |
| Petrol | −0.0600 | 0.847*** | 0.00433 | 0.852*** |
| | (0.0676) | (0.0357) | (0.00266) | (0.0505) |
| Pharmaceutical OTC | 0.0147 | 0.840*** | 0.00329 | 0.866*** |
| | (0.206) | (0.0604) | (0.00253) | (0.0437) |
| Pharmaceutical prescription | −0.00683 | 0.751*** | −0.00488** | 0.800*** |
| | (0.0355) | (0.0747) | (0.00199) | (0.0521) |
| Telecommunications | 0.0105 | 0.800*** | 0.000203 | 0.766*** |
| | (0.0117) | (0.0361) | (0.000497) | (0.0728) |
| Toys | 0.0574 | 0.815*** | 0.0000834 | 0.862*** |
| | (0.0673) | (0.0761) | (0.00116) | (0.0715) |
| Travel | −0.0982 | 0.832*** | 0.00603 | 0.861*** |
| | (0.104) | (0.0415) | (0.00518) | (0.0465) |

Marginal effect of advertising expenditures on brand awareness and perceived quality at mean by category. Carryover rate by category. Standard errors in parenthesis. SGMM estimates
$*p = 0.10$; $**p = 0.05$; $***p = 0.01$

category. As the first column of Table 7 shows, for the majority of categories, there is nevertheless insufficient variation to identify an effect of advertising even on awareness: There is a significant positive effect of advertising expenditures on brand awareness for five categories. At the same time, there is a significant positive effect on perceived quality for five categories (third column).

Two caveats are in order. First, we may be capturing the relationship between advertising expenditures and perceived quality across brands: Because the SGMM estimator adds the equations in levels, it relies on more of the cross-sectional variation for identification. Indeed, the FE estimator that relies solely on variation over time within brands detects a significant positive effect of advertising expenditures on perceived quality for just two categories. Second, we are pushing the limit on the number of instruments. Indeed, we are unable to obtain estimates unless we collapse the set of instruments, creating one instrument for each variable and lag, rather than one for each period, variable, and lag.

Second we examine the carryover rate in different categories. As the second column of Table 7 shows, the rate of depreciation for brand awareness ranges from 1−0.875 or 12% for health and beauty to 1−0.751 or 25% for pharmaceutical prescription. For perceived quality the rate of depreciation similarly ranges from 1−0.880 or 12% for appliances to 1−0.766 or 23% for telecommunications (fourth column). Surprisingly, the SGMM estimates indicate that, once we allow for the carryover rate to vary by category, advertising expenditures have a positive significant effect on perceived quality (0.00106 at the mean), although this is not the case for the FE estimates.

In sum, it appears that there are important differences between categories. These differences, in turn, may help to explain why some brands advertise heavily despite already enjoying a high level of brand awareness. A case in point is the fast food category. On average, this category exhibits the highest level of brand awareness and the second-highest level of advertising expenditures after telecommunications (see again Table 2). A brand has an incentive to put substantial resources into advertising if it either has a particularly high response to advertising or a particularly high rate of depreciation. For brands in the fast food category the rate of depreciation is 1−0.859 or 14% for brand awareness (compared to 1−0.837 or 16% in the overall sample) and 1−0.849 or 15% for perceived quality. At the same time, however, the marginal effect of advertising expenditures is 0.0144 for brand awareness (compared to 0.00558 in the overall sample) and 0.000727 for perceived quality. Hence, the response to advertising is particularly high for both brand awareness and perceived quality.

## 5.6 Functional form

Throughout we consider a quadratic functional form for the effect of the level of advertising expenditures on the level of brand awareness and perceived quality. In Table 8 we report results for the estimation of Eqs. 1 and 2 using different functional forms.

We first consider the case of $f(E_{it-1}) = \beta_1 \ln E_{it-1} + \beta_2 (\ln E_{it-1})^2$.[11] There is no effect of advertising expenditures on brand awareness and we find a negative effect of advertising on perceived quality. This may indicate that this functional form is not appropriate in our application.

Next we allow for a quadratic relationship between the level of advertising expenditures on the one hand and the log of brand awareness and perceived

[11]The number of observations differs slightly across specifications because the logarithm of zero is not defined. Our conclusions remain unchanged if we replace $\ln E_{jt-1}$ by $\ln(c + E_{jt-1})$, where $c > 0$ is a constant, in order to be able to use all observations.

**Table 8** Functional form

| | Brand awareness | Perceived quality | ln(brand awareness) | ln(perceived quality) |
|---|---|---|---|---|
| Lagged awareness/quality | 0.886*** | 0.680*** | | |
| | (0.0459) | (0.226) | | |
| Lagged ln(awareness)/ln(quality) | | | 0.825*** | 0.666*** |
| | | | (0.0281) | (0.201) |
| ln(advertising) | −0.119 | −0.00557 | | |
| | (0.775) | (0.0596) | | |
| ln(advertising)$^2$ | −0.00137 | −0.0337* | | |
| | (0.108) | (0.0190) | | |
| Advertising | | | 0.000136** | −0.0000143 |
| | | | (0.0000526) | (0.000146) |
| Advertising$^2$ | | | −0.000000115*** | 3.13e−08 |
| | | | (4.14e−08) | (0.000000152) |
| Marginal effect of advertising at: | | | | |
| Mean | −0.00197 | −0.00435** | 0.000120** | −0.0000102 |
| | (0.00612) | (0.00211) | (0.0000473) | (0.000127) |
| 25th pctl. | −0.0131 | −0.0166** | 0.000133** | −0.0000137 |
| | (0.0424) | (0.00800) | (0.0000518) | (0.000143) |
| 50th pctl. | −0.00494 | −0.00869** | 0.000130** | −0.0000127 |
| | (0.0134) | (0.00414) | (0.0000505) | (0.0000138) |
| 75th pctl. | −0.00165 | −0.00379** | 0.000117** | −0.00000937 |
| | (0.00539) | (0.00184) | (0.0000463) | (0.0000123) |
| Advertising test: | | | | |
| $\beta_1 = \beta_2 = 0$ | Do not reject | Do not reject | Reject** | Do not reject |
| Specification tests: | | | | |
| Hansen $J$ | Reject*** | Do not reject | Reject** | Do not reject |
| Difference-in-Hansen $J$ | Reject** | | Do not reject | |
| Arellano & Bond $AR(2)$ | Reject** | Reject*** | Do not reject | Reject*** |
| Arellano & Bond $AR(3)$ | Do not reject | Do not reject | Do not reject | Do not reject |
| # obs | 1,123 | 795 | 1,148 | 819 |
| # brands | 312 | 267 | 317 | 274 |

Standard errors in parenthesis. SGMM estimates in columns labeled “Brand awareness” and “ln(brand awareness)” and DGMM estimates in columns labeled “Perceived quality” and “ln(perceived quality)”

$^*p = 0.10$; $^{**}p = 0.05$; $^{***}p = 0.01$

quality on the other hand. As Table 8 shows, we still find no effect of advertising expenditures on the log of perceived quality. In contrast, we find a positive effect of advertising on the log of brand awareness.

## 6 Discussion

To our knowledge this is the first study to make use of panel data on a wide range of brands along with recently developed methods for estimating dynamic models to study the effect of advertising on brand awareness and perceived quality. Our panel data allow us to control for the unobserved heterogeneity across brands and to identify the effect of advertising off time-series variation within brands. They also let us account for the endogeneity of advertising.

Our main findings are that advertising expenditures have a significant positive effect on a brand's stock of awareness but no significant effect on its stock of perceived quality. These findings are consistent with previous empirical work and laboratory experiments. The results in Ackerberg (2001), for example, indicate that the primary effect of advertising for the particular brand of yogurt being studied is that of informing consumers. However, the importance of information may vary with the stages of a product's life cycle. Narayanan and Manchanda (2008) find that the responsiveness of physicians to the informative content of detailing and the responsiveness to the persuasive content are negatively correlated over time. Mitra and Lynch (1995) show that, especially in mature product categories, advertising has a much stronger effect on the size of the consideration set than on the relative strength of preferences.

Our research complements and generalizes existing studies by Shachar and Anand (1998), Ackerberg (2001), Narayanan et al. (2005), and Narayanan and Manchanda (2008) that apply econometric models to discern the role of advertising for a single brand or industry. The key idea used in these studies to distinguish between informative and persuasive advertising is that informed consumers should not be affected (or as affected) by informative advertising as uninformed consumers whereas the effect of persuasive advertising should be independent of the amount of information that is available to consumers. The difficulty lies in identifying the amount of information that is available to consumers. The common approach is to proxy for available information with usage experience: once consumers have used the brand, they must be aware of its existence and should know its characteristics, so informative advertising should not affect them any more. Since usage experience is often not directly observable, this empirical strategy is largely limited to newly introduced brands.[12]

[12] Anand and Shachar (2004) pursue a different methodology that is not limited to newly introduced brands, although the data requirement may prevent more wide-spread application. Their study of advertising for television shows in the form of previews highlights advertising as a vehicle of matching and information rather than an instrument of persuasion.

The current paper contributes to our understanding of the nature of advertising in two ways. By using data on over 300 brands across 19 product categories, we are able to say something more general about the effect of advertising than just for a single brand or industry. In addition, our direct measures of the level of information possessed by consumers and of their quality perceptions allow us to study the channel through which advertising affects consumer choice without making assumptions about the amount of information that is available to consumers on the basis of their purchase behavior.

While our main findings highlight advertising as a means of providing information to consumers, there are important differences between categories. In some categories at least advertising may also be a means of altering quality perceptions. This conclusion suggest that a long enough time series on advertising expenditures, perceived quality, and brand awareness may prove ideal to identify and quantify the various effects of advertising for a specific category (or even for specific brand) in isolation. At the same time, however, our results hint at the role of the competitive environment that cannot be adequately captured without a broad enough cross section.

It is furthermore important to note that our analysis focuses on the short-run relationship between advertising expenditures, brand awareness, and perceived quality. That is, we can only say that advertising has no short-run influence on perceived quality. Again this is dictated by the data. It is of course still possible that advertising affects perceived quality, but only after a period of time. On the other hand, given that we have six years worth of data, the short run in our model is fairly long. It is unclear whether, in practice, the time horizon of firms is much longer than that. Therefore, even if advertising had an effect in the long run, brand managers may not be willing to expend resources today in order to reap benefits that are that far in the future.

Our findings may also help to resolve the puzzling fact that advertising has little effect on sales (e.g., Assmus et al. 1984; Lodish et al. 1995). Recall that sales are measured as quantity sold times sales price. Since our results suggest that advertising has no effect on perceived quality, it presumably has no effect on consumers' willingness to pay. On the contrary, by making consumers aware of more brands, advertising should be procompetitive and put downward pressure on prices. Hence, if price decreases sufficiently, then sales remain constant or even decrease in response to advertising even if quantity increases.[13] Investigating this question further presents a promising venue for further research.

[13] A long standing problem in estimating the effect of advertising on sales is the so-called data interval bias (Clarke 1976). The impact of advertising is misestimated to the extent that the flow of sales and the flow of advertising are not properly matched up over the course of a period. In our setting, the dependent variables are a brand's stocks of perceived quality and awareness. This may mitigate the data interval bias because these stocks encompass all current and previous flows and thus are more likely to pick up the impact of advertising.

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