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Advertising Effects Under Consumer Heterogeneity – The Moderating Role of Brand Experience, Advertising Recall and Attitude

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Abstract

Measuring the effects of advertising on consumers' purchase decisions is an important yet difficult task in retailing because the effect can depend on both current and past advertising efforts and on the co-occurrence of other marketing instruments. Consumers may have different evaluations and preferences for advertising that can determine its effectiveness, and these can change over time based on factors such as recall of and attitude toward advertisements. The proposed econometric framework examines the purchase decisions of potentially heterogeneous consumers by means of the widely used random coefficient logit model for aggregate sales and information about perceptions of advertising at the consumer level, that is, tracking data. These tracking data assess individual responses to two consumer metrics that are related to consumers' (I) recent experience with the consumption of the brand and (II) recall and appreciation of advertisements. The empirical application indicates that both consumer metrics and heterogeneity can be important for retailing researchers and managers by revealing the effects of advertising and determining the influence of other marketing instruments, such as price.

Keywords: Advertising effects; Random coefficient logit; Store-level sales; Consumer-level tracking; Consumer metrics; Pricing

Motivation

A central problem in retailing and related fields is measuring the effect of marketing instruments, such as advertising activities, on actual sales of consumer goods. Both managers and academics need to quantify these effects on consumer behavior due to explicit and implicit reasons. First, retailers are interested in determining their own advertising efforts or those conducted in collaboration with brand advertisers to determine the outcomes in proportion to efforts or to improve strategic planning. For retailers, it is also implicitly relevant to evaluate and disentangle in the presence of advertising the effect of other marketing instruments such as prices on consumer demand and substitution patterns. Relevant economic outcomes of advertising efforts for fast-moving consumer goods are in general purchases at retail stores. However, for several reasons, the link between advertising activities and consumer purchase decisions is typically difficult to establish in practice. (a) Advertising strategies develop in a dynamic and competitive setting in which their effects carry over into the future, and a consumer's contact with advertising often diverges from the actual moment of purchase at the retailer. (b) Accounting for advertising efforts is complicated by the co-occurrence of a brand's other marketing instruments and its competitors' marketing instruments. (c) Most importantly, it is well known that consumers can have individual specific and heterogeneous sensitivities to marketing efforts in general, such as for prices or promotions (e.g., Rossi and Allenby 1993; Zenetti and Otter 2014). Therefore, the effectiveness of advertising may differ among individual consumers.

This paper proposes an approach that jointly accounts for issues (a)–(c), particularly with the help of consumer metrics, such as consumers' previous experiences with the brand and their recall of and attitude toward advertising. Advertising effectiveness can theoretically be affected by these measures. Consequently, this study addresses two relevant research questions. *(RQ1) First, the paper investigates the impact of potential heterogeneity in preferences and consumer metrics (that is, a*

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consumer's recall of and attitude toward a brand's advertising and a consumer's recent experience with the brand) on the measurement of advertising effectiveness. (RQ2) Second, the study examines the relevance of this investigation in terms of economic implications by elasticities of demand.

In contrast to previous research, we allow for heterogeneity of preferences and consumer metrics in the analysis of advertising effects on the individual purchase decision. For this purpose, the random coefficient logit model for aggregate data serves as the basis for the analysis. Within this setup, the consumer utility can be subject to both current and past advertising via a goodwill stock in which goodwill and its effects may be altered by consumers' perceptions of advertising. Despite the popularity of the model, there is, to the best of our knowledge, no such approach in the literature. The outcomes of an empirical example show that considering consumer metrics and heterogeneous advertising effects may considerably improve the assessment of advertising effectiveness and their implications for managerial decisions. Therefore, practitioners and academics should carefully examine whether leaving aside heterogeneous consumer metrics is appropriate.

The remainder of this paper is structured as follows. First, we outline the background and details of the measurement of advertising effects in the literature, the proposed conceptual framework of this approach and the hypothesized expected effects. After detailing the elements of investigation of our approach by means of an empirical example, we outline the methodological framework and its practical implementation. Subsequently, the paper discusses the results of the empirical application and concludes with a summary, retailing implications and areas for future research.

Background and Overview

Measuring Advertising Effects in the Literature

In many product categories, firms budget invest considerably large budgets in advertising. Usually, the purchases made by consumers are the most relevant outcomes of advertising efforts (Manchanda et al. 2006). Based on theoretical grounds, discrete choice models – in which consumers choose among several purchase options or opt not to buy – are well established in the analysis of demand for differentiated products using aggregate data in quantitative retailing and marketing research (e.g., Berry 1994; Chintagunta and Nair 2011). A choice model that allows us to account for consumers' individual and, therefore, heterogeneous preferences is the random coefficient logit model (Berry, Levinsohn, and Pakes 1995). According to Park and Gupta (2011), this model has become the "most widely used approach for analyzing differentiated product markets." In this context, the concept of goodwill, which is defined as an accumulation of past advertising efforts, has been shown to be an appropriate link between consumer utility and advertising (e.g., Dubé, Hitsch, and Manchanda 2005). Goodwill depreciates over each period, and advertising provides a means to replenish goodwill. A criticism in this area is that research results may be driven by the structure of the model rather than by variation in the data. For instance, the data analyst must make assumptions about how advertising effectiveness changes over time, because of different amounts of past spendings and shifts due to changes in consumers' evaluations and perceptions of an advertisement.

Advertising agencies or brand managers often focus on directly available measures of consumer metrics, such as aided advertising recall, attitude toward advertising or previous brand experience. The consumer metrics in our empirical example are related to theoretical advertising effectiveness (e.g., Danaher and Mullarkey 2003; De Pelsmacker, Geuens, and Anckaert 2002; Till and Baack 2005; Zenetti et al. 2014). Based on a comprehensive literature review, Vakratsas and Ambler (1999) conclude that advertising effectiveness is driven by the theoretical three-dimensional space of cognition, affection, and experiences related to a brand or product (cf. Hilgard 1980). The cognitive dimension of advertising effectiveness refers to information processing through thinking and mental activity and is typically measured by unaided or aided recall or awareness (Aaker 1991; Barry and Howard 1990). The affective component of advertising effectiveness represents the emotion-based attitudes and internal feelings of a consumer toward the advertisement (Barry and Howard 1990) and can be accounted for in terms of the attitude, liking/appreciation, and desire induced by advertising (Batra and Ray 1986; Cohen, Pham, and Andrade 2008). The conative dimension expresses intended or actual behavior with respect to previous experience and is measured, for example, by consumers' previous experiences or purchase intentions (Barry and Howard 1990; Vakratsas and Ambler 1999).

Approach of this Research

In the empirical analysis of this paper, we investigate advertising effects on consumer purchases of fast-moving consumer goods (collected from retail store checkouts). Thereby, we consider information from surveys of consumers (from approximately 6,700 respondents) gathered by a market research agency on behalf of a national brand manufacturer. In practice, larger manufacturers of consumer goods typically collect disaggregated information from representative samples of consumers on a regular basis, which is known as "tracking data", to monitor or evaluate consumer perceptions and preferences (cf. e.g., Bruce, Peters, and Naik 2012; KloseDetering 2001). This information source is available for many product categories, but firms may not take full advantage of its potential. Note that repeatedly surveying samples of different consumers avoids bias from the so-called mere-measurement effect (cf. Dholakia and Morwitz 2002; Morwitz and Fitzsimons 2004; Morwitz, Johnson, and Schmittlein 1993), which would otherwise occur when repeatedly surveying participants in longitudinal consumer panels about, for instance, their recall of advertisements. The interviews contain a set of consumer metrics that reflect the theoretically important dimensions of advertising effectiveness, namely, aided advertising recall (*AdRecall*), attitude toward advertising (*Aad*) and previous brand experience (*BrandExprc*) (e.g., Danaher and Mullarkey 2003; De Pelsmacker, Geuens, and Anckaert 2002; Li 2013; Till and Baack 2005). The details of the consumer metrics are outlined in *Example Application* section.[1]

From the literature, we conclude that (i) in general, advertising effectiveness may critically depend on consumer metrics, that is, *BrandExprc*, *AdRecall* and *Aad*, which are (ii) potentially heterogeneous across consumers. Moreover, (iii) the consumer metrics may be unstable over time because of general variations in consumers' perceptions and preferences, wear-in and wear-out effects and threats of competitor advertising (cf. Bass et al. 2007). Our approach permits us to address points (i)–(iii). Because the framework nests restrictions to homogeneous consumer preferences, the analysis allows to statistically test whether, for example, the effects of advertising and the impacts of consumer metrics are the same across consumers.

Note that the approach particularly differs from the related work of Srinivasan, Vanhuele, and Pauwels (2010), Bruce, Peters, and Naik (2012) and Hanssens et al. (2014), who provide interesting and important results by means of similar demand shifters. These studies employ time series models to analyze the dynamics and dependencies of sales and marketing instruments, and in contrast to our approach, they rely solely on aggregate consumer metrics. This means that consumer metrics and preferences for advertising are restricted to be the same across consumers.

In general, the concept of this paper also differs from "model-free" analyses. Our framework is based on the economic theory of consumer purchase decisions and demand, that is, the micro-foundations of economic product choice. Logit choice models are well established in the economic literature because they provide a link to the theory of utility-maximizing consumers, thereby enabling an economic interpretation of the parameters within an established theoretical framework (Chintagunta and Nair 2011; Dubé et al. 2002). The general effect of advertising on utility is derived from the concept of goodwill, and the effectiveness of advertising can be subject to theoretically important and potentially heterogeneous effects of consumer metrics. This means that our general structural setup is distinctively different from a data-driven or statistical perspective wherein a data analyst is concerned only with the statistical fit of an analysis to the data and may therefore apply "any" available data as an explanatory variable, interactions, or both of these variables with price, advertising or higher-order polynomials in an approximation of the underlying economic structure (cf. e.g., Allenby, Garratt, and Rossi 2010). It also implies that our approach can be integrated into the canon of econometric aggregate choice analysis.

[1] Note that the term "attitude toward advertising" can account for both the cognitive and affective aspects of advertising effectiveness based on the definition of the set of "thoughts and feelings consumers have about an ad" (Kirmani and Campbell 2009; Shimp 1981). Both components are theoretically distinct but can be practically interrelated. In general, the cognitive and affective components of advertising effectiveness can be intermingled due to the operationalization of the measure, as is the case in our data set. The respondents can only insightfully evaluate their affective attitude toward an advertisement if they recall having seen that advertisement (see *Example Application* section).

Schematic Overview and Hypotheses

Fig. 1 provides a schematic overview of the conceptual framework introduced above. This outline illustrates how the elements of the framework are interlaced within the exploration of advertising effects on the purchase decisions of heterogeneous consumers and presents the hypothesized effects (see below).

The econometric approach of this paper is straightforward and conceptually simple: consumer metrics that are related to the theoretical dimensions of advertising effectiveness may alter the direction and strength of the relation between advertising and consumer utility and choice decision.[2] Doing so makes intuitive sense: more advertising may increase the likelihood of a purchase (and increase utility). Given that consumers can have different perceptions and evaluations of advertising, we consider that the effectiveness of advertising may differ across consumers. Note that we also test for further proximate direct effects of consumer metrics on utility in our empirical example, which implies that there might be effects without advertising efforts. In our application, we found insufficient empirical evidence of such a relationship. Without the support of advertising, consumer metrics show only limited effects (see *Results of the Empirical Example* section).

In the following, we develop hypotheses related to the effects of consumer metrics and advertising. In general, we expect consumers' ability to recall an advertisement and their attitude toward the ad to enhance the effectiveness of the advertisement. Recall and appreciation of advertising have been found to considerably affect aggregate sales, although these metrics are not part of the conventional brand equity pyramid (e.g., Hanssens et al. 2014; Keller 2001; Srinivasan, Vanhuele, and Pauwels 2010).[3] If consumers' recall of advertising and appreciation for an advertisement is strong, then the depreciation of goodwill may slow, and the effect of goodwill on utility may increase because a consumer may be able and willing to effectively process the communicated information (MacInnis, Moorman, and Jaworski 1991; Meyers-Levy and Malaviya 1999. Based on these considerations, we formulate the subsequent hypothesis.

Hypothesis 1 (H1). Consumers' recall of an advertisement (i.e., AdRecall) and their attitude toward the ad (i.e., Aad) enhance the effectiveness of the advertisement, that is, these factors enhance the effect of goodwill on utility (the direct effect on advertising effectiveness – H1a) and goodwill retention (the indirect effect on advertising effectiveness – H1b).

The anticipated direction of the effect of *BrandExprc* appears more complex (cf. Hoch and Ha 1986; Smith 1993). At first sight, previous experience with consumption of the brand might increase the persuasiveness of advertising due to an increase in the credibility of and identification with a firm's advertising. However, especially for relatively simple, fast-moving consumer goods, consumers are expected to rely more strongly on their

[2] Note that both the short- and long-term effects of advertising may be affected by consumer metrics via goodwill.

[3] We thank an anonymous reviewer for making this point.

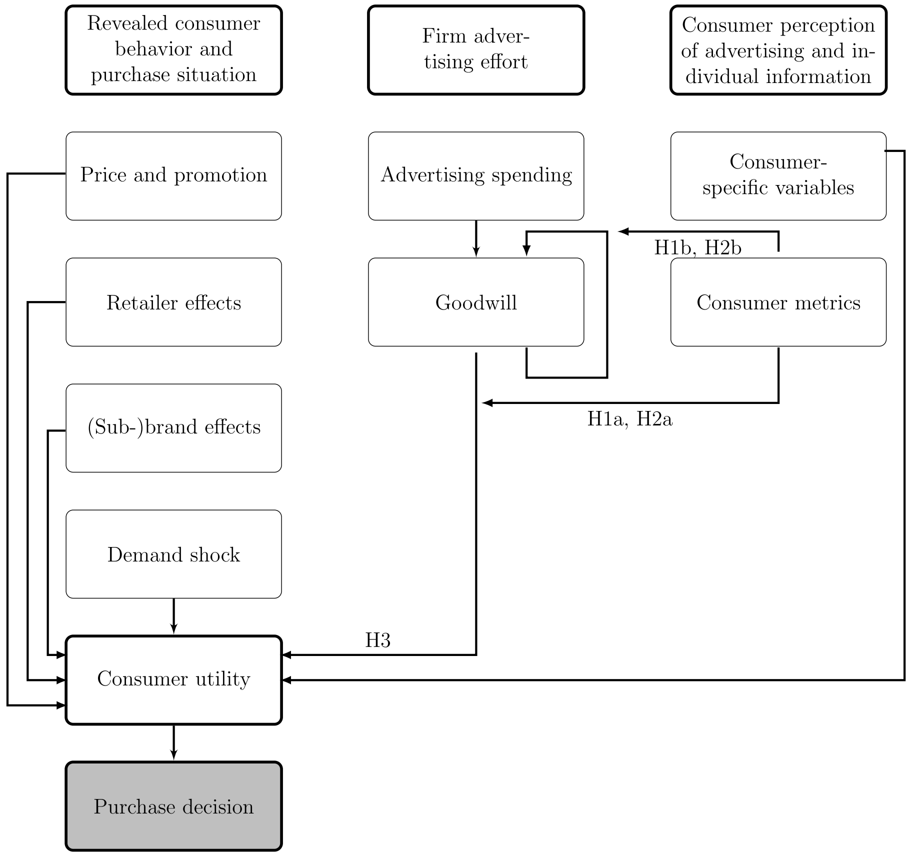

Fig. 1. Schematic overview of the conceptual framework.

own experience; thus, the effect of advertising is thought to diminish (Bhattacherjee and Sanford 2006; Hoch and Ha 1986). Further, Erdem and Keane (1996) found that previous brand experiences may matter more than advertising in an analysis of the long-run effects of noisy information about product experience and advertising. The following hypothesis is thus proposed.

Hypothesis 2 (H2). Consumers' previous brand experience (i.e., BrandExprc) reduce the effectiveness of advertisement, that is, it reduces the effect of goodwill on utility (the direct effect on advertising effectiveness – H2a) and goodwill retention (the indirect effect on advertising effectiveness – H2b).

There are indications in the literature that the effect of advertising on the purchase decisions of some consumers may be nonpositive (e.g., Speck and Elliott 1997). This matter can be investigated in detail following our approach because it allows for heterogeneous consumer preferences. For instance, if customers strongly dislike a particular advertisement or advertising in general, an increase in advertising effort may reduce the attractiveness of the product and the purchase probability (cf. e.g., Rojas-Mendez and Davies 2005). Nevertheless, the overall effect of advertising on market share is still expected to be predominately positive (cf. e.g., Assmus, Farley, and Lehmann 1984; Sethuraman, Tellis, and Briesch 2011). This means that also when accounting for heterogeneity, the gross effect is anticipated to be positive for most consumers – even if consumer metrics, unobserved preferences or both reveal partly a negative influence on effectiveness. The above considerations lead to the following hypothesis.

Hypothesis 3 (H3). Overall, advertising positively affects the purchase decision of the vast majority of consumers.

Example Application

We apply the above approach to investigating the effects of advertising on the purchase decisions of heterogeneous consumers to the empirical example of ground coffee in the fast-moving consumer goods category. To this end, we analyze 6,832 aggregate purchase observations in the German market over the period from the first week of 2000 to the last week of September 2001. The average per capita consumption of raw coffee was 6.7 kg, which corresponds to a total consumption of 549,025 tons of raw coffee on average per year (European Coffee Federation 2001). In terms of revenue, coffee was the most frequently consumed beverage in Germany, followed by mineral water and beer. During the period considered, the domestic coffee industry earned 4.09 billion Euros in revenue per annum at the retail level. Producers of ground coffee typically emphasize the importance of advertising as a means to support their national brands and influence consumers' product choices. Therefore, these producers spend a significant percentage of their revenues on television (TV) advertising. The manufacturers invested approximately 134 million Euros in TV advertisements. Ground coffee was one of the most frequently advertised products on national TV in the observation period (KloseDetering 2001).

The next section briefly describes the three elements of the investigation and data sources in our approach: (i) Revealed consumer purchase behavior from nationally representative sales information (collected via store-level scanner data). (ii) Firms' advertising efforts in terms of national advertising budgets. (iii) Consumer's perceptions of advertising and individual information (provided by tracking data that are representative of the group of consumers in the product category).

Revealed Consumer Behavior and Advertising Effort

A market research company, Madakom (GS1 Germany), collected information about consumers' purchases and firms' marketing activities via a nationally representative sample of retail stores. The stores belong to six major retail chains (i.e., Edeka, Markant, Metro, Rewe, Spar, and Tengelmann).[4] Our investigation focuses on the five highest-selling and most important (in terms of volume) coffee brands (i.e., Jacobs, Melitta, Dallmayr, Tchibo, and Eduscho) sold in the main relevant package size of 500 grams (approximately 98% of all units are sold as packages of this size). We analyze a total of thirteen sub-brands of these five major national brands, which together constitute more than 70% of volume-weighted sales. The store-level sales information includes marketing activities related to the stores' prices and promotional support. Because the stores' feature promotions and in-store promotions frequently appear together, we employ the mean of both variables and name it *Promotion*. The market share of the outside good is on average approximately 94%. This size is typical in analyses of consumer demand using scanner data (e.g., Jiang, Manchanda, and Rossi 2009; Musalem, Bradlow, and Raju 2008).[5] Section *Methodological Framework and Implementation* details the derivation of the market shares.

A market research company collected and provided monthly gross TV advertising budgets for the thirteen sub-brands. Note that throughout the study, the advertising campaigns remained the same for all sub-brands. Accordingly, the advertising budgets represent the amount of money spent on broadcasting. A large anonymous manufacturer commissioned the collection of the advertising budgets and tracking data described in the next subsection and made it available to us. The national brand manufacturers primarily use TV advertising, which accounts for more than 90% of their total advertising expenditures. The fact that expenditures for TV advertising are reported many months before the store-level scanner data are reported enables the initialization of a goodwill production function. Fig. 2 shows the TV budgets for each sub-brand during the analyzed period of store-level sales. Tchibo engages in umbrella advertising; therefore, its advertising budget is assigned to each sub-brand in equal proportion. Table 1 provides a descriptive overview of the sub-brands' market shares, prices, promotional efforts and advertising expenditures. The sub-brands tend to differ in their market shares.[5] A sanity check confirms that sub-brands with high market shares generally exhibit lower prices, greater promotional support and larger advertising budgets than do sub-brands with low market shares.

Consumers' Perceptions of Advertising and Individual-Level Information

Individual-level information for consumers in the product category, denoted as advertising tracking data, was collected by a professional market research company that conducted monthly face-to-face interviews with approximately 320 respondents based on a repeated cross-sectional design (approximately 6,700 respondents in total). The respondents are representative of the target group of coffee consumers, and the questionnaires are similar across industries and marketing research institutes. Because the tracking data are collected at the brand level, we cannot differentiate among sub-brands. Thus, we assign identical values to the sub-brands and match the monthly tracking data to the weekly sales data proportionally to the number of weeks.[6]

The tracking data measure the respondents' previous recent experience with the consumption of the brand (denoted as *BrandExprc*) as follows. The respondents were asked to think about the recent past and state which brands they had purchased/consumed, which is easier to answer than trying to remember the exact date and quantity of consumption.[7] Moreover, we account for the respondents' capacities for aided advertising recall (denoted as *AdRecall*). In addition to advertising recall, the tracking data record whether each respondent recalled a sub-brand's advertising slogan. However, we do not use this measure because it is more specific than the general recall measure and because the slogan recall measure relates to only one part of the advertisement (i.e., the advertisement's key message). Consumers may remember an advertisement even if the slogan is unclear. A consumer's attitude toward advertising is reflected by the following three measures: whether the

[4] The discount stores belonging to the Aldi or Lidl chain do not cooperate with syndicated services, which is similar to Walmart in the US. However, during the study period, Aldi sold only private labels and no national brands, whereas Lidl sold primarily private labels. These private label products were not advertised on TV. Note that we additionally control via an outside choice and unobserved shocks to demand for purchases at other competing markets (see *Methodological Framework and Implementation* section).

[5] The size of the market is given by the total revenue of a store in a particular week (cf. *Methodological Framework and Implementation* section). This accounts for a flexible total consumer demand that can constitute even larger or unusual gains in market share or category sales and is not limited by a conventionally reached upper bound (cf. Jiang, Manchanda, and Rossi 2009; Musalem, Bradlow, and Raju 2008).

[6] For weeks that have days in two months, we employ the number of weekdays (including Saturday but not Sunday because stores are closed on Sundays) in each month.

[7] Note that ground coffee generally represents a rather simple, nondurable consumer good; consequently, its purchase and consumption can create a meaningful experience with the product (cf. e.g., Hoch and Ha 1986; Wright and Lynch 1995). This situation may be different for products that are more complex or are more difficult to evaluate, such as mobile electronic devices or new and used cars, where the product experience may require a certain amount of time to evolve.

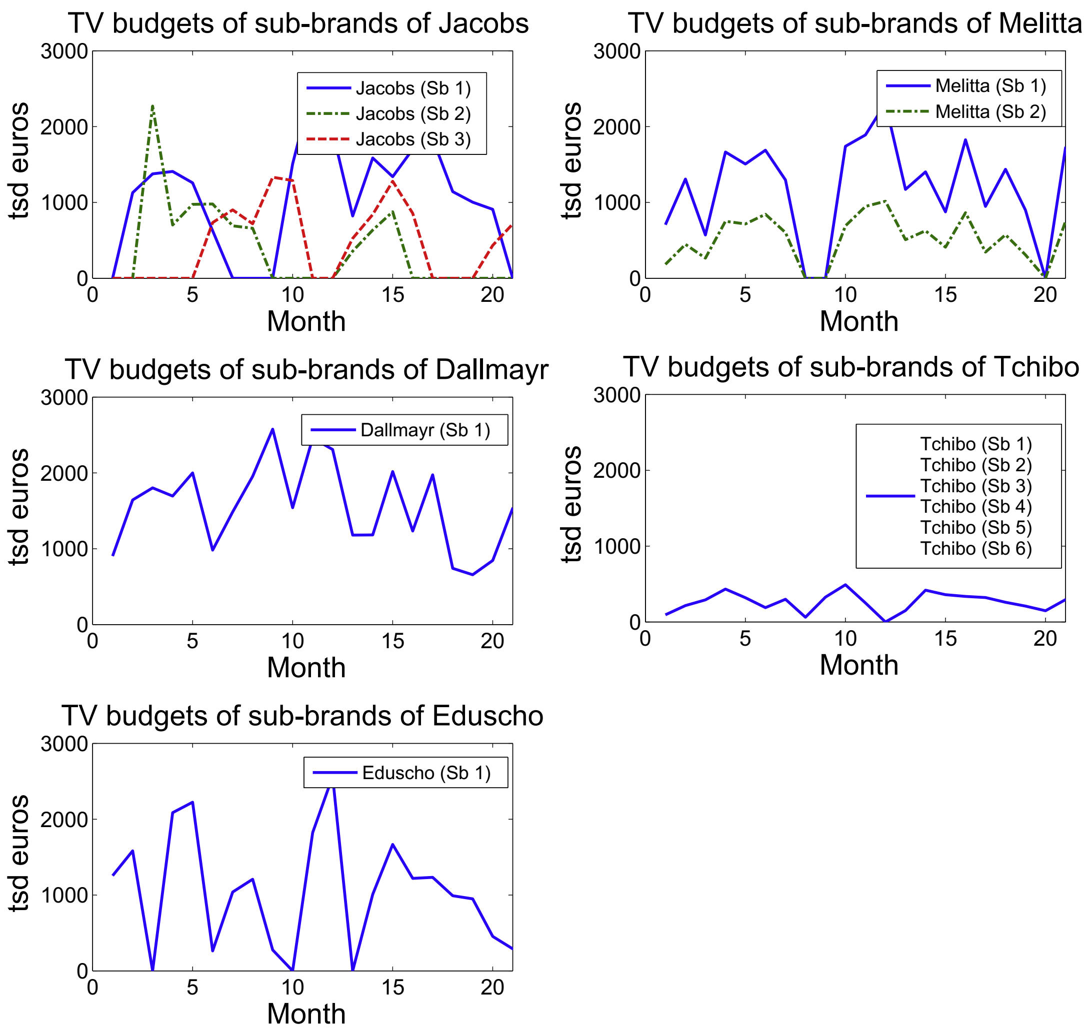

Fig. 2. Advertising effort: monthly spending on television (TV) advertising in thousands of Euros.

respondent likes/appreciates a brand's advertisement, whether the advertisement induces a desire for brand's products and whether the advertisement is unlikely to be forgotten (a perceived impression).[8] The respondents stated whether they agreed or disagreed with these statements on a 5-point Likert scale. The resulting Cronbach's alpha of 0.9 indicates good internal consistency. To enable an easily interpretable consumer metric, the mean of these values was divided, without loss of generality, by 5, which is the number of levels on the Likert scale. We denote the resulting metric "attitude toward the advertisement" (*Aad*).[9]

[8] Note that a consumer's perception and evaluation of how likely an advertisement is to be forgotten represents a perceived impression of the advertisement and is evidently different from a measure of, for example, recall.

[9] We also considered whether it was preferable to follow the advice of Bergkvist and Rossiter (2007) and use a single item to account for the respondents' attitudes toward the advertisements. In particular, we tested whether a respondent's appreciation for an advertisement alone is sufficient as an explanatory variable. The results of the estimation were similar to those of the previous specification, but the overall performance of the model declined.

In the theoretical specification, we allow for two parameters corresponding to advertising effectiveness, as detailed in the next section: (i) the influence of the average *Aad* on advertising effectiveness and (ii) the individual deviation from the average effect for consumers according to their observed *Aad* metric. Clearly, respondents cannot evaluate advertisements that they do not recall having seen. Hence, the market research company collected the *Aad* information in our data for consumers who recalled the advertisement and, in practical application, *AdRecall* and *Aad* are not operationally separable observable from each other. Due to this "natural" lack of more detailed information, it is reasonable to presume that consumers that did not recall an advertisement do not differ in the average *Aad* from other consumers on average. In general, to assess effect (i), we mean-center the individual observed *Aad* metric and estimate the effect of the mean separately in the practical implementation. We also find that *BrandExprc* and the product of *Aad* and *AdRecall* are uncorrelated; that is, the Pearson correlations of the average monthly values, overall and for each brand, are not significantly different from zero at a significance level of, for example, 5%.

Table 1
Mean values of weekly quantity sold (in tons, approximately nationwide), market share (as a percentage), promotion (as a percentage), price (Euros per kilogram), and TV budget (thousands of Euros per month) for each sub-brand.

Brand	Quantity	Market share	Promotion	Price	TV budget
Jacobs (Sb 1)	633.1	1.25	18.68	7.49	1,050
Jacobs (Sb 2)	137.4	0.28	17.20	7.55	439
Jacobs (Sb 3)	32.2	0.06	10.52	8.13	484
Melitta (Sb 1)	367.7	0.75	19.06	6.69	1,217
Melitta (Sb 2)	112.6	0.24	17.76	6.75	536
Dallmayr (Sb 1)	419.7	0.84	14.71	8.02	1,606
Tchibo (Sb 1)	29.5	0.07	2.13	10.76	251
Tchibo (Sb 2)	341.4	0.70	12.47	8.61	251
Tchibo (Sb 3)	54.2	0.12	3.69	9.43	251
Tchibo (Sb 4)	56.9	0.12	3.74	9.42	251
Tchibo (Sb 5)	110.6	0.24	8.28	7.66	251
Tchibo (Sb 6)	69.1	0.15	9.22	8.03	251
Eduscho (Sb 1)	429.8	0.87	16.33	7.19	1,300

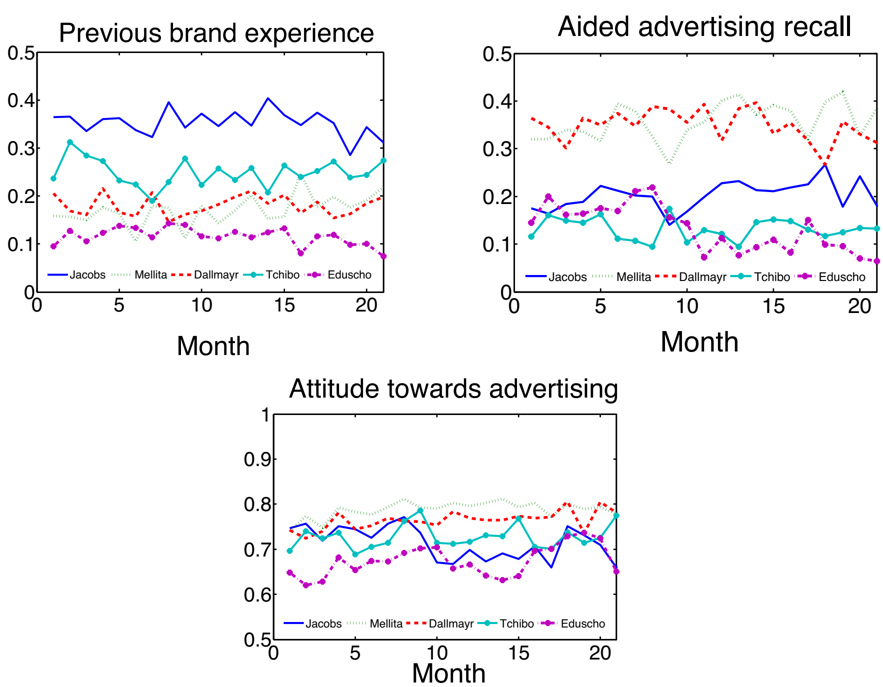

Fig. 3. Previous brand experience (*BrandExprc*), aided advertising recall (*AdRecall*), and attitude toward advertising (*Aad*) by month. (Note that to produce informative illustrations, the two subfigures at the top show values in the range from 0 to 0.5; the bottom subfigure, from 0.5 to 1.)

Fig. 3 displays the evolution of the three consumer metrics, *BrandExprc*, *AdRecall*, and *Aad*, over time. The tracking data also provide information about the respondents' demographics: gross household income, *Income*, and respondent age, *Age*. The respondents' gross monthly household incomes range in categories from 500 Euros and less to 4,000 Euros and over.[10] The middle of each category serves as the value of *Income* and is scaled by 1,000. The mean monthly income is 1,440 Euros, with a standard deviation of 1,190 Euros, and the mean age is 40.1 years, with a standard deviation of 10.6 years. The ages of the respondents range from 18 to 59 years.

[10] As an approximate overall median value, we assign a value of 5,000 Euros to the highest income category.

Methodological Framework and Implementation

This section provides a step-by-step exposition of the methodological framework for heterogeneous consumers' purchase decisions. At the end, we give an overview of the modular components of the consumer utility and their relationship to each other (see Fig. 4).

Consumer Purchase Decisions

A consumer maximizes her or his utility when choosing among J product alternatives or not buying a product. The utility u_{ijm} of consumer $i = 1, \ldots, I$ for product $j = 0, \ldots, J$ (i.e., a sub-brand) in market $m = 1, \ldots, M$ is the following (Nevo 2000):

$$u_{ijm} = \delta_{jm} + \mu_{ijm} + \varepsilon_{ijm}. \quad (1)$$

In our empirical application, a market m represents a given retailer in a given week, and δ_{jm} is the mean value of the utility of sub-brand j at market m, which is the same for all consumers. Here, μ_{ijm} denotes a consumer-specific deviation of consumer i from the mean utility (Berry, Levinsohn, and Pakes 1995), and ε_{ijm} is the extreme value distributed error term of the logit model (e.g., Train 2009). For identification, δ_{0m} and μ_{i0m} are set to zero for the nonpurchase (or outside good) option with $j=0$. δ_{jm} includes the following components:

$$\begin{aligned}\delta_{jm} &= (Sub\text{-}brand_{jm})\beta_s + (Retailer_{jm})\beta_r \\ &\quad + \beta_p(Promotion_{jm}) + \alpha\ \ln(p_{jm}) \\ &\quad + \vartheta_{jm}\Gamma(G_{jm}) + \xi_{jm},\end{aligned} \quad (2)$$

where ($Sub\text{-}brand_{jm}$) and ($Retailer_{jm}$) represent dummy variables with parameters β_s and β_r to control for all sub-brand and retailer-specific constant effects, respectively.[11] Further explanatory variables include the following marketing instruments: the influence of advertising, which is represented by $\Gamma(G_{jm})$, that is, a functional form representation of goodwill with parameter ϑ_{jm} (the details are outlined in the subsequent subsection), the promotional support (denoted as *Promotion*) with parameter β_p and the price variable p_{jm} with parameter α.[12] The utility accounts for an additional structural error term (or demand shock) ξ_{jm}, which is a surrogate for information observed by the consumers and the supplying firms but unobserved by the data analyst. The influence of the structural error term is again discussed as part of the parameter estimation in *Results of the Empirical Example* section. A consumer's specific sensitivity to marketing instruments that deviates from the overall average preference of consumers is represented as follows:

$$\begin{aligned}\mu_{ijm} &= \sigma_1\nu_{1i} + \sigma_2\nu_{2i}(Promotion_{jm}) + \sigma_3\nu_{3i}\ln(p_{jm}) \\ &\quad + (\sigma_4\nu_{4i} + \varpi_{ijm})\Gamma(G_{jm}) + \pi_1 Income_i + \pi_2 Age_i.\end{aligned} \quad (3)$$

In general, this deviation from the mean utility is explained by (observed) consumer-specific variables D_i and unobserved variables ν_i. The consumer-specific variables D_i are Age_i, $Income_i$ and the consumer metrics. As outlined in sections *Motivation* and *Background and Overview*, the consumer metrics may alter the accumulation of goodwill, influence the effectiveness of goodwill or do both for an individual consumer. Therefore, we examine whether the consumer metrics explain the parameters ϑ_{jm} and ϖ_{ijm} and the accumulation of goodwill G_{jm}, as described in detail in the next subsection. Here, π_1 and π_2 are the parameters of the effect of Age_i and $Income_i$, and σ_k, $k=1, \ldots, K$ can be interpreted as the standard deviation of the following $K=4$ random coefficients: an overall constant denoted as *Constant*, $Promotion_{jm}$, $ln(p_{jm})$, and $\Gamma(G_{jm})$. The random coefficient from the constant yields the same effect for each sub-brand.[13] As is common practice, unobserved heterogeneity is represented by a normally distributed vector $\nu_i = (\nu_{1i}, \ldots, \nu_{Ki})'$ (e.g., Goeree 2008; Jiang, Manchanda, and Rossi 2009; Musalem, Bradlow, and Raju 2009): $\nu_i \sim N(0, I_K)$, where I_K denotes the identity matrix of dimension K. Thus, the market share s_{jm} of sub-brand j at market m results in the following:

$$s_{jm} = \int_D \int_\nu \frac{\exp(\delta_{jm} + \mu_{ijm})}{1 + \sum_{k=1}^{J} \exp(\delta_{km} + \mu_{ikm})} \phi(\nu) d\nu\, dP_D(D), \quad (4)$$

where $D_i \sim P_D(D)$ is the distribution of the consumer-specific variables, and $\phi(\cdot)$ denotes the density of the (multivariate) standard normal distribution.

Advertising Effects on Utility

Because advertising can have both short- and long-term impacts, we examine the direct and indirect influences of advertising on utility via the common concept of goodwill stocks of sub-brands (cf. e.g., Chintagunta, Kadiyali, and Vilcassim 2006; Clarke 1976; Dubé, Hitsch, and Manchanda 2005). Firms advertise to build a sub-brands' stock of goodwill, which declines in the absence of advertising. The goodwill retention, or depreciation, rate λ_{jt_m}, $0 \le \lambda_{jt_m} \le 1$, informs how much goodwill is transferred to the next period t_m. To attain independence from the initial level of goodwill, we utilize a long initialization period with an additional advertising budget data of three years prior to the estimation sample. We find that the goodwill stock of product $j=1, \ldots, J$ at period $t_m = 1, \ldots, T$ is best represented in our empirical example (see below) by the following expression:

$$G_{jt_m} = \sqrt{A_{jt_m}} + \lambda_{jt_m} G_{j(t_m-1)}. \quad (5)$$

Recall that in the empirical application, a market represents a particular retailer in a particular week. The advertising budgets and, hence, the goodwill are therefore the same for all retailers in a given period. To emphasize that goodwill develops over time (rather than retailers), we distinguish periods $t_m = 1, \ldots, T$ in the notation of this paragraph and use the subscript m to denote that a period depends on a market m. The specification of the overall form of goodwill is based on the formal selection of several typical and common alternative specifications from the literature. We describe the details in appendixes *Constrained and Restricted Specifications and Endogeneity* and *Overall Functional Form of Goodwill*. The deduced root transformation of the advertising budgets shown in Eq. (5) allows us to account for diminishing marginal returns of advertising for goodwill, which is a typical and reasonable property in the context of advertising effects (e.g., Bagwell 2007). As outlined in the appendix, we find the

[11] Tengelmann is the reference category for the retailer-specific constants.

[12] The variable for price is log-transformed because this transformation allows us to account for diminishing marginal returns of price and better describes the observations (analogous to, e.g., Jiang, Manchanda, and Rossi 2009).

[13] Note that in the empirical analysis, we compared several modified specifications in which *Age* and *Income* affect $ln(p_{jm})$ or $\Gamma(G_{jm})$. However, we did not find empirical evidence for such a specification (see also, *Results of the Empirical Example* section).

effect of goodwill on consumer utility to be best represented in our empirical application by the following expression:

$$\Gamma(G_{jt_m}) = \ln(G_{jt_m} + 1). \tag{6}$$

The logarithmic transformation (after adding 1 to avoid computing the logarithm of 0) in Eq. (6) is sensible from an economic perspective because it accounts for diminishing marginal returns of goodwill for utility and is consistent with the findings from the literature (e.g., Doyle and Saunders 1990; Dubé, Hitsch, and Manchanda 2005).

Advertising Effectiveness for Heterogeneous Consumers

As previously discussed, our approach examines whether there are direct and indirect effects of consumer metrics on advertising effectiveness. As subsequently described in detail, we examine the extent to which there is a direct effect of consumer metrics on the impact of goodwill on the mean utility (Eq. (7)) and on the consumer-specific deviation from the mean (Eq. (8)):

$$\vartheta_{jm} = \theta_1 + \theta_2(Aad \cdot AdRecall)_{jm}, \tag{7}$$

$$\varpi_{ijm} = \pi_3(BrandExprc_{ijm}) + \pi_4(Aad_{ijm} \cdot AdRecall_{ijm}). \tag{8}$$

The parameter θ_1 represents the baseline average effect of $\Gamma(G_{jm})$. The parameter θ_2 stands for the influence of the average effect of $(Aad \cdot AdRecall)_{jm}$ for a product j and market m, and π_4 denotes the amount of the individual deviation from the average effect. In other words, controlling for all other influences on utility, θ_2 shows whether variations in market shares for the same levels of goodwill are attributable to changes in consumers' ability to recall and their preferences for advertisements, where π_4 yields individual deviations from the average effect. A large parameter π_4, for instance, refers to the case in which the recall and appreciation of the advertisement increases the effect of the goodwill stock on the purchase decision of a fraction of consumers. π_3 denotes the influence of a consumer's experience with consumption of the brand on the effect of goodwill. In general, the retention rate λ_{jt_m} can affect the shape of the goodwill production function. Therefore, our approach investigates whether and in what manner λ_{jt_m} is altered by the consumer metrics.[14] Because the retention rate determines how much previous goodwill was transferred to the next period, we analyze the effects of one-period-lagged consumer metrics. Doing so also enables us to separately examine the mean direct altering effect of the consumer metrics by ϑ_{jm} and their indirect altering effect on the retention rate. In other words, the retention rate of the brand's goodwill can be subject to the fraction of consumers who have brand experience, their average recall and evaluation of the advertisement or both attributes. Hence, the retention rate λ_{jt_m} is decomposed as follows:

$$\lambda_{jt_m} = \tau(\gamma_0 + \gamma_1(BrandExprc)_{j(t_m-1)} + \gamma_2(Aad \cdot AdRecall)_{j(t_m-1)}), \tag{9}$$

where γ_0, γ_1, and γ_2 are parameters. To ensure that the retention rate λ_{jt_m} always takes a value between 0 and 1, we apply a logistic transformation τ. The logistic function $\tau(a)$ of argument a is $\tau(a) = \frac{\exp(a)}{1+\exp(a)}$. This is a common transformation which ensures that a function's target set ranges from 0 to 1 (for example, this transformation is the canonical link function in corresponding generalized linear models).[15] The computation of the advertising elasticity of demand is outlined in appendix *Advertising Elasticity*. Note again that goodwill is the same for all retailers in a period t_m (i.e., the same at a purchase occasion m), and recall that in our application, advertising budget information is available on a monthly basis. Therefore, we assess goodwill first over months and match the outcome to weeks proportionally to their number of weeks (cf. *Example Application* section). To simplify representation, the notation G_{jm} is employed for the goodwill of product j at market m (where a market m again represents a given retailer in a given week).

Summarizing, Fig. 4 provides an overview the modular components of consumer demand and their relationships.

Alternative Specifications and Estimation

Based on the hypotheses developed in *Background and Overview* section, advertising effectiveness may be subject to both direct and indirect effects of consumer metrics (denoted as the "Complete" case). Alternatively, the effects may be only direct (denoted as "Direct"), indirect (denoted as "Indirect") or neither (denoted as "Base"). Hence, we investigate the effects of advertising on consumer choice by comparing the following four alternative specifications:[16]

i. "**Basic**" – without the effects of consumer metrics (and allowing for random coefficients, as is also the case for (ii)–(iv));
ii. "**Indirect**" – when the depreciation rate of goodwill λ_{jm} is allowed to be altered by consumer metrics via parameters γ_1 and γ_2;
iii. "**Direct**" – when individual consumer metrics are interacted with the direct effect of advertising, that is, via the parameters θ_2, π_3 and π_4 on $\Gamma(G_{jm})$; and
iv. "**Complete**" – when the effectiveness of advertising and the depreciation rate of goodwill are allowed to be altered by consumer metrics via the parameters γ_1, γ_2, θ_2, π_3, and π_4.

[14] Note that the tracking data are repeated cross-sectional data, and therefore, λ_{jt_m} must be portrayed at the consumer aggregate level.

[15] We rescale, without of loss of generality, the explanatory variables of the retention rate by a factor of 10, which roughly corresponds to a standardizing so that the parameter values are of an appropriate size (cf. e.g., Rossi, Allenby, and McCulloch 2005).

[16] For comparison, we also analyze the following two simplified settings. "**Constrained**"– without the effects of consumer metrics and without random coefficients – and "**Restricted**"– without random coefficients but including (homogeneous) effects of consumer metrics. The outcomes of these specifications are shown in Table 4 in the appendix.

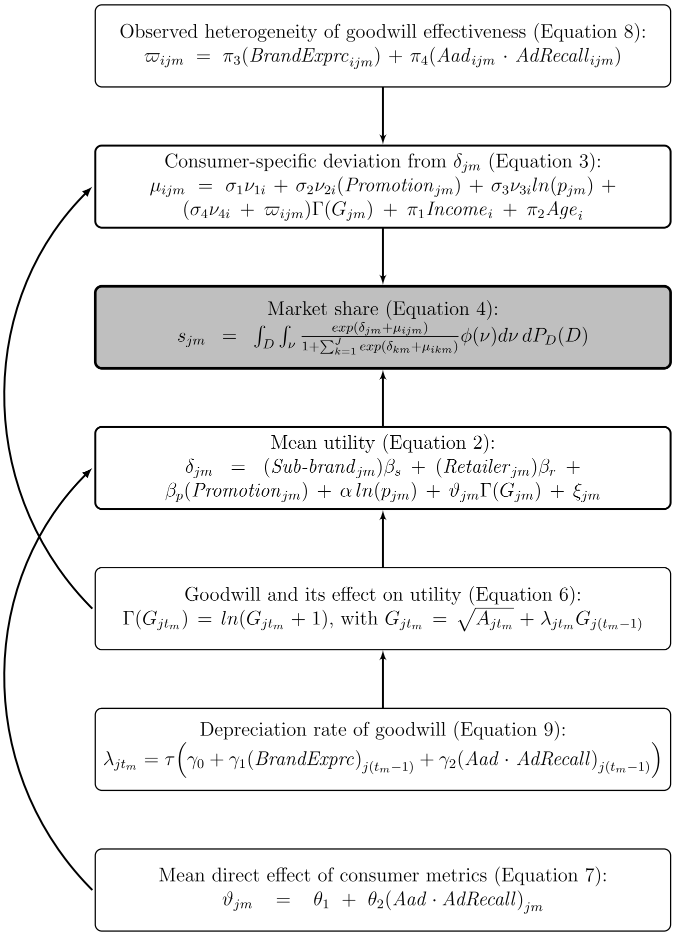

Fig. 4. Methodological framework for consumer demand: overview of the functional representations of the components (for product $j = 1, \ldots, J$ at market $m = 1, \ldots, M$ (with corresponding period $t_m = 1, \ldots, T$) and consumer $i = 1, \ldots, I$).

We employ the generalized method of moments (GMM) for the parameter estimation (Berry, Levinsohn, and Pakes 1995; Nevo 2000). In practice, firms typically set prices or advertising budgets strategically to maximize profits or increase market shares. Therefore, these marketing mix variables can be correlated with unobserved effects on demand, that is, with demand shock ξ, and can create an endogeneity problem (Villas-Boas and Winer 1999). To control for potential endogeneity and obtain unbiased outcomes, we employ general instrumental variable techniques. Appendix *Methodological Details* provides the details.

Results of the Empirical Example

We compare alternative specifications using two particularly suited selection criteria: the Bayesian information criterion and the Hannan-Quinn information criterion (Andrews and Lu 2001), denoted as MMSC-BIC and MMSC-HQIC, respectively.[17] These information criteria are the analogues within the GMM framework to widely used measures for likelihood-based estimations (cf. e.g., Schwarz 1978). Andrews and Lu (2001) mathematically showed that the criteria lead to the selection of the true parameter and moment restrictions under weak assumptions and an increasing sample size, given that the true specification is in the set investigated. The criteria favor specifications that better fit the data but simultaneously penalize overparametrization (i.e., a smaller number of valid overidentification restrictions for the GMM estimation due to the additional parameters to calibrate). The MMSC-BIC and MMSC-BIC values' weights fit with the observations and the number of overidentification restrictions slightly differently. The selection process can ultimately be based on a formal statistical test – the GMM distance test – because all of the specifications are nested within the Complete setting (e.g., Baum, Schaffer, and Stillman 2003).

Although all four specifications satisfy the overidentification test (Hansen 1982), the MMSC-BIC and MMSC-HQIC values show that the Indirect and Complete models are preferable overall. The Complete specification has the lowest GMM objective value. The distance test results show significant differences among the models and lead to the conclusion that the Complete specification is preferable overall. Because of the dynamics of the goodwill production function, we test for each sub-brand if the GMM error terms (i.e., the demand shocks) are autocorrelated. The Lagrange Multiplier tests (Breusch and Pagan 1980) do not reject the null hypothesis that there is no first-order autocorrelation at the 5% level of significance.[18] Note that we conducted further sensitivity checks with respect to the robustness of the outcomes to alternative specifications or shocks to model components. We also performed additional in- and out-of-sample comparisons of market share predictions. The results confirmed the overall appropriateness of the Complete specification (the details are outlined in a web appendix).

In the following discussion, we concentrate on the results from the Complete specification. The parameter estimates yield the expected signs and are different from zero at a significance level of 5% and under asymptotic normality. In particular, the parameters accounting for observed and unobserved consumer preference heterogeneity are all significantly different from zero (i.e., π_1 to π_4 and σ_1 to σ_4). Furthermore, the ranking of the mean sub-brand parameters (i.e., β_{p1} to β_{p13}) is mostly in accordance with their market shares and price levels. The retailer-specific constants (i.e., β_{r1} to β_{r5}) reflect differing market shares across retail chains. This outcome is consistent with the information provided by industry experts, who state that, for example, the Rewe, Spar, Edeka, and Tengelmann retailers generate a larger proportion of their revenues through food products. The firms' sales increase significantly if a sub-brand is on promotion, and their sales decline if prices increase (cf. β_p and α).[19]

[17] The model and moment selection criteria are defined as follows: MMSC-BIC = $\tilde{J}_n - S \cdot \ln(n)$, and MMSC-HQIC = $\tilde{J}_n - S \cdot Q \cdot \ln(\ln(n))$, where $\tilde{J}_n$ denotes the value of the GMM objective times the number of observations n, and S represents the number of valid overidentification restrictions. According to Andrews and Lu (2001), the multiplier Q for MMSC-HQIC is set to 2.1.

[18] The results of applying the Box-Pierce-Ljung test (Box and Pierce 1987; Ljung and Box 1978) are the same.

[19] Recall that parameter values alone are not necessarily meaningfully interpretable in terms of the effect size because the effect also depends on the

The mean effect of advertising on utility results as the main effect of goodwill (i.e., θ_1) and the interaction effect θ_2 of the influence of goodwill and consumers' mean valuations of the advertisement (i.e., their attitudes toward the advertisement). The interaction effect accounts for time-varying changes in consumers' preferences for a brand's advertisement. Both effects are significant and positively impact utility, and thus, they show that advertising has, on average, a positive influence on market shares via goodwill. As we subsequently outline, the random coefficients offer detailed insights into the importance of observed and unobserved heterogeneity. The random coefficients that are related to unobserved heterogeneity (i.e., σ_2 and σ_3) show that preferences for promotion and price differ significantly across consumers. The outside good option for coffee becomes less (more) attractive depending on a consumer's affinity for coffee (cf. σ_1). The estimate referring to income (i.e., π_1) shows that the attractiveness of coffee products tends to increase with income. Coffee is a relatively expensive fast-moving consumer good (cf. e.g., Gordon, Goldfarb, and Li 2013).[20] Sub-brands are less attractive to older consumers, controlling for other explanatory variables (cf. π_2).

The parameters for the influence of consumer metrics in Table 2 offer interesting insights into the effectiveness of advertising. If the respondents had experience with a brand, the effectiveness of advertising declines (cf. π_3). Consumers appear to rely more on their previous brand experiences than on advertising, which is a similar result to that found in research which analyzed the long-run effects of noisy information about product experience and advertising (Erdem and Keane 1996). The above outcome thus confirms the results of experimental research from Hoch and Ha (1986), who reported that consumers' product experience can be a significant driver of advertising effectiveness and that consumers may be less reliant on advertising if they have sufficient experience with the product. Moreover, the positive influence of advertising on utility increases if the respondent's recall and attitude toward an advertisement increase (cf. π_4 and θ_2). We hence can reject neither Hypothesis H1a nor Hypothesis H2a. If a respondent recalls and appreciates an advertisement, the advertisement's positive marginal effect on the respondent's utility increases, even if the effectiveness of advertising decreases due to brand experience.

We find that goodwill depreciates more quickly if consumers had a previous brand experience (cf. γ_1). Conversely, goodwill depreciates more slowly if consumers recall and appreciate a particular advertisement (cf. γ_2). This result is consistent with observations that advertising awareness and liking were found to influence sales, though these metrics are not part of the conventional brand equity pyramid (e.g., Hanssens et al. 2014; Keller 2001; Srinivasan, Vanhuele, and Pauwels 2010). The average estimates of the retention rate of goodwill are approximately between 0.91 and 0.96, which are in the range of retention rates reported in other studies (e.g., Dubé, Hitsch, and Manchanda 2005). Because the coefficients γ_1 and γ_2 are more difficult to directly interpret due to the logit transformation $\tau(a)$, we describe the effects of the explanatory variables as elasticities. If brand experience increases by 1%, the retention rate decreases by approximately −0.13%, on average (median: −0.08%). Similarly, if recall and appreciation increase by 1%, the rate of goodwill accumulation increases by approximately 0.30%, on average (median: 0.24%). Therefore, we conclude that the effect sizes are moderate and that the marginal effects of recall of and attitude toward advertising dominate the marginal effect of previous brand experience. Therefore, Hypotheses H1b and H2b are not rejected.

Interestingly, some consumers may gain disutility from advertisements. For example, a consumer may receive disutility from advertising if he or she has a strong negative preference due to unobserved variables or a low value of $(Aad_{ijm} \cdot AdRecall_{ijm})$ or if he or she has a previous brand experience. However, we find that the proportion of consumers who gain a negative utility from advertising is below 1%. Thus, we conclude that overall the vast majority of consumers is positively affected by advertising. Hence, Hypothesis H3 is not rejected. In summary, the outcomes indicate that advertising affects purchase decisions depending on the heterogeneous perceptions of consumers, that is, consumer metrics, and preferences. Consumer metrics show a significant direct influence on advertising effectiveness through their interactions with the influence of goodwill on utility and a significant indirect influence on long-term advertising effectiveness via the depreciation rate of the goodwill production function.

Advertising and price elasticities

Elasticities are the basis for retailer and manufacturer pricing and advertising budgeting because they provide information about competition in a market and about substitution patterns of consumers (including the outside option) (cf. e.g., Musalem, Bradlow, and Raju 2009). These implied substitution patterns directly influence model implications, such as the prediction of market shares, when marketing instruments are changed or competing firms' estimated profits (e.g., Berry, Levinsohn, and Pakes 1995; Train 2009). Allowing for heterogeneous consumer preferences, the random coefficient model can account for flexible substitution patterns among competing brands (e.g., Nevo 2000).[21] We further find that both short- and long-term advertising effects are subject to the consumer metrics of brand experience, as well as recalling and liking a brand's advertisements. To illustrate the current effects of advertising on consumers' present and future purchase decisions, we compute both long- and short-term advertising elasticities. By short-term, we mean advertising effects that occur in the same week as the

value of the corresponding explanatory variables. A meaningful and informative summary of the effect that is also comparable across data sets and estimation outcomes is given, for example, by the price elasticity of demand (cf. e.g., Train 2009).

[20] From nineteen compared fast-moving consumer goods categories in the cited study, only one was more expensive on average (prices were compared using the volume-equivalent units used by the Industrial Research Institute).

[21] An additional empirical analysis confirms that allowing for heterogeneous consumer preferences is important for explaining consumers' substitution patterns due to, e.g., increasing prices (cf. the web appendix).

Table 2
Parameter estimates of the following specifications: Basic, Indirect, Direct, and Complete (“Par.” stands for “Parameter”, “Est.” stands for “Estimated value”, “Std” abbreviates standard deviation, Υ denotes the overidentification test statistic and κ the 95%-quantile from the distribution of Υ).

		Basic		Indirect		Direct		Complete	
Effects of consumer metrics on advertising effectiveness									
Indirect		No		Yes		No		Yes	
Direct		No		No		Yes		Yes	
Variable	Par.	Est.	(Std)	Est.	(Std)	Est.	(Std)	Est.	(Std)
Mean influence									
Jacobs (Sb 1)	β_{p1}	2.88*	(0.25)	2.63*	(0.24)	3.89*	(0.27)	3.95*	(0.26)
Jacobs (Sb 2)	β_{p2}	2.02*	(0.25)	1.85*	(0.23)	3.08*	(0.26)	3.19*	(0.26)
Jacobs (Sb 3)	β_{p3}	1.00*	(0.25)	0.87*	(0.23)	2.31*	(0.26)	2.28*	(0.26)
Melitta (Sb 1)	β_{p4}	1.71*	(0.24)	0.00	(0.26)	2.50*	(0.26)	1.03*	(0.28)
Melitta (Sb 2)	β_{p5}	0.93*	(0.24)	−0.68*	(0.25)	1.80*	(0.25)	0.40	(0.27)
Dallmayr (Sb 1)	β_{p6}	2.60*	(0.26)	1.06*	(0.27)	3.39*	(0.27)	2.11*	(0.29)
Tchibo (Sb 1)	β_{p7}	2.64*	(0.26)	1.83*	(0.25)	3.78*	(0.27)	3.20*	(0.28)
Tchibo (Sb 2)	β_{p8}	3.68*	(0.25)	2.85*	(0.24)	4.79*	(0.26)	4.19*	(0.27)
Tchibo (Sb 3)	β_{p9}	2.40*	(0.25)	1.58*	(0.25)	3.51*	(0.27)	2.92*	(0.27)
Tchibo (Sb 4)	β_{p10}	2.54*	(0.25)	1.72*	(0.25)	3.65*	(0.27)	3.06*	(0.27)
Tchibo (Sb 4)	β_{p11}	1.67*	(0.24)	0.82*	(0.24)	2.75*	(0.26)	2.14*	(0.26)
Tchibo (Sb 6)	β_{p12}	1.45*	(0.25)	0.61*	(0.24)	2.54*	(0.26)	1.93*	(0.26)
Eduscho (Sb 1)	β_{p13}	2.49*	(0.25)	1.16*	(0.26)	3.45*	(0.27)	2.37*	(0.28)
Edeka	β_{r1}	0.04*	(0.02)	0.04	(0.02)	0.05*	(0.02)	0.05*	(0.02)
Markant	β_{r2}	−0.07*	(0.02)	−0.07*	(0.02)	−0.07*	(0.02)	−0.07*	(0.02)
Metro	β_{r3}	−0.26*	(0.02)	−0.25*	(0.02)	−0.27*	(0.02)	−0.27*	(0.02)
Rewe	β_{r4}	0.46*	(0.02)	0.45*	(0.02)	0.49*	(0.02)	0.48*	(0.02)
Spar	β_{r5}	0.38*	(0.02)	0.38*	(0.02)	0.41*	(0.02)	0.40*	(0.02)
Promotion	β_p	1.34*	(0.04)	1.29*	(0.04)	1.37*	(0.03)	1.31*	(0.03)
Price (log-transformed)	α	−7.64*	(0.31)	−7.47*	(0.29)	−8.63*	(0.23)	−8.49*	(0.24)
$\Gamma(G)$	θ_1	0.57*	(0.02)	0.68*	(0.03)	0.48*	(0.04)	0.62*	(0.04)
$\Gamma(G) \cdot Aad \cdot AdRecall$	θ_2					0.26*	(0.05)	0.15*	(0.05)
Retention rate									
Constant	γ_0	1.98*	(0.12)	−0.66	(2.15)	2.42*	(0.19)	−0.54	(2.51)
BrandExprc	γ_1		(0.00)	−0.82*	(0.27)		(0.00)	−0.79*	(0.29)
Aad · AdRecall	γ_2		(0.00)	0.77*	(0.23)		(0.00)	0.76*	(0.28)
Unobserved heterogeneity									
Constant	σ_1	1.11*	(0.09)	1.13*	(0.10)	0.96*	(0.09)	0.95*	(0.10)
Promotion	σ_2	0.23	(0.27)	0.20	(0.29)	0.57*	(0.21)	0.56*	(0.21)
Price (log-transformed)	σ_3	1.42*	(0.11)	1.32*	(0.10)	1.70*	(0.07)	1.61*	(0.07)
$\Gamma(G)$	σ_4	0.17*	(0.03)	0.13*	(0.03)	0.18*	(0.02)	0.15*	(0.02)
Observed heterogeneity									
Income	π_1	0.60*	(0.02)	0.59*	(0.03)	0.51*	(0.02)	0.49*	(0.02)
Age	π_2	−0.04*	(0.00)	−0.04*	(0.01)	−0.04*	(0.00)	−0.04*	(0.00)
Observed heterogeneity of goodwill effectiveness									
$\Gamma(G) \cdot BrandExprc$	π_3					−0.23*	(0.02)	−0.17*	(0.02)
$\Gamma(G) \cdot Aad \cdot AdRecall$	π_4					1.47*	(0.08)	1.13*	(0.08)
Information criteria and Υ									
Υ		784.9		760.7		754.8		735.5	
κ		922.1		920.0		918.9		916.9	
MMSC-BIC		−6746.5		−6753.1		−6750.2		−6751.8	
MMSC-HQIC		−3116.7		−3131.8		−3133.1		−3143.2	

* Significant difference from zero at the 5% level.

Table 3
Price, long-term and short-term advertising elasticities of demand for the Complete and Basic specifications ("Std" denotes the standard deviations over the observations).

	Complete						Basic					
	Price elasticity		Long-term advertising elasticity		Short-term advertising elasticity		Price elasticity		Long-term advertising elasticity		Short-term advertising elasticity	
	Mean	(Std)	Mean	(Std)	Mean	(Std)	Mean	(Std)	Mean	(Std)	Mean	(Std)
Jacobs (Sb 1)	−5.084	(0.215)	0.648	(0.176)	0.105	(0.031)	−4.894	(0.169)	0.569	(0.140)	0.093	(0.027)
Jacobs (Sb 2)	−5.247	(0.175)	1.177	(0.435)	0.177	(0.048)	−5.025	(0.149)	0.994	(0.306)	0.152	(0.037)
Jacobs (Sb 3)	−5.225	(0.177)	1.448	(0.736)	0.338	(0.498)	−5.012	(0.152)	1.204	(0.656)	0.287	(0.460)
Melitta (Sb 1)	−5.405	(0.186)	0.167	(0.037)	0.020	(0.004)	−5.085	(0.160)	0.623	(0.137)	0.104	(0.021)
Melitta (Sb 2)	−5.470	(0.185)	0.216	(0.035)	0.026	(0.004)	−5.140	(0.154)	0.751	(0.120)	0.124	(0.018)
Dallmayr (Sb 1)	−5.217	(0.243)	0.171	(0.032)	0.021	(0.003)	−4.902	(0.162)	0.528	(0.091)	0.090	(0.011)
Tchibo (Sb 1)	−5.031	(0.158)	0.553	(0.051)	0.074	(0.009)	−4.769	(0.123)	0.885	(0.081)	0.150	(0.015)
Tchibo (Sb 2)	−5.080	(0.176)	0.545	(0.049)	0.073	(0.008)	−4.829	(0.154)	0.866	(0.078)	0.147	(0.015)
Tchibo (Sb 3)	−5.124	(0.164)	0.557	(0.051)	0.075	(0.009)	−4.858	(0.130)	0.888	(0.081)	0.150	(0.015)
Tchibo (Sb 4)	−5.122	(0.153)	0.556	(0.051)	0.075	(0.009)	−4.857	(0.127)	0.888	(0.081)	0.150	(0.015)
Tchibo (Sb 4)	−5.310	(0.137)	0.562	(0.051)	0.076	(0.009)	−5.028	(0.134)	0.893	(0.083)	0.151	(0.015)
Tchibo (Sb 6)	−5.277	(0.155)	0.561	(0.051)	0.076	(0.009)	−5.001	(0.137)	0.893	(0.082)	0.151	(0.015)
Eduscho (Sb 1)	−5.257	(0.187)	0.245	(0.059)	0.030	(0.008)	−4.977	(0.159)	0.623	(0.138)	0.101	(0.024)

current advertising effort (see *Advertising Elasticity* section in the appendix for further details). Based on the demand estimates, we compute the price and advertising elasticities shown in Table 3.[22,23]

The elasticities all have the expected signs, that is, the mean own-price elasticities are negative, and the cross-price elasticities are positive. Analogously, the mean own-advertising elasticities are positive, and the cross-advertising elasticities are negative (shown in the web appendix). The price elasticities listed in Table 3 have an average value of −5.22 and differ not only across brands but also across sub-brands. The outcomes are in accordance with other empirical results for the coffee category (Draganska and Klapper 2007; Draganska and Klapper 2011; Guadagni and Little 1983; Krishnamurthi and Raj 1991). Although the magnitudes of the elasticities appear somewhat larger than the average findings, the results are within the range of overall empirical generalizations (e.g., Bijmolt, van Heerde, and Pieters 2005). Because our approach accounts for heterogeneous consumer preferences, it can reveal fractions of price-sensitive consumers who have stronger reactions to price changes than do average price-sensitive consumers, which in turn can result in (absolutely) larger elasticities (cf. Draganska and Klapper 2011). The average short-term advertising elasticity is approximately 0.09, and the long-term average is approximately 0.57; these are noteworthy effects that are similar to other findings in the literature (cf. also Erdem and Keane 1996).[24] The advertising elasticities for the Jacobs and Tchibo sub-brands are higher than those of the other sub-brands. This result is driven by the goodwill levels, which are low for both brands due to the advertising spending in combination with the consumer metrics (cf. Figs. 2 and 3); specifically, Jacobs has a relatively low retention rate, and Tchibo's advertising budgets are relatively small. Low goodwill levels indicate greater potential for advertising to stimulate purchases; in other words, the marginal effects are larger because goodwill production yields both diminishing marginal effects of advertising on goodwill and diminishing marginal effects of goodwill on utility.

Table 3 lists the outcomes from the Basic specification, that is, a "standard" random coefficient model that does not allow for the effects of consumer metrics, next to the elasticities for the preferred Complete specification. There are clear differences in the implications from these two specifications, not only in the price elasticities, which tend to be more positive, on average, in the limited Basic case but also (and especially) in the advertising elasticities. Allowing for the effects of consumer metrics, the advertising elasticities are larger, on average, compared to those of the Basic specification with reduced information. Deviations in the short-term elasticities also occur.

These deviations of the mean elasticities from ignoring (rather than considering) the effects of consumer metrics are all significantly different, employing approximate Welch tests

[22] The web appendix provides the corresponding cross-elasticities for price and advertising (long-term).

[23] Note that the advertising elasticities are interpreted under the presumption that the average effect of the consumer metrics remains the same at 1% and thus a relatively small increase in spending. Analyzing a potential functional relationship of budgets and consumer metrics is beyond the scope of this study. (See appendix *Constrained and Restricted Specifications and Endogeneity* for the details of how we control for such potential issues.)

[24] The average short-term advertising elasticity found by Tellis (2009) was 0.1, and Sethuraman, Tellis, and Briesch (2011) report an average value of 0.12 (median 0.05). Assmus, Farley, and Lehmann (1984) report an average long-term advertising elasticity of approximately 0.41 (Sethuraman, Tellis, and Briesch 2011). The average long-term advertising elasticity found by Sethuraman, Tellis, and Briesch (2011) is 0.24, whereas these authors report that 17% of the long-term elasticities are larger than 0.5.

at a significance level of 5% (except for the short-term elasticity of Jacobs' sub-brand 3).

From an economic perspective, comparing the absolute percentage deviations of the elasticities from both specifications, we find particularly large biases in the advertising elasticities when ignoring the effects of consumer metrics, which range from approximately 12% to more than 270% for the long-term advertising elasticities.[23,25] Note that the biases in the advertising elasticities when ignoring the effects of consumer metrics cause a variety of contrary consequences of advertising effectiveness (cf. the subsequent paragraph *Retailing Implications*). For instance, the allocation of additional advertising budget based on the rule-of-thumb of relative elasticities (cf. e.g., Baidya and Basu 2011) leads to differences in the budget allocation of up to eight (long-term) and thirteen (short-term) percentage points (shown in web appendix W.2). This means that 18% (long-term) or 24% (short-term) of the budget would be sub-optimally allocated if consumer metrics are ignored (i.e., under the Basic specification). In summary, the outcomes indicate that considering the effects of consumer metrics on advertising effectiveness can substantially improve, statistically and economically, the outcomes of the demand analysis.

Return on Investment

To put the results into perspective, we compute the return of investment (ROI) of the advertising effort analogously to Wildner and Modenbach (2015). The idea behind this calculation is to assess the monetary increase in sales due to advertising and to evaluate the value in relation to spending. For this purpose, we simulate revenues for two scenarios, either with advertising support during the first year of our observations or without such support. In the remaining of the 90 considered weeks, there is no support from advertising in either scenario. For this simulation, all explanatory variables are the same as in the observed setting, except for advertising effort. Because the two scenarios differ only in advertising effort, changes in revenue are due to advertising.[26] The short-term ROI is the difference in the revenue of the first year divided by advertising spending. The long-term ROI is the outcome if we consider the changes in revenues for all observations. We project the market shares to overall national sales using the corresponding market sizes.[27] The ROI results yield values of approximately 1.47 over the short term and 3.42 over the long term. This outcome is in the overall range of the findings reported by Wildner and Modenbach (2015), who find a short-term ROI of approximately 1.7 in the coffee and tea category in Germany in 2010 (with an average of approximately 1.15 across all 22 considered product categories).[28] While we find that the short-term ROI from the Basic specification ignoring consumer metrics is similar in size, the long-term ROI value of approximately 3.64 is, to some extent, overestimated.

Conclusion

For managers and scholars in retailing and related fields, measuring advertising effects on actual sales is a key task. However, deriving advertising effects in a real-world situation is in general difficult because advertising can be effective to differing degrees for different consumers due to individual sensitivities toward it. The introduced approach allows for these heterogeneity effects. In doing so, we do *not* need to make assumptions about how advertising effectiveness changes over time. On the contrary, we explore whether advertising effectiveness changes due to changes in consumers' recall and attitude toward advertisements. Typical tracking data provide this information about consumers' heterogeneous cognitive and emotional evaluations of a brand's advertisement and previous experience with a brand (denoted as consumer metrics) that are related to the theoretical dimensions of advertising effectiveness (Vakratsas and Ambler 1999). The outcome of our empirical example indicates that both consumer metrics can have a significant influence on short- and long-term advertising effectiveness. Goodwill, that is, the accumulation of past advertising efforts, depreciates more quickly if consumers had a previous recent experience with the brand. However, goodwill depreciates more slowly if consumers tend to recall and appreciate an advertisement. In addition, a consumer's brand experience reduces the direct effectiveness of advertising. Utility increases if a consumer's attitudes toward an advertisement and his or her ability to recall the advertisement increase. The effect of experience is dominated by the effect of recalling and appreciating an advertisement.

Retailing Implications

The discussed approach and findings from the application are important and interesting for retailing managers who aim to determine the effects of advertising. Managers may benefit from this approach when planning their advertising campaigns or in their collaborations with brand advertisers. Including heterogeneous effects on consumers allows to consider that advertising may not only shift the demand curve outwards but can also rotate it. The results suggest, for instance, that advertising is more effective for buyers without recent brand experiences. Executives may be interested in focusing on these segments of consumers via targeted advertising in certain TV channels, programs or regional areas. Likewise,

[25] The web appendix shows that the elasticities for the Restricted case, that is, if preferences are restricted to be the same for all consumers, also reveal sizable deviations from the Complete case.

[26] However, it is important to note that the scenario without support of advertising strongly differs from the observations. Thus, we must exercise caution when interpreting the outcomes (e.g., Lucas 1976).

[27] The data set also contains information about overall store revenues. With additional information about total yearly revenues per retail chain (from M+M Eurodata), we assess the proportion of observed sales in relation to the overall national market and accordingly project the results to the national level.

[28] Their long-term ROI is not directly comparable with this study, as the authors analyze four instead of approximately one additional year.

managers can profit from addressing consumers who particularly appreciate the brand's advertisements or advertising in general and targeting these people to effectively use their funds. Depending on the distribution of consumer preferences, retailers should aligning their marketing strategies with the effects from advertising, for example, via special pricing and support activities to fully benefit from thorough knowledge of consumer demand.

The findings of the empirical example lead to the conclusion that it can be necessary to account for both heterogeneity and consumer metrics when examining advertising effectiveness. The resulting elasticities are noticeably corrected for price and considerably corrected for advertising, which leads to significantly better-informed decisions. Otherwise, the effect of advertising appears to be overestimated (cf. *Results of the Empirical Example* section and the web appendix). If retailers do not account for consumer heterogeneity toward advertising, this can also lead to suboptimal managerial decisions with respect to other marketing instruments. We investigate this point further for retail pricing using three scenarios that vary by whether retailers do or do not completely control for advertising effects when analyzing consumer demand. Such scenarios can reflect the outcome if a retailer does not cooperate with manufacturers and hence has no information about factors such as advertising budgets or consumer metrics. Thus, the evaluation does not consider (A) the effects of consumer metrics on advertising (i.e., the Basic specification), (B) additionally ignores heterogeneity of consumer preferences (i.e., the Constrained setting) or (C) also neglects the influence of advertising as a whole. In this analysis, we suppose that retailers are local monopolists that maximize profits in a market according to price (conditional on the other effects on consumer utility; cf. e.g., Villas-Boas and Zhao 2005).[27] In a numerical experiment, we assess the consequences of the three scenarios for retail profits (details are provided in the web appendix). The approximate yearly loss in national profit for the retailers totals over 4,500,000 Euros (an average of more than 760,000 Euros and a maximum of more than 1,400,000 Euros per retailer) in Case (C), that is, without considering advertising effects; more than 2,000,000 Euros (an average of more than 340,000 Euros and up to more than 650,000 Euros) in Case (B), that is, without taking heterogeneity of preferences into account; and more than 400,000 Euros (an average of approximately 70,000 Euros and up to more than 100,000 Euros) in Case (A), that is, when ignoring information from consumer metrics. The results thus indicate considerable economic implications. In conclusion, both academics and practitioners should carefully determine whether accounting for the effects of consumer metrics and heterogeneity is necessary in evaluations of advertising effects and subsequent derivations of managerial implications.

Limitations and Future Research

Several limitations of this study offer opportunities for future research. First, it would be interesting to compare the empirical results of this study to outcomes for different product categories and countries to gain a broader picture of the effects.[29] There are a number of directions for further development of this approach. Such advancements may involve accounting for potential consumer stock-keeping behavior or state-dependence versus variety-seeking behavior (Dubé, Hitsch, and Rossi 2010). In our empirical example, we tested for this behavior but did not find evidence of clear effects. Future research with access to more detailed data may be able to employ information about evaluations of advertisements by consumers who did not recall having seen an advertisement. Different waves of consumers were questioned in the tracking interviews to avoid repeated-measurement bias (Morwitz and Fitzsimons 2004). In this context, an interesting and open topic for future research would consider how to conduct an analysis of individual-specific goodwill measurements. All advertising campaigns remained in place throughout this study. It would be insightful of future research to examine the importance of accounting for consumer-specific preference via consumer metrics to evaluate the effects of different advertising campaigns. Further research could also focus on supply-side implications, such as optimal advertising budget allocation in the presence of advertising effects and heterogeneous consumers. The results of this study make clear that although much recent research in retailing and marketing focuses on online activities, the substantial economic implications of traditional advertising activity continue to require in-depth research.

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Appendix

Constrained and Restricted Specifications and Endogeneity

In this subsection, the results of the following cases are discussed: the ordinary least squares (OLS), the two-stage least squares (2SLS, i.e., the Constrained) and the Restricted setting. The Restricted setting corresponds to the Complete specification when heterogeneity of consumer preferences is ignored, that is, when the parameters σ_1, σ_2, σ_3, σ_4, π_1, π_2, π_3 and π_4 are all restricted to zero. In the following, we also examine the appropriateness of the employed instrumental variables in accordance with Baum, Schaffer, and Stillman (2003). For the OLS and 2SLS settings, we use the same explanatory variables as outlined previously. The variables include constants for each sub-brand and retailer (where Tengelmann is the reference category), the variables for price and promotional support and the

[29] For categories with products that are complex and difficult to evaluate, brand experience may be framed by additional information from advertising and may ultimately increase advertising effectiveness as re-framed, perceived prior evidence of an advertisement claim (Hoch and Ha 1986).

Table 4
Parameter estimates and model statistics of the OLS model, the Constrained (i.e., the 2SLS) and Restricted specifications ("Est." stands for "Estimated value", "Std" abbreviates standard deviation, Υ denotes the overidentification test statistic and κ the 95%-quantile from the distribution of Υ).

Variable		OLS		Constrained (2SLS)		Restricted	
	Par.	Est.	Std	Est.	Std	Est.	Std
Jacobs (Sb 1)	β_{p1}	2.78	(0.13)	0.14	(0.19)	1.49	(0.17)
Jacobs (Sb 2)	β_{p2}	1.72	(0.12)	−0.83	(0.18)	0.49	(0.17)
Jacobs (Sb 3)	β_{p3}	0.57	(0.12)	−1.96	(0.18)	−0.77	(0.17)
Melitta (Sb 1)	β_{p4}	1.54	(0.13)	−0.97	(0.18)	−1.19	(0.21)
Melitta (Sb 2)	β_{p5}	0.65	(0.12)	−1.81	(0.18)	−2.14	(0.21)
Dallmayr (Sb 1)	β_{p6}	2.57	(0.14)	−0.14	(0.20)	−0.01	(0.22)
Tchibo (Sb 1)	β_{p7}	2.48	(0.13)	−0.37	(0.20)	0.24	(0.20)
Tchibo (Sb 2)	β_{p8}	3.40	(0.12)	0.75	(0.19)	1.25	(0.19)
Tchibo (Sb 3)	β_{p9}	2.15	(0.13)	−0.56	(0.19)	−0.03	(0.20)
Tchibo (Sb 4)	β_{p10}	2.29	(0.13)	−0.42	(0.19)	0.11	(0.20)
Tchibo (Sb 4)	β_{p11}	1.32	(0.12)	−1.18	(0.18)	−0.76	(0.19)
Tchibo (Sb 6)	β_{p12}	1.12	(0.12)	−1.43	(0.18)	−0.99	(0.19)
Eduscho (Sb 1)	β_{p13}	2.33	(0.13)	−0.24	(0.19)	−0.18	(0.21)
Edeka	β_{r1}	0.00	(0.02)	0.01	(0.02)	0.00	(0.02)
Markant	β_{r2}	−0.11	(0.02)	−0.10	(0.02)	−0.11	(0.02)
Metro	β_{r3}	−0.22	(0.02)	−0.24	(0.02)	−0.23	(0.02)
Rewe	β_{r4}	0.36	(0.02)	0.35	(0.02)	0.35	(0.02)
Spar	β_{r5}	0.34	(0.02)	0.31	(0.02)	0.33	(0.02)
Promotion	β_p	0.39	(0.02)	1.46	(0.03)	1.26	(0.03)
Price (log-transformed)	α	−5.46	(0.04)	−4.46	(0.08)	−5.01	(0.08)
$\Gamma(G)$	θ_1	0.39	(0.02)	0.51	(0.02)	0.46	(0.04)
$\Gamma(G) \cdot Aad \cdot$ AdRecall	θ_2					0.07	(0.01)
Retention rate:							
Constant	γ_0	1.65	(0.12)	1.89	(0.12)	−0.78	(2.10)
BrandExprc	γ_1					−1.12	(0.25)
Aad · AdRecall	γ_2					0.83	(0.23)
F-value		1,972.6					
F-quantile		1.544					
R^2		0.864					
Adjusted R^2		0.864					
BIC		8,942.6					
Υ				888.4		852.4	
κ				928.3		925.2	
MMSC-BIC				−6,696.0		−6,705.6	
MMSC-HQIC				−3,040.6		−3,062.9	

influence of advertising. We explore the influence of advertising by the means of several different specifications of the goodwill production function, as described in the subsequent section of this appendix. The retention rates for both the OLS and the 2SLS models are nonlinearly estimated such that the parameters minimize the sum of the squared errors with respect to the objective of the GMM (cf. *Methodological Details* section). The Table 4 shows the results.

Note that the settings yield a good overall goodness of fit and the resulting parameter values all have the expected signs, that is, they are face valid. We observe that the absolute magnitude of the effects of goodwill increases and that the influence of price decreases when we account for endogeneity. This occurs to a lesser extent when effects of aggregate consumer metrics are additionally considered. These changes are accompanied by a shift of the sub-brands' fixed effects, whereas the parameters of the retailer constants remain in a similar range. The consideration of the consumer metrics in the restricted model improves the derivation of the advertising effect in terms of the information criteria. For the OLS model, the Bayesian information criterion (BIC) is shown, and for the 2SLS and Restricted models the values of the MMSC-BIC and the MMSC-HQIC (Andrews and Lu 2001).[17,30]

To control for potential endogeneity, we use the following five instrumental variables for price: raw coffee costs lagged by zero, one and two periods and the mean of all sub-brand prices lagged by one and two periods. Doing so accounts for competitive price-setting behavior based on previous prices. The raw coffee cost consists of price information of traded contracts at

[30] The criteria are the ones introduced in *Methodological Framework and Implementation* section. Andrews and Lu (2001) showed that under fairly weak assumptions, the use of the criteria leads to the selection of the true parameter and moment restrictions for an increasing sample size, given that the true specification is among the set investigated. Both criteria favor model specifications that better fit to the data but at the same time penalize overparametrization.

the New York Stock Exchange.[31] Since the price of raw coffee is set worldwide at the stock exchange, the raw coffee price can be considered as nearly exogenous for the German market. Raw coffee costs are also highly correlated with the ground coffee prices because it is the main ingredient. We employ the monthly, in the advertising industry common, measure of cost per mille (CPM) as instruments for the advertising budgets.[32] Additionally, we make use of available radio, newspaper and magazine advertising budgets because these budgets are correlated with TV advertising expenditures and we utilize the TV budgets lagged by one period as instrumental variables. Thus, in total there are six instrumental variables to control for potential endogeneity of the advertising budgets. The full set of instrumental variables is interacted with constants for the combinations of sub-brands and retailers to control for sub-brand and retailer specific effects. In accordance with Baum, Schaffer, and Stillman (2003), we check the appropriateness of the applied instruments. We observe that prices are significantly correlated with all of the instrumental variables. The same holds true for the TV advertising budgets or the influence of goodwill and its instrumental variables.

Furthermore, we conduct separate instrumental variable regressions of price and goodwill on their respective instrumental variables. The *F*-value is 80.4 for the regression of price and 134.6 for the regression of goodwill on the instrumental variables.[33] We also utilize the coefficient of determination, R^2, in the instrumental variable regression to identify the risk levels in the finite samples that the instrumental variables may lead to biased and, thus, inconsistent estimates instead of correcting for endogeneity. The R^2 for the regression of price is 0.92, and that of the influence of goodwill is 0.95. Since more than one endogenous variable exists in the model, we also check the partial R^2 statistic (see, e.g., Godfrey 1999; Shea 1997). The partial R^2 of price is 0.75, whereas the partial R^2 of goodwill is 0.90. Thus, we conclude that the endogenous variables can be explained by their instruments and, therefore, consider the instrumental variables as valid. Moreover, the Durbin-Wu-Hausman Test (Durbin 1954; Hausman 1978; Wu 1973) rejects the null hypothesis that the OLS model is consistent and fully efficient. Due to this reason, we conclude that the use of instrumental variables is necessary. These test results are confirmed by the over-identification test in Table 4, which does not reject the appropriateness of the instrumental variables. In other words, the variables satisfy the orthogonality condition with regard to the error terms. Furthermore, the test confirms that the implied model specification is appropriate (Hansen 1982).

In general, the consumer metrics may be potentially subject to current and past advertising budgets. In this case, we could therefore express the consumer metrics as a function of current and past advertising budgets plus an error term $\zeta_m = (\zeta_{1m}, \ldots, \zeta_{Jm})'$ at market *m*. ζ_m would be interpreted as surrogate of what of the consumer metrics is not explained by advertising budgets. However, in general, such a setting would *not* induce an endogeneity problem due to a potential correlation of ζ_m and ξ_m, in particular for $BrandExprc_m$ (i.e., the previous experience with the consumption of the brand). At first, note that the instrumental variables instrument for prices, advertising budgets, functions and lagged functions of spendings, such as the goodwill. This includes for example also the effect of lagged consumer metrics on the retention rate of goodwill. Secondly, next to these comprehensive controls, $BrandExprc_m$ is per definition uncorrelated with ξ_m because it explicitly refers to the past experience with the consumption of the brand. We also test for autocorrelation and control for heteroscedasticity and autocorrelation of ξ (cf. *Results of the Empirical Example* section and appendix *Methodological Details*). In general, an advantage of the GMM methodology is that even in a case when the weighting matrix would not have been exactly accounted for, this could lead to less efficient but nevertheless would lead in any case to consistent outcomes (see, e.g., Greene 2011).

Overall Functional Form of Goodwill

This subsection outlines the process by which the overall functional form of goodwill is investigated. The selection process for an appropriate specification is conducted by the means of the following two criteria: the Bayesian and the Hannan-Quinn information criterion, denoted as MMSC-BIC and MMSC-HQIC (Andrews and Lu 2001).[17,30] To attain independence from the initial level of goodwill, our model utilizes an initialization period and additional advertising budget data of three years prior to the estimation sample. We incorporate the advertising budgets into the goodwill production function in terms of thousands of Euros. The selection criterion values for different common and popular specifications of the overall form of goodwill, motivated from the literature of advertising effects, are summarized in Table 5.

In our empirical example, the best specification is obtained when the current advertising effort is square root transformed and the cumulative past advertising effort is added as lagged goodwill weighted by the retention rate. The root transformation allows to account for diminishing marginal returns of advertising on goodwill which yields a typical and reasonable property in the context of advertising (e.g., Bagwell 2007). The current goodwill affects the utility log-transformed (after adding 1 to avoid computing the logarithm of 0). The logarithmic transformation is in accordance with previous literature (e.g., Doyle and Saunders 1990; Dubé, Hitsch, and Manchanda 2005) and it is sensible from an economic point of view since it allows to

[31] There are six different contract prices that differ in their dates of expiration. We summarize the information by the means of the first principal component of the six prices as a cost index, which accounts for approximately 90.1% of the total variation; since the contract prices of raw coffee are considerable correlated. The average of the raw coffee cost index in terms of months is employed as instrumental variable. Note that if a calendar week spans two different months, the values are accordingly distributed in proportion to the number of days in each month.

[32] The CPM information is available for twelve major TV stations. We employ the first two principal components as cost information indices, which account for approximately 72.4% of the total variation.

[33] Staiger and Stock (1997) report that a *F*-value smaller than ten indicates weak instruments in the regression of an endogenous variable on its instrumental variables.

Table 5
Comparison of different goodwill specifications. (The note to ⋆ is given in the text below.)

Goodwill production function	Functional form of goodwill			
	$\Gamma(G_{jt_m}) = G_{jt_m}$		$\Gamma(G_{jt_m}) = \ln(G_{jt_m}+1)$	
	MMSC-BIC	MMSC-HQIC	MMSC-BIC	MMSC-HQIC
$G_{jt_m} = A_{jt_m} + \lambda G_{j(t_m-1)}$	−6,653.6	−2,998.3	−6,692.9	−3,037.6
$G_{jt_m} = (1-\lambda)A_{jt_m} + \lambda G_{j(t_m-1)}$	−6,653.6	−2,998.3	−6,684.7	−3,029.4
$G_{jt_m} = A_{jt_m} \cdot G^{\lambda}_{j(t_m-1)}$	−6,642.2	−2,986.8	−6,665.2	−3,009.9
$G_{jt_m} = A^{1-\lambda}_{jt_m} \cdot G^{\lambda}_{j(t_m-1)}$	−6,651.2	−2,995.8	−6,667.5	−3,012.2
$G_{jt_m} = \ln(1+A_{jt_m}) + \lambda G_{j(t_m-1)}$	−6,673.2	−3,017.8	⋆	⋆
$G_{jt_m} = (1-\lambda)\ln(1+A_{jt_m}) + \lambda G_{j(t_m-1)}$	−6,673.2	−3,017.8	−6,687.5	−3,032.1
$G_{jt_m} = \ln(1+A_{jt_m}) \cdot G^{\lambda}_{j(t_m-1)}$	−6,641.8	−2,986.4	−6,671.2	−3,015.9
$G_{jt_m} = \ln(1+A_{jt_m})^{1-\lambda} \cdot G^{\lambda}_{j(t_m-1)}$	−6,655.8	−3,000.4	−6,665.0	−3,009.6
$G_{jt_m} = \sqrt{A_{jt_m}} + \lambda G_{j(t_m-1)}$	−6,657.9	−3,002.5	**−6,696.0**	**−3,040.6**
$G_{jt_m} = (1-\lambda)\sqrt{A_{jt_m}} + \lambda G_{j(t_m-1)}$	−6,657.9	−3,002.5	−6,678.3	−3,022.9
$G_{jt_m} = \sqrt{A_{jt_m}} \cdot G^{\lambda}_{j(t_m-1)}$	−6,642.1	−2,986.7	−6,664.3	−3,008.9
$G_{jt_m} = \sqrt{A_{jt_m}}^{1-\lambda} \cdot G^{\lambda}_{j(t_m-1)}$	−6,644.1	−2,988.7	−6,656.2	−3,000.8

account for diminishing marginal returns of goodwill on utility. ⋆ Note that in one case, $G_{jt_m} = \ln(1 + A_{jt_m}) + \lambda G_{j(t_m-1)}$ and $\Gamma(G_{jt_m}) = \ln(G_{jt_m} + 1)$, the model fits in general well to the data but the functional form is not consistent with the firms' advertising budgets (i.e., even with a relatively high retention rate of 0.96, a brand manufacturer that spent one or two million Euros on advertising in period $t_m - 1$ and nothing on advertising in period t_m is clearly worse off than a manufacturer that spent one hundred thousand Euros in both periods). Thus, this goodwill-generating function cannot explain that companies set their advertising budgets to the observed values.

Advertising Elasticity

The short-term advertising elasticity η^m_{jkm} results as the following expression:

$$\eta^m_{jkm} \equiv \frac{A_{km}}{s_{jm}}\frac{\partial s_{jm}}{\partial A_{km}} = \frac{\sqrt{A_{km}}}{2s_{jm}(1+G_{km})} \cdot \int_D\int_\nu\int_\xi (\vartheta_{km} + \varpi_{ikm} + \sigma_4 \nu_{4i}) \times s_{ijm}(I(j=k) - s_{ikm})\phi(\nu)d\nu dP_D(D)dP_\xi(\xi), \quad (10)$$

where $I(a)$ denotes an indicator function that is 1 if the argument a is true and 0 otherwise. Since advertising in the current period, that is, in t_m, can impact the next period's market shares, that is, in $t_m + 1$, we calculate the percentage change of the next period's market shares in accordance with an one-percent increase of the current period's advertising. We denote this value as $\eta^{m(+1)}_{jkm}$. Thus, $\eta^{m(+l)}_{jkm}$, the effect of a firm's advertising effort in t_m on the firm's market share in $t_m + l$ results as follows:

$$\eta^{m(+l)}_{jkm} \equiv \frac{A_{km}}{s_{jm_{(+l)}}}\frac{\partial s_{jm_{(+l)}}}{\partial A_{km}} = \frac{\sqrt{A_{km}}\prod_{\bar{l}=1}^{l}(\lambda_{jm_{(+\bar{l})}})}{2s_{jm_{(+l)}}(1+G_{km_{(+l)}})} \cdot \int_D\int_\nu\int_\xi (\vartheta_{km_{(+l)}} + \varpi_{ikm_{(+l)}} + \sigma_4\nu_{4i})s_{ijm_{(+l)}} \times (I(j=k) - s_{ikm_{(+l)}})\phi(\nu)d\nu\, dP_D(D)\, dP_\xi(\xi). \quad (11)$$

We compute the long-term effect of advertising for the 90% duration interval T^a (see, e.g., Clarke 1976):[34]

$$r_{jkm} = \sum_{l=0}^{T^a} \delta^l \eta^{m(+l)}_{jkm}, \quad (12)$$

where δ represents the discount factor of one week, which corresponds to a yearly interest rate of 10%. Note that in Eqs. (11) and (10), we numerically integrate over the empirical distribution $P_\xi(\xi)$ of the demand shock. To control for potential variations of ξ across markets, the current ξ serves as local mean of the in-sample distribution (and the accordingly one period lagged values for the out-of-sample distribution) together with locally adaptive variances of the empirical distribution according to Silverman (1986). By the means of Copula techniques, we numerically integrate over 300 draws from Halton sequences of the distribution of ξ (Train 2009).

Methodological Details

A market m represents a retailer in a given week. Therefore, we can determine the market share of each sub-brand by

[34] To ensure a conservative derivation of T^a, the average minimum retention rate is applied.

information about the total revenue of a retailer in a particular week: We compute each sub-brand's within-group market share based on the quantities of coffee sold and then multiply the resulting numbers by the retailer's weekly market share of the coffee industry.[35] In order to calibrate the demand parameters, one needs to evaluate the expected market share based on Eq. (4). The tracking data contain the information from roughly 6,700 respondents in total, with approximately 320 respondents per month. The market research company provided weights that ensure the comparability and representativeness of the tracking data across months and therefore, we employ these weights to sample 320 respondents per month. To numerically integrate out the unobserved heterogeneity of the random coefficients, we use draws from Halton sequences (Train 2009) because these draws induce fewer simulation errors than the same number of standard random draws (e.g., Bhat 2001; Hensher 2001).[36] For the parameter estimation, we employ the generalized method of moments, denoted as GMM (Berry, Levinsohn, and Pakes 1995; Nevo 2000). To reveal the global minimum of the GMM objective function, we apply different starting values for the estimation procedure and use a tight convergence tolerance level for the outer loop of the estimation to attain stable results (see, e.g., Dubé, Fox, and Su 2012). To control for heteroscedasticity and autocorrelation of the structural error terms in the sample, we employ the Newey and West (1987) estimator when computing the standard errors of the calibrated parameters. As recommended (e.g., Greene 2011), we apply as the maximum lag length, p_{lag}, $p_{lag} = \lceil 90^{\frac{1}{4}} \rceil = 4$. $\lceil y \rceil$ stands for the floor of a value y.

The empirical test of the exogeneity of prices and advertising rejects the exogeneity assumption. Therefore, to control for endogeneity of prices and advertising, we employ in total five instrumental variables for price and eight instrumental variables for advertising. To control for sub-brand and retailer specific effects, the full set of instrumental variables is interacted with constants for the combinations of sub-brands and retailers. Appendix *Constrained and Restricted Specifications and Endogeneity* describes the instrumental variables and the tests used to check for their appropriateness and for endogeneity. We check for temperature and additional temporal, for example, seasonal effects in general (described in the web appendix). The results suggest to dispense temperature or additional temporal explanatory variables and in particular do not show empirical evidence, for example, for seasonal events such as Christmas, national Easter holidays or summer versus winter.

[35] We also used the retailers' weekly revenues to determine the number of consumers who visited their stores. Based on industry reports, the average checkout sum per outlet can be determined. Hence, the number of consumers can be estimated by dividing each retailer's weekly revenues by this number. In our empirical analysis, we found that the estimates are relatively insensitive to these definitions of market size.

[36] The literature suggests that 100 draws from Halton sequences may induce fewer simulation error than 1,000 standard random draws.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jretai.2016.02.004.

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