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Nitin Mehta, Xinlei (Jack) Chen, Om Narasimhan,

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Informing, Transforming, and Persuading: Disentangling the Multiple Effects of Advertising on Brand Choice Decisions

Nitin Mehta

Rotman School of Management, University of Toronto, Toronto, Ontario M5S 3H7, Canada,
nmehta@rotman.utoronto.ca

Xinlei (Jack) Chen

Sauder School of Business, University of British Columbia, Vancouver, British Columbia V6T 1Z4,
jack.chen@sauder.ubc.ca

Om Narasimhan

Carlson School of Management, University of Minnesota, Minneapolis, Minnesota 55455
onarasimhan@csom.umn.edu

Prior behavioral research has suggested that advertising can influence a consumer's quality evaluation through informative and transformative effects. The informative effect acts directly to inform a consumer of product attributes and hence shapes her evaluations of brand quality. The transformative effect affects the consumer's evaluation of brand quality by enhancing her assessment of her subsequent consumption experience. In addition, advertising may influence a consumer's utility directly, even without providing any explicit information—this is the persuasive effect.

In this paper, we propose a framework that formally models the processes through which all three effects of advertisements impact consumers' brand evaluations and their subsequent brand choice decisions. In particular, we model source credibility, confirmatory bias, and bounded rationality on the part of consumers, by appropriately modifying the standard Bayesian learning approach. Our model conforms closely to prior behavioral literature and the experimental findings therein. In our empirical analysis, we get significant estimates of both informative and transformative effects across brands. We find interesting temporal patterns across the effects; for instance, the importance of transformative effects seem to grow over time, while that of informative effects diminishes. Finally, we conduct policy experiments to examine the impact of increased ad intensity on advertising effects, as well as the role played by consumption ambiguity.

Key words: advertising effects; informative effects; persuasive effects; structural models; consumer learning; policy experiments; bounded rationality; confirmatory bias

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1. Introduction

Advertising, it has been conjectured in prior literature, shapes consumer preferences in multiple ways. The first, most obvious effect is that advertising informs the consumer of product attributes and hence raises awareness and knowledge of the true quality of the brand. This has been called the *informative* effect of advertising (Bucklin 1965, Lavidge and Steiner 1961). Second, advertising may directly influence a consumer's brand evaluations through such cues as celebrity endorsements and music, even without providing any explicit information. This has been referred to as the *persuasive* or *prestige* effect of ads (Aaker and Stayman 1990, Batra and Ray 1986). Third, advertising can influence how consumers experience and evaluate the quality of the

product from subsequent consumption. This effect has been evocatively referred to as the *transformative* effect of advertising (Deighton 1984, 1988) and is the focus of our paper. It is important at the outset to differentiate the transformative effect from the informative and persuasive effects. One key feature helps us do that—transformative effects have an impact only *in the presence of consumption*. If the consumer watches the ad and does not consume thereafter, there can be, by definition, no transformative effect. By contrast, both informative and persuasive effects exist independently of subsequent consumption. Thus, unlike the informative or persuasive effects, the transformative effect does not change consumers' brand evaluations *immediately after* they are exposed to the advertisements, but instead shapes consumers' evaluations

by influencing what they learn about the brand's quality/attributes from their *subsequent* consumption experience. Prior research suggests that these effects are not mutually exclusive, i.e., an advertisement can have informative, persuasive, and transformative effects. Our goal in this paper is to develop a model that accommodates all three effects, while hewing closely to behavioral and economic theories of advertising, and to estimate this model using real-world data.

A number of papers have suggested diverse theoretical rationale for the informative effects of advertising (e.g., hierarchy-of-effects models, such as Lavidge and Steiner 1961 or Aaker et al. 1992; alternative frameworks are provided by Greenwald 1968 and Fishbein and Ajzen 1975). This literature suggests that the effect is strongest when involvement is high and when advertisements provide information about brand attributes that are relevant and verifiable, leading to greater confidence on the part of the consumer in her assessments of the brand's quality (Nelson 1970, 1974; Holbrook 1978).

Regarding the persuasive effect, a stream of literature based on the Elaboration Likelihood Model (Petty et al. 1983) suggests that under low involvement situations, the peripheral route to persuasion dominates, and consumers pay attention to the execution elements of the ad more than to any information provided. The key is that consumers' brand evaluations are enhanced even without the cognitive evaluation of attributes (Aaker and Norris 1982, Zajonc and Markus 1980).¹ Before we move on to the transformative effect, for the sake of completeness, we should mention the "signaling" role of advertising that has been modeled theoretically (Kihlstrom and Riordan 1984, Milgrom and Roberts 1986), and estimated econometrically (Ackerberg 2003, Erdem et al. 2006). These papers suggest that the quantity of advertising can itself signal quality—the consumer interprets higher advertising intensity as a signal of higher quality.²

A relatively smaller literature has examined the transformative role of advertising. A major strand of this work draws on behavioral literature to suggest that message and subsequent consumption experience interact (Slovic et al. 1977, Gilovich 1981). Hoch and Deighton (1989) suggest the following process of transformation. Consumers perceive ads to be biased, because they realize that ads are coming from a partisan source whose interests are not necessarily aligned

with their own. However, because they do not know the exact amount of this bias, consumers treat the ad as a tentative hypothesis, which they test during subsequent consumption. If the advertising message connects tightly with the consumption experience, i.e., in some sense, the ad tells consumers which attributes to look out for during subsequent consumption, it leads to a confirmatory bias in learning from the consumption experience. In other words, learning from consumption serves to confirm the expectations created by the ad, and biases in the ad message get manifested in learning from consumption. Because the behavioral underpinnings and econometric estimation of the transformative effect are a cornerstone of this paper, it helps to elaborate on the process just outlined.

The transformative effect. To start with, why would ads result in consumers forming a tentative hypothesis about the quality of the brand? This is because even though consumers perceive the ads to be biased, they are not aware of the extent of the bias, and they do not reject the message altogether. The ad facilitates this process when it encourages a "willing suspension of disbelief" (the attributes are presented in a suggestive rather than didactic fashion). Clearly, on this point alone, ads can influence subsequent consumption experiences. However, crucially, the impact is a great deal more than this—prior literature suggests that consumers are predisposed to confirming the hypotheses suggested by the ad, while verifying its claims during consumption.

Why does this happen? Researchers suggest this is because of consumers' information processing limitations. During consumption, consumers get evidence that is both consistent and inconsistent with the ad-based expectations. If consumption occurs during low involvement conditions, consumers learn through top-down learning, or passive observation, where they pay more attention to ad-consistent evidence and less to ad inconsistent evidence (Hoch and Deighton 1989, Snyder and Swann 1978). Thus, what consumers learn about the brand's quality/attributes through consumption is consistent with the expectations laid out by the ads. This would happen if there is a match between the attributes suggested by the ad and the attributes observed during consumption. In sum, the biases in the ad get transferred to the information the consumer learns about the product from subsequent consumption.

The above description of the transformative effect still leaves two important questions unanswered. First, what determines the strength of the transformative effect? Apart from the content of the ad itself (appropriately suggestive of the attributes and the best way to evaluate them during the subsequent consumption experience), and consumer involvement

¹ Econometrically, the persuasive effect has been modeled through a term directly affecting the utility. As we discuss later, this is best understood, conceptually, using the Becker-Murphy (1993) notion of advertising as a complementary good.

² While we mention the signaling effect here for completeness, we do not model it in the paper.

(lower is better because it encourages learning by passive observation), an important determinant is the ambiguity of the consumption experience. Hoch and Ha (1986) found that top-down processing of information (thus enhancing the transformative effect) was the norm when the consumption experience was ambiguous. Clearly, if consumption provides unambiguous evidence, it also allows any ad claims that are potentially biased to be easily refuted, and the information learned from consumption dominates consumers' brand evaluations. On the other hand, if the consumption experience is noisy, then consumers could interpret the consumption experience as being consistent with their ad-based expectations.

Second, are consumers aware that their evaluations from consumption are being influenced by their ad-based expectations in this fashion? If they are aware of this influence, they will discount it, hence negating the transformative effect. Prior literature suggests that this is unlikely to happen, because consumers privilege their product experiences, i.e., they grant a special status to conclusions learned from experience and suffer from an illusion of control (Langer 1975). As such, they do not doubt the credibility of what they learn from consumption (Hoch and Ha 1986, Hoch and Deighton 1989).

Modeling challenges. The modeling of all three effects of advertising carries with it a number of challenges. Prior literature has used the Bayesian learning paradigm to model informative and persuasive effects structurally (Erdem and Keane 1996, Ackerberg 2003). We argue that the standard Bayesian learning model has to be modified along multiple dimensions to model transformative effects for the following reasons.

(a) *Source credibility.* Standard Bayesian learning models assume that each ad is an independent and unbiased signal of the brand's true quality, or even if the signal is biased, the consumer knows the extent of the bias exactly. In practice, consumers are aware that advertising messages are motivated by a desire to influence, and are generally wary of the credibility of the source. This suggests that consumers know advertising messages are biased, but do not know the exact extent of this bias. The first challenge is to build an appropriate model of how consumers form expectations of the brand's quality from ads, which accommodates this feature.

(b) *Confirmatory bias.* In a standard Bayesian learning model, (prior) ad signals and (post) consumption signals are assumed to be independent pieces of information. That is, ad signals have no impact on how subsequent consumption is evaluated. The idea behind confirmatory bias, however, is that ad-based expectations influence what the consumer sees during

subsequent consumption. As discussed earlier, advertising provides a frame for consumers to evaluate consumption experiences within. This leads to precisely the kind of nonindependence suggested by Fischhoff and Beyth-Marom (1983) and Hoch and Deighton (1989), i.e., one piece of data (ad signals) creates a context that affects the interpretation of a new piece of data (the consumption experience). A modified Bayesian learning model has to account for the correlation between ad expectations about the brand's quality, and the information that the consumer learns about the brand's quality from subsequent consumption evaluations.

(c) *Consumer bounded rationality.* The confirmatory bias just discussed clearly suggests that consumers are not unboundedly rational. This sits uneasily with the tenets of the standard Bayesian learning model, where consumers get independent ad and consumption signals, and update their quality beliefs each period on the basis of both these signals in a rational Bayesian fashion. Carried to its logical extreme, consumers would be aware of the confirmatory bias induced by ads and would accordingly discount information learned from consumption in a rational Bayesian fashion. Clearly, one cannot have transformation in this scenario. As argued above, consumers do not seem to take into account the transference of biases from ad-based expectations to consumption, while evaluating consumption experiences. It seems appropriate, therefore, to allow consumers to *not* discount what they learn from consumption experiences, even if that learning is biased by prior ads.³

All this suggests two ways to proceed. One can either abandon the Bayesian learning framework (with no clear alternative in sight) or modify it to accommodate the deviations mentioned above. We choose the latter approach, because it lets us retain a relatively parsimonious framework that has proved useful in earlier work, while also providing a ready benchmark for comparison purposes. A formal treatment of how we modify the Bayesian learning model is deferred to §2, where we discuss model development.

In the rest of the introduction, we list our research objectives and discuss briefly how we accomplish them. In so doing, we also present a gist of our main findings. This is followed by a brief review of the relevant literature.

³ Bounded rationality enters our model only as it relates to the impact of ads, i.e., consumers are unaware that their consumption evaluations are being transformed by ads. Further discussion of other aspects of bounded rationality is provided in the conclusions section.

1.1. Research Objectives and Contributions

(a) *To propose a formal framework that explicitly models the process through which the informative and transformative effects of advertisements impact consumers' brand evaluations and their subsequent brand choice decisions:*⁴ We view the modeling of source credibility, confirmatory bias, and bounded rationality as a major contribution of the paper. These three components are at the heart of our structural model of advertising's impact on brand choice, and we accommodate them so as to hew closely to behavioral theories of advertising.

(b) *To calibrate our model on observed data:* We calibrate our proposed model on single-source data for liquid laundry detergents. In our empirical analysis, we find significant, albeit modest, informative and transformative effects of advertisements across brands. Among our results, we find that the parameter capturing the extent to which consumers suspect the credibility of ads as a source of information is significant and varies across brands. Similarly, the confirmatory bias (the extent of transference of biases from ads to subsequent consumption experiences) is significant and varies across brands.

(c) *To conduct policy experiments to assess the impact of changing advertising effects:* We conduct a number of policy experiments to tease out the pattern of variation in the effects of advertising across brands. For instance, we examine what the temporal patterns of informative, transformative, and persuasive effects are, i.e.—are some effects more powerful at the beginning of the learning period versus later? We also look at the impact of informative and transformative effects on the clout and vulnerability of brands. Thus we conjecture that increasing informative effects primarily serves to increase the brand's competitive clout but does not substantially change its vulnerability, while increasing transformative effects primarily serves to decrease the brand's vulnerability but does not significantly impact its competitive clout. We find evidence supporting this conjecture. We also investigate the impact of changes in ad intensity on market share, again intertemporally for all three effects.

1.2. Related Empirical Literature

While the literature on the effects of advertising is vast, there are two main streams that are of relevance to this study. Both of these examine the effects of advertising in a field setting, typically using econometric methods on scanner panel data for frequently purchased consumer goods. The first set of studies includes, among many others, Pedrick and Zufryden

(1991) and Lodish et al. (1995) for testing informative effects, and Tellis (1988) and Deighton et al. (1994) for testing transformative effects. These studies have employed reduced-form specifications to capture the effects of advertising on consumer evaluations—they generally find weak informative effects and non-significant transformative effects. We suggest that they find nonsignificant results because they do not model the process by which consumers' brand evaluations are shaped by the different effects of advertising. Modeling the process helps avoid errors that could result in biasing the effects.

Another set of papers consists of structural approaches to testing the impact of advertising (Ching 2003, Erdem and Keane 1996, Erdem et al. 2006, Mukherji et al. 2004, Narayanan et al. 2005) invariably using a quality learning specification. Erdem and Keane (1996) is a pioneering effort that models the informative effect of ads in the laundry detergent category, accounting for forward-looking risk-averse consumers. Consumers are modeled as learning about quality through advertising and consumption signals in a standard Bayesian learning setting. Ackerberg (2003) and Narayanan et al. (2005) build on this work—the former models persuasive and signaling effects in the yogurt category, while the latter models informative and persuasive effects in pharmaceutical drugs. Both these papers model persuasive effects as directly influencing the utility of the consumer (e.g., ads enhancing the prestige associated with the brand). This direct term affecting a consumer's utility essentially captures all the effects of advertising that are not otherwise modeled structurally. The way the persuasive effect has been modeled econometrically is perhaps best understood by conceptualizing it a la Becker and Murphy (1993). In their story, advertising can be viewed as a complement to the product desired, which makes it natural to include advertising "consumed" directly in the utility the product provides. While calling this a "persuasive" effect does not map on exactly to the behavioral literature on the subject, it is a more satisfactory way to explain why one needs a term directly affecting the utility of the consumer. Finally, Erdem et al. (2006) also consider the informative, signaling, and persuasive effect of ads, but adds a role for price as a signal of quality.

None of the above papers explicitly allows ads to influence the evaluation of consumption experiences in a manner consistent with the notion of transformation. In addition, none of them accounts for features such as source credibility or confirmatory bias, both of which are the impetus behind our modification of the standard Bayesian learning framework.

Mukherji et al. (2004) is the only paper that has attempted to explicitly model the interaction of consumption with marketing communication. However,

⁴ As mentioned earlier, while we do model persuasive effects, this is done in a fairly simple fashion, consistent with prior literature. We include persuasive effects for the sake of completeness and do not view their modeling as an important contribution of this paper.

their specification has no role for transformation as is conceptualized in the literature. In the model of Mukherji et al. (2004), the ads are assumed to be unbiased signals of the brand's true quality (thereby assuming that ads are a credible source of information), and the only interaction that is allowed between ads and consumption is one that makes for faster learning about the brand's true quality from consumption if the consumer has watched ads before (thereby implying that there is no confirmatory bias).

The rest of the paper is organized as follows. In §2, we discuss our model specification, followed by a discussion of the data, estimation methodology, and estimation results in §3. We also report the results of a number of policy experiments in §3. Section 4 concludes with limitations and suggestions for future research.

2. Model Development

2.1. Model Overview

The basic premise of our model is that consumers are uncertain about product quality, and hence attempt to learn about it. There are two sources that can shape a consumer's evaluations: advertising and consumption. In our model, the consumer's information from advertising constitutes an *advertising set*, while her information from consumption experiences constitutes a *consumption set*. She updates each of these sets as she gets more information from an advertising message or from her consumption experience. Therefore, the informative effect of ads, which is the immediate impact of ads on quality learning, comes through the advertising set; while the information learned from consumption and, consequently, the transformative effect of ads, comes through the consumption set. On each purchase occasion, the consumer mixes evaluations from the two sets to come up with her overall quality evaluation for each brand. At this point, it is useful to highlight the following fact. Of the three advertising effects that we wish to model, only the informative and transformative effects impact consumer learning. The persuasive effect enters the utility function directly and *does not* affect learning about quality. The discussion that follows focuses exclusively on how consumers *learn* about true quality and, consequently, ignores the persuasive effect. We incorporate the persuasive effect when we obtain the final utility expression for the consumer.

2.2. Utility Specification and Evolution of Consumer's Overall Quality Evaluations

On each purchase occasion, a consumer forms quality evaluations of each brand on offer and, based on these evaluations, picks a brand to purchase. Consider a product category with $j = 1$ to J brands. We

assume that the consumer's expected indirect utility from brand j on purchase occasion t can be approximated as a function of brand j 's overall quality evaluation, $q_{j,t}$, price, $p_{j,t}$, and feature and display variables. Because prior literature has found significant risk aversion in many categories (Erdem and Keane 1996) and highlighted the possible misspecification arising from ignoring this term (Byzlov and Shachar 2004), we incorporate risk aversion through a mean-variance specification. The indirect utility is given as:⁵

$$E_t U_{j,t} = \theta E_t(q_{j,t}) + \theta r E_t[q_{j,t} - E_t(q_{j,t})]^2 - \gamma_p p_{j,t} + \gamma_f Feat_{j,t} + \gamma_d Disp_{j,t} + \gamma_{per,j} Per_{j,t} + \varepsilon_{j,t}. \quad (1)$$

The parameter θ denotes the consumer's intensity of preference for quality, r represents her degree of risk aversion, γ_p represents her price sensitivity, γ_f represents the impact of features, γ_d represents the impact of display, $\gamma_{per,j}$ represents the brand-specific persuasive effect of advertising, and $\varepsilon_{j,t}$ represents a type 1 extreme-valued random variable that is independent across all consumers, brands, and purchase occasions. $Feat_{j,t}$ and $Disp_{j,t}$ represent the presence or absence of features and displays, respectively, for brand j at time t . $Per_{j,t}$ is defined as the number of ads seen by a consumer between $t-1$ and t , divided by the number of minutes of television watched during that period (Ackerberg 2003). This term captures the persuasive effect of ads. The rationale of including it directly in the utility function follows Becker and Murphy (1993), in that the intensity of advertising is a product characteristic like calories or taste that provides utility to consumers. The specification here suggests that consumers receive more utility from consuming a product with higher ad intensities.

We assume the true quality of brand j to be q_j . The consumer does not have enough information to estimate precisely the true quality of any brand in the product category.⁶

Formally,

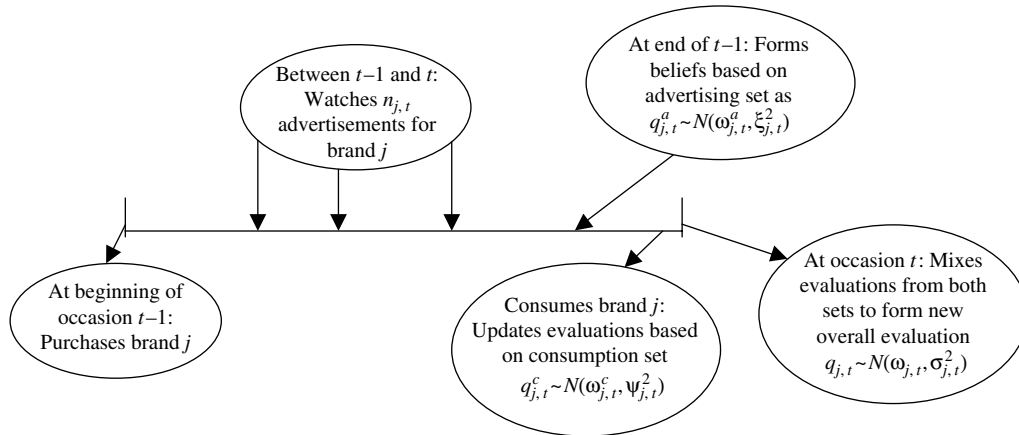
$$q_{j,t} \sim N(\omega_{j,t}, \sigma_{j,t}^2) \quad \forall j, t, \quad (2)$$

where $\omega_{j,t}$ denotes the consumer's estimate of the expected overall quality of brand j at purchase occasion t , and $\sigma_{j,t}^2$ denotes the extent of her uncertainty about brand j 's quality at purchase occasion t .

⁵ For notational convenience, we have suppressed the subscript for the consumer.

⁶ An alternative formulation would be in terms of product attributes and uncertainty surrounding the mean levels of these attributes. To the extent that one considers only one attribute, as in Erdem and Keane (1996), the two approaches are identical (see also Mehta et al. 2003).

Figure 1 Sequence of Events between Purchase Occasions $t - 1$ and t



Formally, we assume that the consumer constructs her overall evaluations of the quality of any brand j at occasion t , $q_{j,t}$, by mixing her quality evaluations from two information sets, the *advertising* set $A_{j,t}$ and the *consumption* set $C_{j,t}$. The division of the consumer's information set into two parts facilitates the exposition of the informative and transformative effects; the advertising set contains information that the consumer learns from the informative effects of ads, and the consumption set contains information that the consumer learns from consumption experiences and the transformative effects of ads.

Defining the advertising set. The advertising set, $A_{j,t}$, contains the cumulative information that the consumer has learned about brand j 's quality from its advertisements prior to occasion t . We represent the evaluations based on the advertising set $A_{j,t}$ as $q_{j,t}^a \sim N(\omega_{j,t}^a, \xi_{j,t}^2)$. The inverse of the variance $\xi_{j,t}^2$ represents the precision of the information conveyed by an advertisement; the higher this precision, the greater is the information learned from past advertisements. Similar to Erdem and Keane (1996), we assume the evaluations based on the advertising set at occasion t to be formed from all advertisements seen prior to occasion t .⁷ Note that the advertising set contains information learned from the informative effect of ads.

Defining the consumption set. The consumption set, $C_{j,t}$, contains cumulative information about the consumer's assessment of brand j 's true quality from her consumption experiences prior to occasion t . These consumption experiences can be pure (i.e., no impact of advertising) or transformed (shaped by advertising), depending on whether the consumer has not seen advertisements for the brand prior to purchase or has seen them, respectively. Regardless, we represent the consumer's evaluations of brand j 's quality

at purchase occasion t based on the consumption set $C_{j,t}$ as $q_{j,t}^c \sim N(\omega_{j,t}^c, \psi_{j,t}^2)$. Similar to our assumptions on advertising, we assume that all consumption experiences prior to occasion t have an impact on the consumer's quality evaluation based on her consumption set at occasion t . To reiterate, the consumption set contains information learned from the consumption experience and the transformative effect of ads.

Overall quality inference. Given evaluations from the advertising and consumption sets, the consumer mixes the two in a standard Bayesian fashion to get the mean and variance of her *overall* quality evaluations, $q_{j,t}$, at purchase occasion t , as

$$\omega_{j,t} = \left(\frac{\omega_{j,t}^c}{\psi_{j,t}^2} + \frac{\omega_{j,t}^a}{\xi_{j,t}^2} \right) \left(\frac{1}{\psi_{j,t}^2} + \frac{1}{\xi_{j,t}^2} \right)^{-1} \quad \text{and} \quad \frac{1}{\sigma_{j,t}^2} = \frac{1}{\psi_{j,t}^2} + \frac{1}{\xi_{j,t}^2}. \quad (3)$$

Figure 1 illustrates the evolution of quality evaluations of a typical consumer by laying out the sequence of events that occur between purchase occasions $t - 1$ and t .

The consumer purchases brand j at the beginning of purchase occasion $t - 1$. In the time period following her purchase, till the end of occasion $t - 1$, she receives $n_{j,t}$ advertisements of brand j . At the end of purchase occasion $t - 1$, she forms her quality beliefs based on her advertising set, $A_{j,t}$, i.e., $q_{j,t}^a \sim N(\omega_{j,t}^a, \xi_{j,t}^2)$. After having formed these beliefs, she consumes the purchased brand j . This consumption experience may be transformed by the advertisements that she has observed before t . Following her consumption experience, she updates her quality beliefs of brand j based on her consumption set, $C_{j,t}$, i.e., $q_{j,t}^c \sim N(\omega_{j,t}^c, \psi_{j,t}^2)$. At the beginning of purchase occasion t , she mixes her evaluations based on the advertising set ($A_{j,t}$), and the consumption set ($C_{j,t}$) to form her overall quality beliefs, denoted by $q_{j,t} \sim N(\omega_{j,t}, \sigma_{j,t}^2)$. She uses these

⁷ We do not, however, consider advertisements seen further back in time as "decaying" in impact. We discuss this issue further in the concluding section of the paper.

overall quality beliefs to make her purchase decision at occasion t . Note from Equation (3) that the evolution of quality beliefs, $q_{j,t}$, depends on the evolution of beliefs based on her advertising set, $q_{j,t}^a$, and the evolution of beliefs based on her consumption set, $q_{j,t}^c$. We now discuss how each of these component beliefs evolves, while emphasizing the changes made to the standard Bayesian learning model necessitated by a consideration of source credibility, confirmatory bias, and bounded rationality.

2.2.1. Evolution of Consumer's Quality Evaluations Based on Her Advertising Set: Accounting for Source Credibility. Consider the case where the consumer receives $N_{j,t}$ (where $N_{j,t}$ is the sum of advertisements received between all purchase occasions, i.e., $N_{j,t} = \sum_{s=0}^t n_{j,s}$) advertising exposures of brand j between occasions 0 and t . Let $\chi_{ij,r}$ be the r th (where $r \in 1, \dots, N_{j,t}$) advertising signal for brand j received by the consumer between purchase occasions $t-1$ and t . In the standard Bayesian learning model, we would assume that the signals $\chi_{ij,r}$ are distributed around the true quality q_j , and are independent across all brands and all consumers. Neither of these holds once we consider *source credibility* issues. As discussed earlier, we now have to account for the fact that advertisers are not viewed as nonpartisan communicators.

We can accommodate source credibility by incorporating the idea that the advertising signal attempts to convey a quality that differs from the true quality by some amount, which represents the “bias” in the signal. Formally, we can write the r th ad signal of brand j as follows:

$$\chi_{ij,r} = q_j + b_j + \delta_j \zeta_{ij,r}, \quad (4)$$

where q_j is the true quality of brand j , b_j is the true bias in the ad, δ_j is the inverse of the level of precision in the ad message about the quality it is trying to portray, and $\zeta_{ij,r}$ is a random error that is independently and identically distributed (IID) across all r and t .

Now, if the consumer knows the extent of the bias exactly, she can discount it to obtain an unbiased ad signal, centered on the true quality q_j . It is not very reasonable to believe that the consumer knows the amount of bias exactly (but, for instance, does not know the quality of the product). We therefore consider the more realistic (and interesting) case where the consumer has beliefs about the bias, denoted as $N(\bar{b}_j, \sigma_{b_j}^2)$, where \bar{b}_j is her belief of the mean bias, and $\sigma_{b_j}^2$ reflects her uncertainty around this mean.⁸ Note that her belief of the mean bias could well be

greater than the “actual” bias in the ads—this would capture the situation where the consumer thinks that the source is less credible than it actually is. The uncertainty, in turn, could be high for a number of reasons—perhaps most obviously, because the brand is new and the consumer does not know much about the source yet. Given these beliefs, the consumer discounts the ad signal by the mean bias, and gets the adjusted ad signal

$$\chi_{ij,r}^{adj} = q_j + b_j - \bar{b}_j + \delta_j \zeta_{ij,r}. \quad (5)$$

It is important to note that the consumer's ad-based expectations are based on this discounted ad signal. However, she does not know the value of $(b_j - \bar{b}_j)$. Thus, from her perspective, $(b_j - \bar{b}_j)$ will be a random variable, $\sigma_{b_j} \varepsilon_{b_j}$, whose value remains the same across all ads. This implies that the discounted ad signal from the consumer's perspective would be given by

$$\chi_{ij,r}^{adj} = q_j + \sigma_{b_j} \varepsilon_{b_j} + \delta_j \zeta_{ij,r}. \quad (6)$$

The discounted ad signal leads to two differences from the standard Bayesian learning model. First, observe that because the consumer discounts each ad by a constant amount \bar{b}_j , the random error $\sigma_{b_j} \varepsilon_{b_j}$ is the same for all ads of a brand j . This suggests that ad signals of brand j get serially correlated.⁹ Note that this correlation arises endogenously because of the assumption that advertisers suffer from source credibility issues, and the consequent discounting. Second, the variance of the discounted ad signal is larger than in the standard Bayesian learning case; $\delta_j^2 + \sigma_{b_j}^2$ in the discounted case, as compared to just δ_j^2 for the standard case.

The correlation between ad signals engendered by the presence of source credibility, in turn, suggests that the informativeness of N ad signals is no longer N times the informativeness of a single signal. If the consumer receives $N_{j,t}$ advertising exposures for brand j between purchase occasions 0 and t , her quality evaluations based on her advertising signals at purchase occasion t would be $q_{j,t}^a \sim N(\omega_{j,t}^a, \xi_{j,t}^2)$, where

$$\omega_{j,t}^a = \frac{1}{N_{j,t}} \sum_{r=1}^{N_{j,t}} \chi_{ij,r}^{adj} \quad \text{and} \quad \xi_{j,t}^2 = \delta_j^2 / N_{j,t} + \sigma_{b_j}^2. \quad (7)$$

her beliefs about ad bias in the next period. One could think of a more complicated situation where the consumer constantly updates her beliefs on the bias, based on what she learns about the product. This would set up a feedback loop from consumption to advertising that is absent from the current model. While making for a more satisfactory description, it would likely render the model intractable.

⁹ The result that source credibility leads to serial correlation between the ad signals accords well with the findings of Hoch and Deighton (1989, p. 7), who state that “in learning through education, they [consumers] are alert to source credibility and are sensitive to the fact that repeated ads from a manufacturer are not independent.”

⁸ Note that the consumer assumes a constant bias in advertisements. The implication of this is that the consumer does not let what she learns from consumption in the current period influence

How much extra do $N_{j,t}$ ads convey, versus one ad? To answer this, note that the informativeness of one ad signal is just $1/(\delta_j^2 + \sigma_{bj}^2)$, while the informational value of $N_{j,t}$ ads can be obtained from Equation (7) above as $1/(\delta_j^2/N_{j,t} + \sigma_{bj}^2)$. Therefore, the ratio of the informational value of $N_{j,t}$ ads to the informational value of one ad is $\tau_{jt}^2 = (\delta_j^2 + \sigma_{bj}^2)/(\delta_j^2/N_{j,t} + \sigma_{bj}^2)$, or simply $\tau_{jt}^2 = N_{j,t}((s_j^2 + 1)/(N_{j,t}s_j^2 + 1))$, where $s_j^2 = \sigma_{bj}^2/\delta_j^2$ is the ratio of the uncertainty in the consumer's beliefs of the bias in the ads of brand j relative to the noise in the advertising signal of brand j . Notice that τ_{jt}^2 is less than $N_{j,t}$, the ratio for the standard Bayesian learning model. Also note that as the uncertainty around the bias increases, the ratio declines; for zero uncertainty, the ratio becomes $N_{j,t}$, exactly as in the standard case. Finally, note from Equation (7) that the presence of σ_{bj}^2 ensures that the consumer's beliefs will never converge to the true quality, even with infinite exposures. There is a bias in ad expectations, $\sigma_{bj}\varepsilon_{bj}$, which never goes to zero. This is in contrast to the Bayesian learning model, where the consumer converges to the true quality given a sufficiently large number of ad signals.

2.2.2. The Evolution of a Consumer's Quality Evaluations Based on Her Consumption Set: Accounting for Confirmatory Bias and Bounded Rationality. Consider the case where the consumer purchases brand j in period $t - 1$. Let $\lambda_{j,t-1}$ be the noisy quality signal received by the consumer from brand j 's consumption at the end of occasion $t - 1$. In the standard Bayesian learning model, the consumption signal can be written as $\lambda_{j,t-1} = q_j + \eta\varepsilon_{c,jt-1}$, which is equivalent to saying that the signal is distributed around the true quality q_j as $\lambda_{j,t-1} \sim N(q_j, \eta^2)$. Here, η is the extent of ambiguity in the consumption signal, or equivalently the inverse of the informational value of one consumption experience. The greater the ambiguity, the less useful is a consumption experience in informing the consumer of the true quality of the brand. Given this signal, we can easily update beliefs based on the consumption set in a Bayesian manner.

A crucial assumption in the standard Bayesian learning model, however, is that advertising does not alter evaluations of the subsequent consumption experience, i.e., prior ads and subsequent consumption signals are independent pieces of information about the brand's quality. The transformative effect suggests the opposite. This effect suggests that as the consumer uses the consumption experience to test the tentative hypotheses that ad signals have led her to form, her ad-based expectations influence what she learns.

Formally, consider the case where the consumer receives $N_{j,t}$ advertisements for brand j , $\{\chi_{jr}\}_{r=1}^{n_{j,t}}$,

between occasions 0 and t , and the consumer consumes brand j just prior to occasion t . From Equation (7), the consumer's ad-based expectations are given as $\omega_{j,t}^a = (1/N_{j,t}) \sum_{r=1}^{N_{j,t}} \chi_{j,r}^{ad}$, whose stochastic specification we can write as $\omega_{j,t}^a = q_j + \sigma_{bj}\varepsilon_{bj} + (\delta_j/N_{j,t}) \sum_{r=1}^{N_{j,t}} \zeta_{j,r}$. The presence of the $\sigma_{bj}\varepsilon_{bj}$ term clearly introduces a bias in the ad-based expectations. Now, the consumer treats these ad-based expectations of brand j as a tentative hypothesis and tests them on consumption of brand j at the end of occasion $t - 1$ (assuming brand j was purchased at occasion $t - 1$). As suggested by Hoch and Deighton (1989), this results in a confirmatory bias in which the biases in the ad-based expectations get transferred to the information about the quality learned from subsequent consumption. We parsimoniously model this by letting the ad-based expectations be correlated with the consumption signal—or specifically, we let the bias error in the ad-based expectations be correlated with the consumption signal with a correlation κ_j . To reiterate, κ_j determines the extent to which biases in ad-based expectations are transferred onto consumption, i.e., the extent to which they help transform evaluations of the consumption experience. This would, in turn, be a reflection of the extent to which there is a match between the attributes suggested in the ad and the brand attributes that can be seen during consumption.¹⁰

Given the assumption that the consumption signal is correlated with the bias in the ad signal, $\sigma_{bj}\varepsilon_{bj}$, with a correlation κ_j , it can be shown that the consumption signal is correlated with the ad-based expectations with a correlation of $\kappa_j\sigma_{bj}/\sqrt{\sigma_{bj}^2 + \delta_j^2/N_{j,t}}$. This expression accords well with much of the behavioral literature discussed earlier. In particular:

(a) It depends on κ_j —the greater the tightness between ads and consumption, the greater is the impact of ads on subsequent consumption.

(b) It depends on the uncertainty surrounding the mean bias belief. The lower the σ_{bj} , the lower the biases in ad-based expectations, and hence the lower the correlation between ad-based expectations and consumption. This maps well into behavioral literature suggesting that if σ_{bj} is small, consumers do not perceive ads to be biased and thus have little incentive to test the attributes suggested by the ads. This, in turn, suggests a smaller impact of ads on consumption.

(c) It depends on the number of ads seen prior to consumption. This follows from behavioral literature, which says that the greater the N , the lower the noise

¹⁰ Note that we have modeled confirmatory bias in a semistructural fashion using the exogenous correlation κ . A discussion of how one could relax this is deferred to the conclusions section.

in the ad-based expectations, the clearer the hypotheses (or frame) that needs to be tested by the consumption experience, and hence the higher the impact of ads on consumption.

Once we accommodate the fact that the consumption signal is correlated with ad-based expectations, the distribution of the consumption signal that is received at the end of occasion $t - 1$ would depend on past advertisements, $\{\chi_{jr}\}_{r=1}^{N_{j,t}}$. It can be shown that the distribution of the consumption signal conditional on past advertisements is given as

$$\lambda_{j,t-1}^T \sim N\left(q_j + \frac{\eta\kappa_j\sigma_{bj}}{\sigma_{bj}^2 + \delta_j^2/N_{j,t}}\left(\frac{1}{N_{j,t}}\sum_{r=1}^{N_{j,t}}\chi_{j,r}^{adj} - q_j\right), \eta^2\left(1 - \frac{\kappa_j^2\sigma_{bj}^2}{\sigma_{bj}^2 + \delta_j^2/N_{j,t}}\right)\right). \quad (8)$$

We have already modified the standard Bayesian learning model to accommodate source credibility and confirmatory bias. The third aspect of the transformative effect—namely, bounded rationality—is implied in the following question: Is the consumer aware of the transference of bias from ads to consumption? If the consumer were aware of this transference, then she would rationally discount it, and there would be no transformation of consumption. We have already discussed this issue at some length in the section on modeling challenges, drawing on Hoch and Deighton (1989). Briefly, we suggest that the rational discounting does not happen because consumers seldom suspect the credibility of their own consumption experiences, instead naively believing that consumption is an unbiased source of information that is not affected by external forces such as ads (Hoch and Ha 1986). In this sense, the consumer is boundedly rational.

Bounded rationality implies that the consumer assumes the transformed consumption signals ($\lambda_{j,t-1}^T$) to be independent of the ad-based expectations while updating her evaluations from consumption. For the consumer, the transformed consumption signals are thus IID draws across purchase occasions, distributed as $\lambda_{j,t-1}^T \sim N(q_j, \eta^2)$. Therefore, we can obtain the consumer's evaluations based on her consumption set at occasion t ($q_{j,t}^c$) by updating her beliefs based on her consumption set at occasion $t - 1$ ($q_{j,t-1}^c$), with the transformed consumption signal ($\lambda_{j,t-1}^T$), in a simple Bayesian fashion as follows:

$$\omega_{j,t}^c = \frac{\omega_{j,t-1}^c/\psi_{j,t-1}^2 + d_{j,t-1}(\lambda_{j,t-1}^T/\eta^2)}{1/\psi_{j,t-1}^2 + d_{j,t-1}(1/\eta^2)} \quad (9)$$

and

$$\frac{1}{\psi_{j,t}^2} = \frac{1}{\psi_{j,t-1}^2} + d_{j,t-1}\frac{1}{\eta^2}.$$

Equation (9) shows the updating mechanism of the quality evaluations from the consumer's perspective. It is worthwhile again to highlight the comparison with the standard Bayesian learning model. Because the consumer is unaware that transformation is truly taking place, the updating mechanism of beliefs (based on the consumption set) *from the consumer's perspective* is the same in both the standard case and in our modified model.

2.2.3. Mixing Advertising and Consumption Sets: The Evolution of a Consumer's Overall Quality Evaluations.

(a) *From the consumer's perspective.* So far, we have derived the evolution of the consumer's brand evaluation based on her *advertising set* in Equation (7) and the evolution of her brand evaluation based on her *consumption set* in Equation (9). Furthermore, Equation (3) shows how the consumer mixes her evaluations from the advertising and consumption sets to get her *overall* quality evaluation of a brand. Combining Equations (7), (9), and (3), we get the expression for the evolution of the mean and precision of consumer's overall quality evaluations at occasion t as

$$\begin{aligned} \omega_{j,t} &= \left(\alpha_{j,t-1}\omega_{j,t-1} + d_{j,t-1}\lambda_{j,t-1}^T \right. \\ &\quad \left. + \beta_j^2\left(\frac{\tau_{j,t}^2}{N_{j,t}}\sum_{r=1}^{N_{j,t}}\chi_{j,r}^{adj} - \frac{\tau_{j,t-1}^2}{N_{j,t-1}}\sum_{r=1}^{N_{j,t-1}}\chi_{j,r}^{adj}\right)\right) \\ &\quad \cdot (\alpha_{j,t-1} + d_{j,t-1} + \beta_j^2(\tau_{j,t}^2 - \tau_{j,t-1}^2))^{-1} \\ \alpha_{j,t} &= \alpha_{j,t-1} + d_{j,t-1} + \beta_j^2(\tau_{j,t}^2 - \tau_{j,t-1}^2), \end{aligned} \quad (10)$$

where $\alpha_{j,t} = \eta^2/\sigma_{j,t}^2$ can be interpreted as the precision in the overall quality beliefs of brand j at occasion t ; $\tau_{j,t}^2 = (\delta_j^2 + \sigma_{bj}^2)/(\delta_j^2/N_{j,t} + \sigma_{bj}^2)$, introduced earlier, is the ratio of the informational value of $N_{j,t}$ ads to one ad; and $\beta_j^2 = \eta^2/(\delta_j^2 + \sigma_{bj}^2)$ is the ratio of the informational value of one ad to the informational value of one consumption experience. The term $\alpha_{j,t-1}\omega_{j,t-1}$ represents the impact of overall evaluations at $t - 1$. Intuitively, if precision at $t - 1$ ($\alpha_{j,t-1}$) is high, evaluations at $t - 1$ would be weighted heavily, thus reducing the impact of informative effects and of transformed consumption. The term $d_{j,t-1}\lambda_{j,t-1}^T$ captures the impact of transformed consumption of the brand purchased at occasion $t - 1$ and consumed at the end of occasion $t - 1$, and the term $\beta_j^2((\tau_{j,t}^2/N_{j,t})\sum_{r=1}^{N_{j,t}}\chi_{j,r}^{adj} - (\tau_{j,t-1}^2/N_{j,t-1})\sum_{r=1}^{N_{j,t-1}}\chi_{j,r}^{adj})$ captures the informational value of $N_{j,t} - N_{j,t-1}$ ads seen between occasions $t - 1$ and t .

(b) *From the analyst's perspective—the stochastic specification of the model.* While the consumer observes the realizations of the advertising signals received between occasions 0 and t , $\{\chi_{j,r}\}_{r=1}^{N_{j,s}}$, and observes the realization of the transformed consumption signal,

$\lambda_{j,t-1}^T$, the analyst does not. The analyst observes only the choices made by the consumer, the number of ads seen between consecutive occasions, and the occurrence of purchase (which is mapped to consumption). Therefore, the terms $(\tau_{j,t}^2/N_{j,t}) \sum_{r=1}^{N_{j,t}} \chi_{j,r}^{adj} - (\tau_{j,t-1}^2/N_{j,t-1}) \sum_{r=1}^{N_{j,t-1}} \chi_{j,r}^{adj}$ and $\lambda_{j,t-1}^T$ in Equation (10), while deterministic from the consumer's perspective, are random variables from the analyst's perspective. Deriving the stochastic specification of these two terms is necessary to get the stochastic specification for the evolution of the overall mean quality evaluations. We do this below.

First, consider the advertising signal, $\chi_{j,r}^{adj}$. The consumer has beliefs about the true bias, b_j ; in particular, she assumes a mean bias of \bar{b}_j , with some uncertainty denoted by σ_{bj} . The analyst does not know either the true bias or the consumer's mean belief, \bar{b}_j . However, given a string of purchase observations across a set of consumers, he can estimate $\Delta b_j = b_j - \bar{b}_j$. Thus, from the analyst's perspective, the r th ad signal would be given as $\chi_{j,r}^{adj} = q_j + b_j - \bar{b}_j + \delta_j \zeta_{j,r}$, which can be written as

$$\chi_{j,r}^{adj} = q_j + \Delta b_j + \delta_j \zeta_{j,r}. \quad (11)$$

This implies that the ad-based expectation at occasion t from the analyst's perspective will be

$$\frac{1}{N_{j,t}} \sum_{r=1}^{N_{j,t}} \chi_{j,r}^{adj} = q_j + \Delta b_j + \frac{\delta_j}{N_{j,t}} \sum_{r=1}^{N_{j,t}} \zeta_{j,r},$$

which can be written as

$$\frac{1}{N_{j,t}} \sum_{r=1}^{N_{j,t}} \chi_{j,r}^{adj} = q_j + \Delta b_j + \frac{\delta_j}{\sqrt{N_{j,t}}} \nu_{j,t}, \quad (12)$$

where $\nu_{j,t} = (1/\sqrt{N_{j,t}}) \sum_{r=1}^{N_{j,t}} \zeta_{j,r}$ is the cumulative ad error, which is a standard normal random variable that is IID across all brands, all purchase occasions, and all consumers. We can now write the stochastic specification of the term $(\tau_{j,t}^2/N_{j,t}) \sum_{r=1}^{N_{j,t}} \chi_{j,r}^{adj} - (\tau_{j,t-1}^2/N_{j,t-1}) \sum_{r=1}^{N_{j,t-1}} \chi_{j,r}^{adj}$. This would be given as

$$\begin{aligned} & \frac{\tau_{j,t}^2}{N_{j,t}} \sum_{r=1}^{N_{j,t}} \chi_{j,r}^{adj} - \frac{\tau_{j,t-1}^2}{N_{j,t-1}} \sum_{r=1}^{N_{j,t-1}} \chi_{j,r}^{adj} \\ &= (q_j + \Delta b_j)(\tau_{j,t}^2 - \tau_{j,t-1}^2) \\ &+ \delta_j \left(\frac{\tau_{j,t}^2}{\sqrt{N_{j,t}}} \nu_{j,t} - \frac{\tau_{j,t-1}^2}{\sqrt{N_{j,t-1}}} \nu_{j,t-1} \right). \end{aligned} \quad (13)$$

Next, consider the consumption signal at $t - 1$ ($\lambda_{j,t-1}^T$) from the analyst's perspective. While the consumer believes her consumption is not transformed by past ad expectations, i.e., that the consumption signal is an unbiased and IID random draw from $\lambda_{j,t-1} \sim N(q_j, \eta^2)$, the analyst knows that the consumption

signal is transformed, with a distribution given in Equation (8). We can rewrite Equation (8) as

$$\begin{aligned} \lambda_{j,t-1}^T &= q_j + \frac{\eta \kappa_{jk} \sigma_{bj}}{\sigma_{bj}^2 + \delta_j^2/N_{j,t}} \left(\frac{1}{N_{j,t}} \sum_{r=1}^{N_{j,t-1}} \chi_{j,r}^{adj} - q_j \right) \\ &+ \varepsilon_{cj,t-1} \eta \sqrt{1 - \frac{\kappa_j^2 \sigma_{bj}^2}{\sigma_{bj}^2 + \delta_j^2/N_{j,t}}}, \end{aligned} \quad (14)$$

where $\varepsilon_{cj,t-1}$ is the pure consumption error, which is a standard normal random variable that is IID across all brands, all purchase occasions, and all consumers. Substituting the stochastic specification for the ad signal from Equation (12), we get the stochastic specification of the transformed consumption signal as

$$\begin{aligned} \lambda_{j,t-1}^T &= q_j + \Delta b_j \frac{\sigma_{bj} \eta \kappa_j}{\sigma_{bj}^2 + \delta_j^2/N_{j,t-1}} + \frac{\sigma_{bj} \eta \kappa_j}{\sigma_{bj}^2 + \delta_j^2/N_{j,t-1}} \\ &\cdot \frac{\delta_j}{\sqrt{N_{j,t-1}}} \nu_{ij,t-1} + \eta \sqrt{\left(1 - \frac{\kappa_j^2 \sigma_{bj}^2}{\sigma_{bj}^2 + \delta_j^2/N_{j,t-1}} \right)} \varepsilon_{cj,t-1}, \end{aligned}$$

which we can rewrite as

$$\begin{aligned} \lambda_{j,t-1}^T &= q_j + \frac{\eta \kappa_j \tau_{j,t}^2 s_j^2}{1 + s_j^2} \left(\frac{\Delta b_j}{\sigma_{bj}} \right) + \frac{\eta \kappa_j \tau_{j,t}^2 s_j}{1 + s_j^2} \left(\frac{\nu_{j,t}}{\sqrt{N_{j,t}}} \right) \\ &+ \varepsilon_{cj,t-1} \eta \sqrt{1 - \frac{\kappa_j^2 s_j^2 \tau_{j,t}^2}{1 + s_j^2}}, \end{aligned} \quad (15)$$

where $s_j^2 = \sigma_{bj}^2/\delta_j^2$ has been defined earlier as the ratio of the uncertainty in the bias beliefs of the consumer to the noise in the advertising signal. Intuitively, there is no transformative effect if $\sigma_{bj} = 0$ or $\eta = 0$, i.e., if either the consumer knows the exact bias in the ads or if the consumption experience is completely unambiguous. Both of these follow from our conceptualization, wherein source credibility and consumption ambiguity are cornerstones of the transformative effect.

Finally, substituting the stochastic specification of $(\tau_{j,t}^2/N_{j,t}) \sum_{r=1}^{N_{j,t}} \chi_{j,r}^{adj} - (\tau_{j,t-1}^2/N_{j,t-1}) \sum_{r=1}^{N_{j,t-1}} \chi_{j,r}^{adj}$ from Equation (13) and $\lambda_{j,t-1}^T$ from Equation (15) into Equation (10), we get the expression for the evolution of the mean of the overall quality evaluations at occasion t , from the analyst's perspective, as

$$\begin{aligned} \omega_{j,t} &= \omega_{j,t-1} \{ \alpha_{j,t-1} \alpha_{j,t}^{-1} \} + \alpha_{j,t}^{-1} \left\{ \beta_j^2 \left((q_j + \Delta b_j)(\tau_{j,t}^2 - \tau_{j,t-1}^2) \right. \right. \\ &\quad \left. \left. + \delta_j \left(\frac{\tau_{j,t}^2}{\sqrt{N_{j,t}}} \nu_{j,t} - \frac{\tau_{j,t-1}^2}{\sqrt{N_{j,t-1}}} \nu_{j,t-1} \right) \right) \right\} \\ &+ \alpha_{j,t}^{-1} \left\{ d_{j,t-1} \left(q_j + \frac{\eta \kappa_j \tau_{j,t}^2 s_j^2}{1 + s_j^2} \left(\frac{\Delta b_j}{\sigma_{bj}} \right) + \frac{\eta \kappa_j \tau_{j,t}^2 s_j}{1 + s_j^2} \right. \right. \\ &\quad \left. \left. \cdot \left(\frac{\nu_{j,t}}{\sqrt{N_{j,t}}} \right) + \varepsilon_{cj,t-1} \eta \sqrt{1 - \frac{\kappa_j^2 s_j^2 \tau_{j,t}^2}{1 + s_j^2}} \right) \right\}. \end{aligned} \quad (16)$$

The first term in curly brackets on the right-hand side (RHS) of Equation (16), $\alpha_{j,t-1}\alpha_{j,t}^{-1}$, captures the weight the consumer puts on the quality evaluation of the previous purchase occasion, $\omega_{j,t-1}$, i.e., the effect of the previous quality evaluation on the current quality evaluation. The second term in curly brackets on the RHS,

$$\beta_j^2 \left((q_j + \Delta b_j)(\tau_{j,t}^2 - \tau_{j,t-1}^2) + \delta_j \left(\frac{\tau_{j,t}^2}{\sqrt{N_{j,t}}} \nu_{j,t} - \frac{\tau_{j,t-1}^2}{\sqrt{N_{j,t-1}}} \nu_{j,t-1} \right) \right),$$

captures the informative effect of ads seen between occasions $t-1$ and t . Finally, the third term in curly brackets on the RHS of Equation (16) captures the impact of the *transformed* consumption experience between occasions $t-1$ and t . More accurately, the terms q_j and $\varepsilon_{cj,t-1}\eta\sqrt{1-\kappa_j^2 s_j^2 \tau_{j,t}^2/(1+s_j^2)}$ capture the pure consumption effect, while

$$\frac{\eta\kappa_j\tau_{j,t}^2 s_j^2}{1+s_j^2} \left(\frac{\Delta b_j}{\sigma_{bj}} \right) + \frac{\eta\kappa_j\tau_{j,t}^2 s_j}{1+s_j^2} \left(\frac{\nu_{j,t}}{\sqrt{N_{j,t}}} \right)$$

captures the transformative effect of ads of brand j purchased at occasion $t-1$ and consumed at the end of occasion $t-1$. Clearly, the transformative effect increases as η , κ_j , and Δb_j increase. We summarize what our model has to say about informative and transformative effects below.

2.3. Summarizing Informative and Transformative Effects

The informative effect of advertisements. $\beta_j^2 \Delta \tau_{j,t}^2 (q_j + \Delta b_j)$ captures the informative effect of $n_{j,t}$ advertisements. This has three elements to it: (a) the informational value of one ad, as captured by β_j^2 (defined earlier in §2.2.3 as $\beta_j^2 = \eta^2/(\delta_j^2 + \sigma_{bj}^2)$), which is an inverse function of the sum of the two variances in the ad signals—the variance of the noise that results from message clarity, δ_j^2 , and the variance of the perceived bias of brand j , σ_{bj}^2 ; (b) the difference between the mean of the advertising signals, $q_j + \Delta b_j$, and the consumer's prior mean quality belief of brand j at $t-1$, $\omega_{cj,t-1}$. The greater this difference, the greater the informative effect of ads; (c) the ratio of the informational value of $n_{j,t}$ ads to the informational value of one ad, as captured by the term $\tau_{j,t}^2 = N_{j,t}/((s_j^2 + 1)/(N_{j,t}s_j^2 + 1))$. Note that this term decreases as $s_j^2 (= \sigma_{bj}^2/\delta_j^2)$ increases.

The Transformative Effect of Advertisements. The impact of the transformed consumption signal is given as

$$d_{j,t-1} \left(q_j + \frac{\eta\kappa_j\tau_{j,t}^2 s_j^2}{1+s_j^2} \left(\frac{\Delta b_j}{\sigma_{bj}} \right) + \frac{\eta\kappa_j\tau_{j,t}^2 s_j}{1+s_j^2} \left(\frac{\nu_{j,t}}{\sqrt{N_{j,t}}} \right) + \varepsilon_{cj,t-1}\eta\sqrt{1-\frac{\kappa_j^2 s_j^2 \tau_{j,t}^2}{1+s_j^2}} \right).$$

This implies that the total effect of the transformed consumption signal is split between the effect of pure consumption (i.e., when $\kappa_j = 0$) and the transformational effect of advertising. In effect, the formulation is an *averaging* process where the effect of pure consumption gets reduced when transformation takes place. The strength of the averaging is determined by the extent of transformation (κ_j), the ambiguity in the consumption experience (η), the extent of consumer uncertainty about the biases in the ads (σ_{bj}^2 ; note that s_j and τ_j are functions of σ_{bj}^2), and the estimated difference between the true bias in ads and consumer beliefs of the mean bias (Δb_j).

3. Data, Estimation, and Analysis

3.1. Data

We estimate the model on single-source scanner panel data on liquid and powdered laundry detergent, collected by A. C. Nielsen, Inc. in the Sioux Falls, South Dakota market. Our reasons for choosing the liquid detergent product category are fourfold. First, some prior research efforts that have tried to demonstrate the multiple effects of advertisements have used the same category (Deighton et al. 1994, Erdem and Keane 1996), permitting easy comparison. Second, prior behavioral research has suggested that transformative effects are usually associated with low-involvement routinized purchase behavior that is typical for the liquid detergent category (Vakratsas and Ambler 1999). Third, Erdem and Keane (1996) have found significant consumption ambiguity in this product category (a result we replicate in §3.3.2), thus suggesting transformation can play a significant role. Fourth, the data set contains the introduction of two new products, which makes it well suited for studying the learning process. Finally, Mehta et al. (2004) have found significant consumer forgetting of quality evaluations in this category. They find a half-life of 20 weeks for information learned from consumption—because our data span more than twice this period, it seems reasonable to suppose that all learning has not ceased.

The liquid detergent data span a 153-week period from 1986 to 1988. Advertising information, however, is available for only the last 51 weeks of this period. We select households for our sample according to the following criteria, which are similar to prior papers that have used these data (e.g., Erdem and Keane 1996). We select households that have (a) a history of purchase as well as of viewing commercials, (b) purchase liquid detergent products more than 80% of the time (as compared to powdered detergent), and (c) purchase liquid detergent at least 20 times in the 153-week period. This leaves us with information on

Table 1 Descriptive Statistics for Liquid Detergent Data Set

| Brand | #ad/(week * person)** | Price (cents/oz.) | Market share | Feature | Display |
|-------|-----------------------|----------------------|-----------------|---------|---------|
| Cheer | 0.1544 | 5.7524 | 0.0702 | 0.0149 | 0.0046 |
| Surf | 0.2359 | 5.2740 | 0.1283 | 0.0556 | 0.0717 |
| Era | 0.5284 | 5.7262 | 0.2351 | 0.0604 | 0.0620 |
| Wisk | 0.7252 | 4.8803 | 0.2525 | 0.0767 | 0.1535 |
| Tide | 0.4737 | 5.6014 | 0.3140 | 0.0727 | 0.1453 |

Note. **The average across households and weeks of the number of ads seen for this brand.

shopping trips and advertising exposures for a panel of 221 households consisting of 2,549 purchase occasions. We use 150 households (1,750 purchase occasions) as our estimation sample and 71 households (739 purchase occasions) as our holdout sample. We have data on five brands: Cheer, Surf, Era, Wisk, and Tide, which together account for 65.4% of the market share in this product category. Of these, Cheer and Surf were introduced in the sample period—the presence of new products means that quality uncertainty is likely to be high, suggesting a role for learning and possibly of advertising influencing this learning. Finally, note that we aggregate data from the SKU level to the brand level using a weighted sum, with the market shares within the brand as weights. Table 1 presents key descriptive statistics for the data.

Specifying Initial Conditions. We know that our data do not encompass the entire choice history of each household in our sample (i.e., they are left truncated). This has implications for what we assume about the prior mean and variance of the quality perceptions. If one does not control for initial choice history, the implicit assumption is that every household has the same prior mean and variance across all brands. Clearly, this is erroneous. A household that has purchased a brand multiple times in the past would presumably have more informed priors than another household that has purchased that brand very little. Similarly, a household that has purchased brand j multiple times would know its quality better than that of brand k , which it rarely buys. In essence, we have to account for the heterogeneity of priors in the sample. To do so, we follow an approach that is similar in spirit to that used in Mehta et al. (2004) and Erdem et al. (2006). Note that because our advertising data cover only the last 51 weeks of our 153-week sample period, we can use the first 102 weeks as a pre-estimation sample to estimate the distribution of priors. To aid exposition, we label the start and end of the preestimation period as T_0 and T_1 , respectively. Formally, at T_0 , let quality perceptions for brand j be distributed as

$$q_{ij,0} \sim N(\omega_0, \sigma_0^2), \quad (17)$$

where (following the reparameterization used in §2.2.3) the prior variance of household i 's quality belief of brand j at the beginning of the preestimation sample (σ_0^2), can be written in terms of the prior precision at the beginning of the preestimation sample (α_0) and the variance in the noise in the consumption signal (η^2) as $\sigma_0^2 = \eta^2 \alpha_0^{-1}$. Note that the mean and the variance of these priors are assumed to be the same across all consumers and all brands.

At T_1 (which is also the beginning of the estimation sample), quality perceptions are distributed as

$$q_{e,ij} \sim N(\omega_{e,ij}, \sigma_{e,ij}^2), \quad (18)$$

where $\sigma_{e,ij}^2$, the variance of household i 's quality belief of brand j at the end of the preestimation sample, can be written in terms of the precision at the end of the preestimation sample ($\alpha_{e,ij}$), and the noise in the consumption signal (η^2), as $\sigma_{e,ij}^2 = \eta^2 \alpha_{e,ij}^{-1}$.

Our objective is to get the specifications of the mean and precision at the end of the preestimation sample (Equation (18)) as a function of (a) the priors in the preestimation sample, Equation (17), and (b) the number of consumption experiences that household i has had with brand j in the preestimation sample.

Consider the case in which household i has had $\sum_{t=T_0}^{T_1} d_{ij,t}$ consumption experiences (which is equal to the number of times household i has purchased j in the preestimation sample). This implies that household i would have received $\sum_{t=T_0}^{T_1} d_{ij,t}$ consumption signals of brand j in the preestimation sample. These signals would result in (a) a reduction in household i 's variance in the quality beliefs of brand j from α_0 to $\alpha_{e,ij}$, and (b) a shift in the mean of household i 's quality evaluations of brand j from ω_0 to $\omega_{e,ij}$. Similar in spirit to Erdem et al. (2006), we specify $\alpha_{e,ij}$ as a function of α_0 and the number of purchases $\sum_{t=T_0}^{T_1} d_{ij,t}$ in the preestimation sample in the following reduced-form fashion:

$$\alpha_{e,ij} = \alpha_0 + k_1 \sum d_{ij,t}; \quad 0 < k_1 < 1. \quad (19)$$

The specification in Equation (19) suggests that the greater the number of purchases of brand j , the higher is $\sum d_{ij,t}$, and hence the greater the increase in precision over the preestimation time period. Furthermore, the parameter k_1 captures the notion of forgetting in a nonstructural way—as k_1 approaches 1, the extent of forgetting diminishes. To specify the mean of household i 's quality evaluations of brand j at the end of the preestimation sample, we need to specify the $\sum_{t=T_0}^{T_1} d_{ij,t}$ consumption signals. However, instead of specifying each consumption signal that the household receives over the preestimation period, we can equivalently think of the consumer as receiving one cumulative consumption signal that results in an

increase in the precision of household i 's quality belief for brand j from α_0 to $\alpha_{e,ij}$. As shown by Erdem et al. (2006), this cumulative consumption signal can be represented as x_{ij}^m , which is distributed as

$$x_{ij}^m \sim N(q_j, \sigma_{x_{ij}}^2), \quad (20)$$

where the variance of the cumulative consumption signal is related to the variance of a single consumption signal (η^2), and the increase in precision from consumer i 's quality beliefs of brand j in the pre-estimation period, as $\sigma_{x_{ij}}^2 = \eta^2(\alpha_{e,ij} - \alpha_0)^{-1}$, or equivalently $\sigma_{x_{ij}}^2 = \eta^2(k_1 \sum_{t=T_0}^{T_1} d_{ij,t})^{-1}$. We thus represent the cumulative consumption signal as $x_{ij}^m = q_j + \sigma_{x_{ij}} \varepsilon_{ij}$, where ε_{ij} is a standard normal random variable that is independent across brands and consumers.

Therefore, given the cumulative consumption signal (x_{ij}^m) in Equation (20) and the distribution of the household's prior mean quality of brand j at the beginning of the preestimation sample in Equation (17), the mean quality evaluation at the end of the preestimation sample can be specified as

$$\omega_{e,ij} = \omega_0 \frac{\alpha_0}{\alpha_0 + k_1 \sum_{t=T_0}^{T_1} d_{ij,t}} + q_j \frac{k_1 \sum_{t=T_0}^{T_1} d_{ij,t}}{\alpha_0 + k_1 \sum_{t=T_0}^{T_1} d_{ij,t}} + \eta \frac{\sqrt{k_1 \sum_{t=T_0}^{T_1} d_{ij,t}}}{\alpha_0 + k_1 \sum_{t=T_0}^{T_1} d_{ij,t}} \varepsilon_{ij}. \quad (21)$$

Equations (21) and (19), respectively, specify the mean and the precision of consumer i 's beliefs about the quality of brand j at the end of the preestimation sample. For identification, similar to Mehta et al. (2004), we impose $\omega_0 = 0$ for all brands. Thus the parameters to be estimated from the pre-estimation sample are α_0 and k_1 .

3.2. Model Estimation

We have introduced 14 parameters in the model so far: (a) the true qualities of the five brands, $\{q_j\}_{j=1}^5$; (b) the ratio of the informative effects of a single advertising exposure to that of consumption, $\{\beta_j\}_{j=1}^5$; (c) the correlation between ads and consumption, $\{\kappa_j\}_{j=1}^5$; (d) the difference between the actual bias in the brands' advertisements and the consumers' mean belief of that bias, $\{\Delta b_j\}_{j=1}^5$; (e) the ratio of the uncertainty in bias beliefs to the noise in the advertising signal, $\{s_j^2\}_{j=1}^5$; (f) the persuasive effect for the five brands, $\{\gamma_{per,j}\}_{j=1}^5$; (g) the consumer's price sensitivity, γ_p ; (h) the noise in the consumption signals, η ; (i) the consumer's feature sensitivity, γ_f ; (j) the consumer's sensitivity to displays, γ_d ; (k) the consumer's quality sensitivity, θ ; (l) the risk-aversion parameter, r ; (m) the precision of overall quality beliefs in the preestimation sample, α_0 ; and (n) the parameter k_1 defined in the estimation of initial conditions earlier.

Table 2 Summarizing Parameters

| Parameter | What it represents |
|--|--|
| q_{jt} | True quality of brand j in time t |
| $\beta_j^2 = \frac{\eta^2}{\delta_j^2 + \sigma_b^2}$ | Ratio of informational value of one ad for brand j to pure consumption effect |
| $s_j = \sigma_{bj} / \delta_j$ | Ratio of uncertainty in bias belief for brand j to noise in the advertising signal |
| κ_j | Correlation between advertising and the consumption set |
| Δb_j | The difference between true bias in advertising and consumer's common belief for product j |
| δ_j | Noise in the advertising signal for product j |
| η | Noise in the consumption signal |
| σ_{bj} | Uncertainty in the bias belief for product j |
| r | Risk-aversion parameter |
| $\bar{\gamma}_p$ | Mean value of price sensitivity across consumers |
| σ_{γ_p} | Standard deviation of the distribution of price sensitivity across consumers |
| $\bar{\gamma}_f$ | Mean value of feature sensitivity across consumers |
| σ_{γ_f} | Standard deviation of the distribution of feature sensitivity across consumers |
| $\bar{\gamma}_d$ | Mean value of display sensitivity across consumers |
| σ_{γ_d} | Standard deviation of the distribution of display sensitivity across consumers |
| $\bar{\gamma}_{per,j}$ | Mean value of persuasive effect across consumers for product j |
| $\sigma_{\gamma_{per}}$ | Standard deviation of the distribution of persuasive effects across consumers |
| α_0 | Consumers' initial rate of learning through consumption |
| k_1 | Parameter used to calibrate initial conditions |
| ω_{0j} | Consumers' prior belief on mean quality |

We also account for unobserved heterogeneity in the price sensitivity, feature and display variables, and in the persuasive effect of ads. To do this, we let the consumer's price sensitivity be normally distributed across the population with mean $\bar{\gamma}_p$ and variance $\sigma_{\gamma_p}^2$, the feature sensitivity be normally distributed with mean $\bar{\gamma}_f$ and variance $\sigma_{\gamma_f}^2$, the display sensitivity be normally distributed with mean $\bar{\gamma}_d$ and variance $\sigma_{\gamma_d}^2$, and the persuasive effect be normally distributed with mean $\bar{\gamma}_{per,j}$ and variance $\sigma_{\gamma_{per}}^2$. For expositional ease, we summarize each of the parameters in Table 2.

Similar to Mehta et al. (2004), we normalize the mean quality sensitivity, θ , to 1. This leaves us with $6J + 11$ parameters to estimate (where $J = 5$ is the total number of brands), denoted as $\zeta \equiv \{q_j, \beta_j, \kappa_j, \Delta b_j, s_j^2, \bar{\gamma}_{per,j}\}_{j=1}^J, \bar{\gamma}_p, \sigma_{\gamma_p}^2, \eta, \sigma_{\gamma_{per}}^2, \bar{\gamma}_f, \sigma_{\gamma_f}^2, \bar{\gamma}_d, \sigma_{\gamma_d}^2, r, \alpha_0, k_1\}$. We use the method of simulated maximum likelihood to estimate these parameters. For reasons of space, we relegate further details on the exact likelihood function, the estimation algorithm, and issues related to the identification of various parameters to the technical appendix.

3.3. Parameter Estimates and Discussion of Results

Goodness of Fit Tests. Table 3 reports log-likelihood values and hit rates for our model for estimation

Table 3 Model Fit for Estimation and Holdout Sample

| Model | Estimation sample | Holdout sample |
|------------------------------|-------------------|----------------|
| Proposed model | | |
| Hit rate (%) | 69.88 | 67.85 |
| Log likelihood | −1,455.71 | −698.61 |
| AIC | 2,993.42 | |
| Deighton et al. (1994) model | | |
| Hit rate (%) | 64.89 | 63.55 |
| Log likelihood | −1,643.34 | −754.22 |
| AIC | 3,366.68 | |

Notes. The Akaike Information Criterion (AIC) is given as $-2L + 2k$, where L is the log-likelihood function, and k is the number of parameters. The proposed model has 41 estimable parameters, while the Deighton et al. (1994) model has 24. A model with a lower AIC is preferred.

and holdout samples. We also report the fit comparison with a modified version of the model specification in Deighton et al. (1994)—for space, parameter estimates for the comparison model are provided in the Technical Appendix, which can be found at <http://mksci.pubs.informs.org>. The utility specification of the modified Deighton et al. (1994) model is given as

$$U_{ij,t} = q_{ij} + a_{i1}(p_{j,t}) + a_{i2}(p_{j,t}N_{j,t-1}) + b_{i1}(\sqrt{N_{j,t-1}}) \\ + b_{i2}(\sqrt{N_{j,t-2}}) + b_{i3}(d_{j,t-1}) + b_{i4}(d_{j,t-1}\sqrt{N_{j,t-1}}) \\ + c_{i1}(Feat_{j,t}) + c_{i2}(Disp_{j,t}) + \varepsilon_{ij,t},$$

where $N_{j,t-1}$ represents the number of advertisements seen by the consumer between purchase occasions 0 and t , $N_{j,t-2}$ represents the number of advertisements seen by the consumer between purchase occasions 0 and $t-1$, and $d_{j,t-1}$ is an indicator variable, equal to 1 if the consumer purchases brand j on occasion $t-1$ and 0 otherwise.

To compare models, we calculate the AIC for both models. The AIC is given as $-2\ln(L) + 2k$, where L is the likelihood and k is the number of parameters. The model with the lower value of AIC is preferred. Our proposed model does better than the reduced form model (AIC of 2,993.42 versus 3,366.68), even though it has a greater number of parameters (41 versus 24).

3.3.1. Results and Discussion of Insights. Parameter estimates for the model are reported in Table 4. We summarize our discussion of the parameter estimates under the following broad substantive areas.

True qualities. Tide has the highest true quality ($q_5 = 4.1653$), followed by Era ($q_3 = 4.1028$), Cheer ($q_1 = 3.9217$), Surf ($q_2 = 3.4792$), and Wisk ($q_4 = 3.1096$). One can think of these as constituting two groupings, with Era and Tide constituting the “high-quality” group and the other three brands forming the “low-quality” group.

Perceived quality beliefs at the beginning of the estimation sample. Based on the estimates of k_1 and α_0 at the

beginning of the preestimation sample (as discussed in §3.1), we can calculate the mean and variance of the perceived quality beliefs averaged across all consumers in the sample. The estimates of these tell us whether there is still potential for learning (and hence a role for informative and transformative effects of ads) in the estimation sample. We get the perceived mean quality belief at the beginning of the estimation sample averaged across all consumers for Cheer as 0.46, for Surf as 0.62, for Era as 1.05, for Wisk as 0.94, and for Tide as 1.10. Similarly, we get the average perceived variance in the consumers’ quality beliefs at the beginning of the estimation sample for Cheer as 1.50, for Surf as 1.44, for Era as 1.34, for Wisk as 1.29, and for Tide as 1.33. Notice that although the new brands (Cheer and Surf) are associated with higher uncertainty in their perceived qualities, the average uncertainty in the established brands is also reasonably high. Even though our context is a mature product category, the uncertainty about perceived qualities can come from various sources—it could be because of the introduction of two new products during the sample period, or because consumers are aware of the quality of only a few products and not the entire set.

Perceived bias in advertisements. In our formulation, consumers attributed a certain mean bias to a brand’s ads (\bar{b}_j), with some variance around this mean (σ_{b_j}). We are able to estimate Δb_j (which is $b_j - \bar{b}_j$). For the variance, we calculate σ_{b_j} from estimated parameters (to see this, note that we have estimates of $s_j^2 = \sigma_{b_j}^2/\delta_j^2$, $\beta_j^2 = \eta^2/(\delta_j^2 + \sigma_{b_j}^2)$ and η^2 . From these, we can calculate σ_{b_j}). Focusing on the variance of the perceived biases in the ads of each of the brands first, one would expect older brands to have a lower variance. Also, to the extent that the ads have been successful in informing consumers of true quality in the past, the variance of the bias should be lower. In line with intuition, the two new products, Cheer ($\sigma_{b_1} = 4.5992$) and Surf ($\sigma_{b_2} = 4.1677$), have the highest variances, i.e., the consumer is most uncertain about the bias in the ads of Cheer and Surf. These are followed by Tide ($\sigma_{b_5} = 3.9937$), Wisk ($\sigma_{b_4} = 3.2429$), and Era ($\sigma_{b_3} = 2.8166$).

As for Δb_j , a positive value for a brand would suggest that the consumer thinks ads for this brand are less biased than what they actually are, while a negative value would suggest the opposite. These perceptions could be affected by a variety of factors, such as the content of the ad or information that affects the credibility of the source. Both Cheer ($\Delta b_1 = -0.9221$) and Wisk ($\Delta b_4 = -2.1250$) seem to suffer from worse source credibility issues than they “deserve”; on the other hand, the consumer discounts the bias in the advertisements of Era ($\Delta b_3 = 2.3707$), Surf ($\Delta b_2 = 1.6819$), and Tide ($\Delta b_5 = 1.1290$) less than is warranted.

Table 4 Parameter Estimates for Proposed Model

| Parameter | What it represents | Estimate | Standard error |
|-------------------------|--|------------|----------------|
| q_1 | True quality of Cheer | 3.9217** | 0.5478 |
| q_2 | True quality of Surf | 3.4792** | 0.5411 |
| q_3 | True quality of Era | 4.1028** | 0.3998 |
| q_4 | True quality of Wisk | 3.1096** | 0.4030 |
| q_5 | True quality of Tide | 4.1653** | 0.3696 |
| β_1 | Ratio of informational value of one ad for Cheer to pure consumption effect | 0.3222* | 0.1842 |
| β_2 | Ratio of informational value of one ad for Surf to pure consumption effect | 0.3704* | 0.1556 |
| β_3 | Ratio of informational value of one ad for Era to pure consumption effect | 0.5361** | 0.1801 |
| β_4 | Ratio of informational value of one ad for Wisk to pure consumption effect | 0.4879* | 0.2104 |
| β_5 | Ratio of informational value of one ad for Tide to pure consumption effect | 0.3906* | 0.1735 |
| s_1 | Ratio of uncertainty in bias belief for Cheer to noise in the consumption signal | 1.1041** | 0.2733 |
| s_2 | Ratio of uncertainty in bias belief for Surf to noise in the consumption signal | 1.1400** | 0.3345 |
| s_3 | Ratio of uncertainty in bias belief for Era to noise in the consumption signal | 0.9915** | 0.3614 |
| s_4 | Ratio of uncertainty in bias belief for Wisk to noise in the consumption signal | 1.0791** | 0.4212 |
| s_5 | Ratio of uncertainty in bias belief for Tide to noise in the consumption signal | 1.0299** | 0.3932 |
| κ_1 | Correlation between advertising and the consumption set for Cheer | 0.1158 | 0.1273 |
| κ_2 | Correlation between advertising and the consumption set for Surf | 0.4965** | 0.1622 |
| κ_3 | Correlation between advertising and the consumption set for Era | 0.5828** | 0.1841 |
| κ_4 | Correlation between advertising and the consumption set for Wisk | 0.0906 | 0.1332 |
| κ_5 | Correlation between advertising and the consumption set for Tide | 0.3533** | 0.1253 |
| Δb_1 | The difference between true bias in advertising and consumer's common belief for Cheer | −0.9221* | 0.4400 |
| Δb_2 | The difference between true bias in advertising and consumer's common belief for Surf | 1.6819** | 0.4531 |
| Δb_3 | The difference between true bias in advertising and consumer's common belief for Era | 2.3707** | 0.4660 |
| Δb_4 | The difference between true bias in advertising and consumer's common belief for Wisk | −2.1250** | 0.8246 |
| Δb_5 | The difference between true bias in advertising and consumer's common belief for Tide | 1.1290** | 0.3404 |
| η | Noise in the consumption signal | 2.0843** | 0.3725 |
| $\gamma_{per,1}$ | Persuasive effect for Cheer | 0.0000 | 0.0141 |
| $\gamma_{per,2}$ | Persuasive effect for Surf | 0.0001 | 0.0062 |
| $\gamma_{per,3}$ | Persuasive effect for Era | 0.0109 | 0.0567 |
| $\gamma_{per,4}$ | Persuasive effect for Wisk | 0.0211 | 0.0113 |
| $\gamma_{per,5}$ | Persuasive effect for Tide | 0.0048* | 0.0251 |
| $\sigma_{\gamma_{per}}$ | Standard deviation of the distribution of the persuasive effect | 0.0093 | 0.0071 |
| r | Risk-aversion parameter | −1.1590** | 0.1391 |
| $\bar{\gamma}_p$ | Mean value of the price sensitivity across the consumer population | 0.6294** | 0.1045 |
| σ_{γ_p} | Standard deviation of the distribution of price sensitivity | 0.3357* | 0.1822 |
| $\bar{\gamma}_d$ | Mean display sensitivity | 0.7042** | 0.1873 |
| σ_{γ_d} | Standard deviation of the distribution of display sensitivity | 0.7245* | 0.3264 |
| $\bar{\gamma}_f$ | Mean feature sensitivity | 1.0856** | 0.2173 |
| σ_{γ_f} | Standard deviation of the distribution of feature sensitivity | 1.2677** | 0.3159 |
| α_0 | Consumers' initial precision of quality beliefs | 1.6708** | 0.1110 |
| k_1 | Parameter used to calibrate initial conditions | 0.4791** | 0.1321 |
| −Log likelihood | | 1,455.7134 | |

Notes. *Significant at 5% level. **Significant at 1% level.

Extent of ambiguity in consumption. We follow Hoch and Ha (1986) and operationalize ambiguity in consumption as an increasing function of the consumption experience variability and a decreasing function of the variability between the true qualities of the different brands. Note that experience variability is just the noise in the consumption signal, η , whose estimate is 2.0843. Furthermore, the variability between the true qualities of the brands can be represented by the standard deviation across the estimates of the true qualities of the five brands, i.e., $\text{stdev}(q_1, q_2, q_3, q_4, q_5)$. Therefore, we can mathematically represent consumption ambiguity as the ratio of the noise in consumption to the standard deviation of the estimates of the true qualities across brands. If the value of this

ratio is greater than 1, consumption ambiguity is high; if the ratio is close to zero, consumption ambiguity is low. Using our estimates of the true qualities for the five brands, we obtain a standard deviation of 0.4499. Therefore, the consumption ambiguity is $2.0843/0.4499 = 4.6329$, which is significantly greater than 1. This implies that consumption ambiguity is significant in the liquid detergent category, and we can reasonably expect advertising to have a transformative effect.

Risk aversion. We find that consumers are significantly risk averse in this category ($r = -1.1590$). This is consistent with prior literature (Erdem and Keane 1996, Byzalov and Shachar 2004), which has also emphasized the importance of controlling for risk

Table 5 Advertising Elasticity Matrix

| Brand | Total advertising elasticity | Informative elasticity | Transformative elasticity |
|-------|------------------------------|-----------------------------|-------------------------------|
| Cheer | 0.0297 (0.0228, 0.0366) | 0.0297 (0.0227, 0.0368) | −0.0000 (−0.0002, 0.0002) |
| Surf | 0.0791 (0.0677, 0.0906) | 0.0689 (0.0582, 0.0795) | 0.0177 (0.0150, 0.0204) |
| Era | 0.1151 (0.0976, 0.1325) | 0.0973 (0.0821, 0.1126) | 0.0103 (0.0091, 0.0115) |
| Wisk | 0.0017 (−0.0023, 0.0057) | 0.0038 (−0.0003, 0.0081) | −0.0022 (−0.0027, −0.0017) |
| Tide | 0.0383 (0.0327, 0.0439) | 0.0324 (0.0274, 0.0375) | 0.0059 (0.0053, 0.0064) |

Note. Numbers in parenthesis represent the 95% confidence interval from parametric bootstrapping.

aversion to obtain unbiased estimates of advertising effects.

Total ad elasticity. Table 5 summarizes ad effects in the form of elasticities. Note that Surf, Era, and Tide do reasonably well on total advertising elasticity, while Cheer and Wisk do poorly. We examine the informative and transformative components of the total advertising elasticity below.

Informative effect of advertisements. As discussed earlier, the informative effect depends on three things. First, the informational value of one ad, as captured by β_j^2 , which is an inverse function of the sum of two variances in the ad signals (the variance of the noise that results from message clarity (δ_j^2) and the variance of the perceived bias of brand j (σ_{bj}^2)). Note that the greater the value of β_j^2 for brand j , the greater the informational value of each brand j 's ad, implying a higher informative effect. Second, the difference or the gap between the mean of the advertising signals ($q_j + \Delta b_j$) and the consumer's prior mean quality belief of brand j at the beginning of the estimation sample ($\omega_{e,ij}$); the larger the gap, the greater the extent of change in quality evaluations after seeing the ads, leading to a greater informative effect. Third, the ratio of the variance of the perceived biases in brand j 's ad to the noise in brand j 's ad ($s_j^2 = \sigma_{bj}^2 / \delta_j^2$). The higher the value of s_j^2 , the lower the marginal impact of each successive ad on the quality evaluations, leading to a lower informative effect. To aid comparison, we calculate the informative elasticities for all five brands, shown in Table 5. Furthermore, Table 6a shows each of the components affecting the informative elasticity for all the brands.

Focusing on the elasticities, note that the rank ordering, from greatest to least informative effects is Era, Surf, Tide, Wisk, and Cheer. This result can be explained on the basis of the three factors discussed above. The result for Era can be understood by observing that Era has a high value of the gap

Table 6a Factors Affecting Informative Elasticity

| Brand | β_j^2 | s_j^2 | $q_j + \Delta b_j - \omega_{e,ij}$ |
|-------|-------------|---------|------------------------------------|
| Cheer | 0.1038 | 1.2191 | 2.5362 |
| Surf | 0.1371 | 1.2998 | 4.5371 |
| Era | 0.2874 | 0.9831 | 5.4140 |
| Wisk | 0.2380 | 1.1645 | 0.0375 |
| Tide | 0.1526 | 1.0608 | 4.1861 |

Table 6b Factors Affecting Transformative Elasticity

| Brand | κ_j | σ_{bj} | Δb_j |
|-------|------------|---------------|--------------|
| Cheer | 0.1158 | 4.5992 | −0.9221 |
| Surf | 0.4965 | 4.1677 | 1.6819 |
| Era | 0.5828 | 2.8166 | 2.3707 |
| Wisk | 0.0906 | 3.2429 | −2.1250 |
| Tide | 0.3533 | 3.9937 | 1.1290 |

(=5.4140), the highest value of β_j^2 (=0.2874), and the lowest value of s_j^2 (=0.9831) among the five brands. Also, Cheer is the worst in informative effects because it has the lowest value of β_j^2 (=0.1038), a high value of s_j^2 (=1.2191), and a low value of the gap (=2.3562). Similarly, Wisk has low informative effects because even though β_j^2 (=0.2380) is high, the gap (=0.0375) is very small and s_j^2 (=1.1645) is high. Finally, Surf and Tide have relatively higher informative effects. Tide has high informative effects primarily because its s_j^2 (=1.0608) is low, while Surf has high informative effects because its gap (=4.5371) is high (perhaps because it is a new brand and consumers discount its ads less than they should).

Transformative effect of advertisements. The transformative effect goes up as (a) κ_j , the closeness with which the ad is associated with the consumption evaluation goes up, (b) σ_{bj}^2 , the perceived variance of the biases in the ad signals goes up, and (c) Δb_j , the magnitude of the residual bias in the ad-based expectations goes up. Given the number of factors in play, it is easiest to compare transformative effects by computing the transformative elasticities, shown in Table 5. Observe that Surf is the highest, followed by Era and Tide. Wisk and Cheer have extremely small transformative elasticities. To gain further insight into each of the factors affecting the transformative elasticity, Table 6b gives values for each of three elements (κ_j , σ_{bj}^2 , Δb_j) for each of the brands.

We can see why Surf has the highest transformative elasticity—its κ_j , σ_{bj} , and Δb_j are all high. Era and Tide have reasonable κ_j and high Δb_j , but their transformative effects are not as high as Surf because their σ_{bj} is lower (which could be because they are well-established brands). Finally, Cheer and Wisk have low transformation in spite of having a high σ_{bj} , because their κ_j and Δb_j are both low.

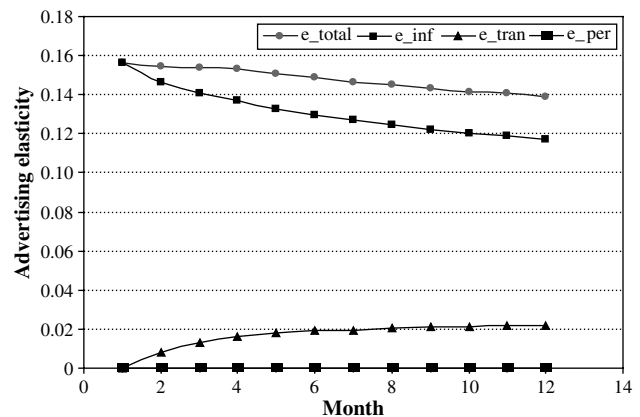
Persuasive effect of advertisements. Most of the persuasive effects (γ_{per}) are insignificant. The only significant effect is that for Wisk. We conjecture that Wisk might be forced to rely on persuasive effects because it has low informative and transformative elasticities. We should note that Akerberg (2001, 2003), who modeled persuasive effects in the yogurt category, in a manner similar to ours, also found insignificant effects. While some prior papers have found significant persuasive effects, it is important to observe two things. First, as discussed earlier, modeling the persuasive effect through a direct term in the utility captures advertising effects that have not been modeled structurally. It is not clear that these effects constitute what the behavioral literature has called “persuasive effects.” Second, Byzaiov and Shachar (2004) show that significant persuasive effects could be a result of specification error, namely, the omission of consumer risk aversion. Because we model both informative and transformative effects structurally, and account for risk aversion, our result on persuasive effects is not surprising.

3.3.2. Further Analysis of the Results.

1. *Decomposing advertising effects. Temporal Pattern.* To examine the impact of advertising effects over time, we conduct the following analysis. Controlling for marketing mix effects, we plot the advertising elasticities for Era over the sample period. We pick Era as a useful brand to focus on because it has reasonable values of both informative and transformative effects. To isolate the effects, we control for variations in consumer purchase patterns and marketing mix effects. To do this, we fix the price, feature, display, and ad intensity for each brand to its average level, and assume each consumer purchases once every four weeks. The curves for the total advertising elasticity as well as the three individual effects are shown in Figure 2a. As expected, informative elasticities are much larger than either transformative or persuasive elasticities. Persuasive effects seem to show no obvious pattern and are fairly low throughout. To see differences in patterns for informative and transformative effects more clearly, we plot two more figures—again for Era. First, we plot the informative and transformative elasticities as a fraction of the total advertising elasticity over time (Figure 2b). Second, we plot the ratio of transformative to informative elasticities over time (Figure 2c). All three figures tell a consistent story, i.e., informative effects are important early on, while transformative elasticities start very low and increase over time.

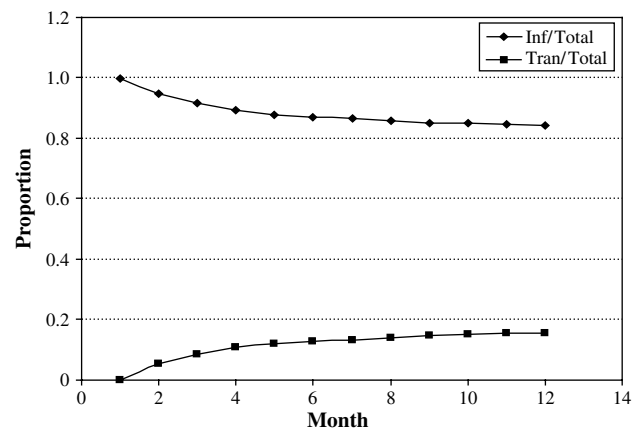
To understand these patterns, note that for informative effects, the temporal pattern comes from learning. As the consumer learns through ads or through consumption, her uncertainty decreases and the marginal

Figure 2a Advertising Elasticities Over Time (Era)



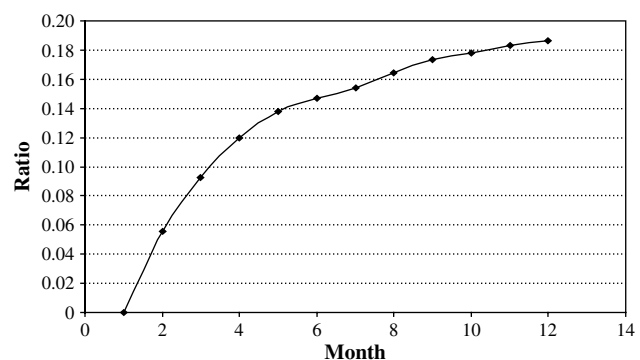
Notes. e_total: Total advertising elasticity; e_inf: Informative advertising elasticity; e_tran: Transformative advertising elasticity; e_per: Persuasive advertising elasticity.

Figure 2b Informative/Transformative Elasticities as Proportions of Total Advertising Elasticities Over Time (Era)



Notes. Inf/Total: Informative elasticity/Total advertising elasticity; Tran/Total: Transformative elasticity/Total advertising elasticity.

Figure 2c Ratio of Transformative to Informative Advertising Elasticity Over Time (Era)



impact of the informative effect of ads on brand utilities decreases. This is exactly what happens for the transformative effect also. However, there is a countervailing force in the latter case. As the consumer

progresses over her purchase history, the number of cumulative ads she sees for a given brand also increases, leading to an increase in the transformative impact of ads on consumption. Thus the total intertemporal change in the transformative elasticities depends on the relative strength of these two forces. Note that in Figures 2a–2c, the transformative elasticities increase over time, which implies that the latter factor (the number of cumulative ads seen) outweighs the former (the extent of uncertainty about quality evaluations).

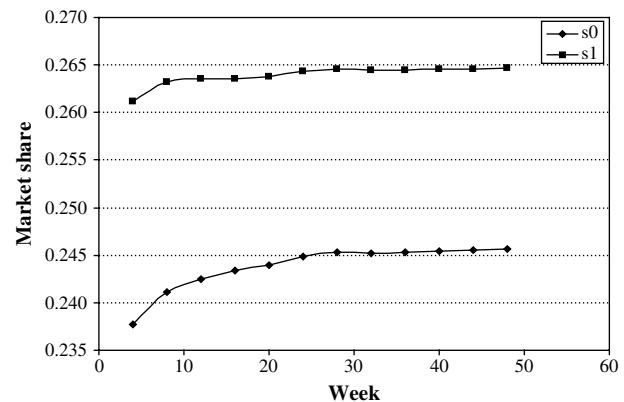
3.3.3. Policy Experiments.

1. Impact of advertising intensity on advertising effects.

In this experiment, we change ad intensity for each brand, defined as the average number of ads seen per household per week, and we examine how this affects the impact of informative and transformative effects on the market share for each brand. We would expect advertising effects to increase with increase in ad intensity. We perform the experiment by varying ad intensity from 0.1 to 0.7 (the average ad intensity in the data for Era is 0.5). To isolate the effect of ad intensity, we control for variations in consumer purchase patterns and marketing mix effects. To do this, we fix the price, feature, and display for each brand to its average level and assume that each consumer purchases once every four weeks. Instead of plotting multiple curves at each ad intensity level, we do the following. We first calculate the overall difference in market share at an ad intensity of 0.7 versus 0.1. Figure 3a shows that the market share is greater with the higher ad intensity, as one would expect. We then divide the market share difference calculated above, at each time, into three components, representing the market share change because of the informative, transformative, and persuasive effects, respectively. We divide each of these components by the total market share change, to normalize. Figure 3b plots these ratios for Era. The pattern buttresses our earlier findings about the temporal pattern of these effects. The initial sharp change in market share is almost entirely because of the informative effect. This attenuates over time, with the transformative effect taking over. The persuasive effect, by contrast, remains fairly constant in its impact on market share.

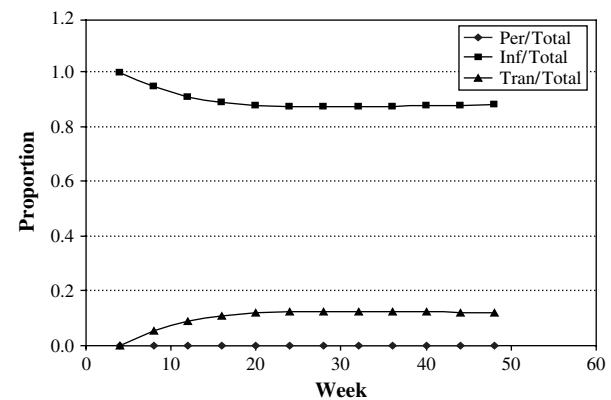
2. Impact of advertising effects on competitive clout and vulnerability. Viewing advertising effects in terms of current users and nonusers, one can say that informative effects are most useful in influencing current nonusers of the product (a group that mainly consists of those that have little experience with the brand), while transformative effects have their maximum impact on current users. Because this is the case, enhancing informative effects should help a

Figure 3a Impact of Ad Intensity on Market Share



Notes. s0: Market share when ad intensity = 0.1; s1: Market share when ad intensity = 0.7.

Figure 3b Impact of Ad Intensity: Informative, Transformative, and Persuasive Advertising Effects as Proportions of Total Market Share Change Over Time



Notes. Per/Total: Proportion of market share change because of persuasive effect; Inf/Total: Proportion of market share change because of informative effect; Tran/Total: Proportion of market share change because of transformative effect.

brand attract a greater number of current nonusers—it should have less impact on current users. Conversely, enhancing transformative effects should help a brand keep a greater number of users who might be tempted to switch brands otherwise—it should have less impact on current nonusers. This maps on in an obvious manner to the concepts of clout and vulnerability, that we now turn to.¹¹ The price elasticity matrix for all the brands, as well their clout and vulnerability, is shown in Table 7.

¹¹ Competitive clout is defined as the share of customers that a brand would attract from the competing brands if it engages in a price cut. Clout for brand j is given as $\sum_{k \neq j} E_{kj}^2$, where E_{kj} is the percentage change in the market share of brand k when there is a 1% decrease in the price of brand j (Kamakura and Russell 1989). Vulnerability is defined as the fractional share brand would lose to the competing brands if they were to offer a price discount. For brand j it is defined as $\sum_{k \neq j} E_{jk}^2$, where E_{jk} is the percentage change in the market share of brand j when there is a 1% decrease in the price of brand k (Kamakura and Russell 1989).

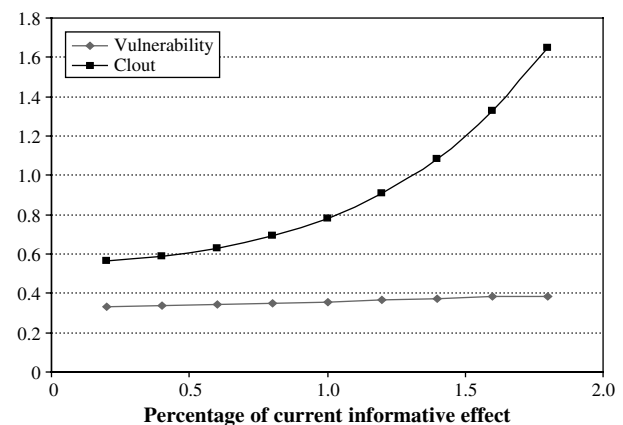
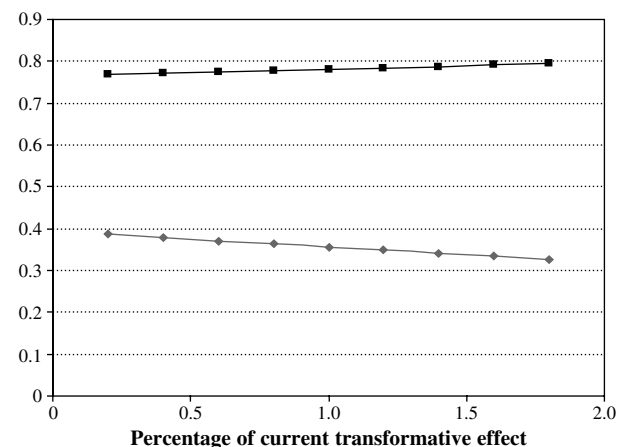
Table 7 Price Elasticities, Clout, and Vulnerability (Era)

| Brand | Price elasticity | | | | |
|---------------|------------------------------|-------------------------------|-------------------------------|-------------------------------|-------------------------------|
| | Cheer | Surf | Era | Wisk | Tide |
| Cheer | −1.9338 (−2.7106, −1.157) | 0.1669 (−0.0309, 0.3647) | 0.1132 (0.0018, 0.2245) | 0.1233 (−0.0156, 0.2623) | 0.1446 (−0.0585, 0.3478) |
| Surf | 0.3095 (0.1150, 0.5040) | −1.7541 (−2.4041, −1.1040) | 0.2384 (0.1375, 0.3393) | 0.2406 (0.1208, 0.3604) | 0.2551 (0.0149, 0.4953) |
| Era | 0.4828 (0.3188, 0.6469) | 0.5447 (0.3911, 0.6982) | −1.2141 (−1.6726, −0.7555) | 0.3847 (0.2781, 0.4913) | 0.3207 (0.0548, 0.5865) |
| Wisk | 0.4901 (0.3046, 0.6757) | 0.5241 (0.3562, 0.6921) | 0.3677 (0.2676, 0.4677) | −1.1094 (−1.5582, −0.6606) | 0.3762 (0.0917, 0.6607) |
| Tide | 0.7329 (0.5819, 0.8839) | 0.7035 (0.5546, 0.8524) | 0.3889 (0.3085, 0.4695) | 0.4725 (0.3743, 0.5707) | −1.2066 (−1.4542, −0.9591) |
| Clout | 0.0768 (0.0572, 0.0964) | 0.2756 (0.1158, 0.4355) | 0.7807 (0.5575, 1.0039) | 0.7917 (0.3779, 1.2055) | 1.4067 (1.0949, 1.7184) |
| Vulnerability | 1.1064 (0.8381, 1.3746) | 1.0942 (0.8233, 1.3652) | 0.3561 (0.2680, 0.4443) | 0.4444 (0.3141, 0.5747) | 0.3304 (0.1379, 0.5230) |

Notes. (a) E_{jk} is the percentage change in the market share of brand j when there is a 1% decrease in the price of brand k ; (b) $\text{Clout}_j = \sum_{k \neq j} E_{kj}^2$ and $\text{Vulnerability}_j = \sum_{k \neq j} E_{jk}^2$; (c) Numbers in parenthesis represent the 95% confidence interval from parametric bootstrapping.

Informative effects. Consider a brand (subsequently referred to as the focal brand) whose true quality is greater than the quality beliefs of its current nonusers. If such a brand engages in a price cut, it will attract some current nonusers (i.e., consumers who were purchasing the competing brands). If the focal brand enhances the informative effects of its advertising, it can increase consumers' perceived quality evaluations. In such a case, if the brand engages in a price cut, it will be able to attract a much larger fraction of its nonusers. This implies that an increase in informative effects serves to increase the competitive clout for such a brand. Next, if a competing brand were to offer a price discount, it would attract some of the current users of the focal brand. Because informative effects have relatively little impact on the quality evaluations of current users, enhancing these effects will not help the focal brand prevent the loss of its customers because of a competitor's price cut. In other words, increasing informative effects would only have a marginal impact on the focal brand's vulnerability. In summary, if a brand's true quality is higher than the perceived quality evaluations of its nonusers, *enhancing informative effects would primarily serve to increase the brand's competitive clout, but will not significantly impact its vulnerability.*

To see if this conjecture holds, we run the following experiment. We vary the informative effect for Era by varying β (recall that $\beta_j^2 = \eta^2 / (\delta_j^2 + \sigma_{\eta_j}^2)$ is the ratio of the informational value of one ad to the informational value of one consumption experience), from 20% of its estimated value to 180% of its estimated value. Next, we compute Era's competitive clout and vulnerability. Figure 4a shows the change in clout and vulnerability as the magnitude of the informative

Figure 4a Impact of Changing Informative Effect on Clout and Vulnerability**Figure 4b** Impact of Changing Transformative Effect on Clout and Vulnerability

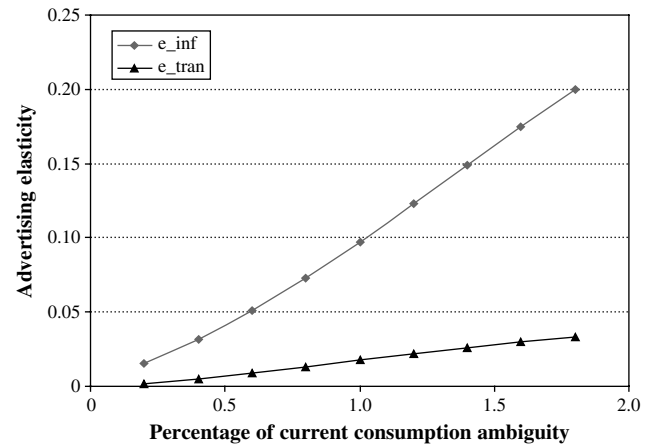
effect increases. The conjecture seems clearly borne out—increasing informative effects primarily serves to increase the brand’s competitive clout but does not substantially change its vulnerability. The managerial implication of this is clear: for a brand with a sufficiently loyal base of consumers, such that losing customers to competing brands is a smaller issue than attracting new customers, enhancing informative effects is very useful. On the other hand, emphasizing informative effects will be of little value for brands with a customer base prone to switching.

Transformative effects. Transformative effects acquire relevance only when accompanied by consumption; clearly, they have no impact on consumers who have never used the focal brand. This suggests that emphasizing transformative effects is not an effective acquisition strategy; in other words, increasing this effect should have little impact on the clout of the focal brand. On the other hand, if the competing brands engage in a price cut, they will attract the current users of the focal brand. Because the focal brand can increase the perceived quality evaluations of its current users by engaging in high transformative effects, increasing transformative effects would make the brand less vulnerable. In summary, *increasing transformative effects would primarily serve to decrease the brand’s vulnerability but will not significantly impact its competitive clout.*

To see if this conjecture holds, we run the following experiment. We vary the transformative effect for Era, by varying κ_j (the tightness of the connection between ads and the consumption experience) from 20% of its estimated value to 180% of its estimated value. Following that, we compute Era’s competitive clout and vulnerability. Figure 4b shows the change in clout and vulnerability as the magnitude of the transformative effect increases. Observe that vulnerability is affected more than clout. The managerial implication of this is clear: for a brand with a relatively weak base of loyal consumers, such that losing customers to competing brands is a bigger issue than attracting new customers, enhancing transformative effects is very useful.

3. Impact of Consumption Ambiguity on Advertising Effects. Our model suggests that greater levels of consumption ambiguity would lead to greater advertising effects, consistent with prior behavioral literature. This is reasonable—the smaller the role of consumption in reducing uncertainty about quality evaluations, the greater the role of other signals, such as advertising. To see this, we perform an exercise similar to Hoch and Ha (1986), who considered transformative effects for two categories with varying levels of ambiguity—paper towels and polo shirts. They found that the transformative effect was higher for the category with a higher level of ambiguity; namely,

Figure 5 Impact of Consumption Ambiguity on Informative/Transformative Advertising Elasticities (Era)



Notes. e_inf: Informative advertising elasticity; e_tran: transformative advertising elasticity.

polo shirts. In a similar fashion, we plot informative and transformative elasticities versus consumption ambiguity by varying the latter from 20% to 180% of its estimated value in our sample. Figure 5 shows the plot for Era. As expected, increasing consumption ambiguity has a positive impact on both informative and transformative effects.

4. Conclusions

In this paper, we propose a formal model of consumer behavior that explicitly details the processes through which the informative and transformative effects of advertisements impact a consumer’s brand evaluations and subsequent brand choice decisions. In addition, we also account for persuasive effects. Our model hews closely to prior behavioral research that has discussed the transformative effect and the confirmatory bias at the heart of the effect. In our empirical analysis, we find significant effects of advertising along both informative and transformative dimensions. We perform policy experiments to uncover the temporal variation in informative and transformative effects across time. We find that informative effects predominate early on in the learning period but then taper off. Transformative effects follow exactly the opposite pattern.

Our study suffers from some limitations, which could be avenues for future research. First, we have not modeled the decay of advertising effects explicitly. One way to incorporate advertising decay in our structural framework would be to model evaluations as being recalled imperfectly because of forgetting. While an interesting extension, this would complicate the model significantly. Furthermore, as suggested by Mehta et al. (2004), the impact of advertising would

only be enhanced if we were to incorporate the forgetting of advertisements in our model. Second, we have modeled confirmatory bias in a semi-structural way by allowing an exogenous correlation between ad-based expectations and the subsequent consumption signal. A completely structural approach would be to formally model the hypothesis testing behavior of the consumer. To do so, we would need to model the fact that the consumer forms a hypothesis that the ad-based expectation is the true quality and tests this hypothesis using the subsequent consumption signal as a datum. As a result of this exercise, the transformed consumption signal would be a convex combination of the true consumption signal and the ad-based expectations. Thus the biases in the ad-based expectations would flow to the transformed consumption signal, endogenously creating correlations between the consumption signal and the ad-based expectations. Modeling this is likely to involve significant complications (Boulding et al. 1999, the only other paper that has modeled confirmatory bias, also does so in a semi-structural manner).

Third, bounded rationality enters our model only as it relates to the impact of ads, i.e., consumers are unaware that their consumption evaluations are being transformed by ads. Future research could consider other elements of bounded rationality, e.g., biases such as the “base rate fallacy” that lead consumers to update in a fashion that deviates from the Bayesian rule (Bar-Hillel 1980). Fourth, we do not have information on the content of advertising in our data. If one had access to such data, one could correlate specific features of ads to the magnitude of the informative and transformative effects. Fifth, while our data are on purchase, the model is formulated around consumption. If consumers consume at a time very different from the purchase time, that could impact our results. It would certainly be useful to model consumption decisions explicitly (Erdem et al. 2006, Sun et al. 2003, Sun 2005). Finally, while we have examined the impact of changing informative and transformative effects, it would be useful to consider how the differential roles played by such advertising could lead to better targeting of advertising (Iyer et al. 2005). In a similar vein, it would be useful to supplement our analysis by considering the profitability of enhancing one or more of advertising’s effects (Sriram et al. 2006), or examining competitive strategy more finely along various dimensions of advertising effects (Steenkamp et al. 2005).

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