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Setting Quality Expectations When Entering a Market: What Should the Promise Be?

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This paper examines optimal advertised quality, actual quality, and price for a firm entering a market. It develops a two-period model where advertised quality influences expectations, and hence trial and the gap between actual quality and expectations determines satisfaction, which in turn impacts second-period sales. In such situations a company makes a choice between advertising high quality and getting trial, but little repeat; and advertising low quality and getting low trial, but high repeat.

Results are derived by numerical methods, as well as analytically for a special case of the model. The model suggests it is optimal to overstate quality when (i) customers rely relatively less on advertising to form quality expectations, and (ii) customers' intrinsic satisfaction with a product is high.

These results are consistent with deceptive advertising cases at the FTC, which showed more deception for unknown firms and for firms whose customers were more satisfied. They are also consistent with the decisions made by future managers (MBAs), except that the respondents would advertise higher (versus lower) quality when advertising was effective.

Key words: customer satisfaction; customer expectations; deceptive advertising; new products; advertised and actual quality

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1. Introduction

A firm about to enter a market needs to balance two important goals: achieving initial trial and creating long-term profitability. Initial acceptance depends heavily on customer expectations about quality, which are partly based on the level of quality represented in ads and other promotional communication (Goering 1985). By contrast, continued (long-run) sales depend largely on actual quality (to the extent customers can evaluate it) and satisfaction (Cronin and Taylor 1992). Because customer satisfaction depends on the gap between quality and expectations (Yi 1990) and providing quality is costly, a tension exists, from a firm's perspective, between raising expectations to increase initial acceptance/trial and lowering expectations to increase satisfaction, and hence future sales.

The main contribution of this paper is threefold. First, we develop a model and explore the optimal level for advertised quality, average actual quality, and price, taking into account customer satisfaction and long-term market potential. The model focuses on firm decisions, using previous findings on customer behavior and satisfaction to develop the demand function the firm faces. Second, we delineate conditions under which firms have an incentive to overstate quality—i.e., advertise deceptively—an issue that is important for marketing managers and regulators alike. Third, we examine how our model conjectures developed in this context match deceptive advertising cases at the Federal Trade Commission (FTC) from mid-1996 to 2002, as well as managerial decisions made in an experiment. While in general we find support for our results and consistency between the FTC data and the experiment with managers, in one case the managerial decisions go in the opposite direction from the model implications.

Our findings suggest that although overstating quality is generally desirable, understating quality may be optimal under certain conditions—for example, when customers are more sensitive to the difference between actual and expected quality, do not discount the advertised quality (as with the case of well-known firms), have a low base level of satisfaction, and especially (and unsurprisingly) when future sales are the major source of profits. Using deceptive advertising cases at the FTC, we find that there is more deception by a firm: (1) when the firm is unknown, and (2) customers were more satisfied relative to the industry. The results of our experiment provide additional support, not only for these two results, but to most of the other model predictions as well.

New products come in many types, including really new products that create markets (a rare event), modest product changes, and entry to existing markets that are new to the company (e.g., across countries). In all these cases, customers are uncertain about product quality. In introducing such products, a firm needs to set expectations for quality (generally via advertising) as well as decide on actual quality and price. In our analysis, we examine these decisions in the context of a product entering a new market where competitors' quality and price levels are already established. The product is new in the sense that (i) it was not available previously in the market and (ii) its quality can be set specific to the new market; i.e., the technology is a decision variable.

The paper proceeds as follows. The next section provides a brief discussion of relevant literature. We then present our model. Next, we estimate several model parameters using data from a field study. We then determine the optimal levels of advertised quality, average actual quality, and price from a firm's perspective via numerical analysis. Empirical analysis involving both FTC data and an experiment are then presented. Finally, we discuss our findings and suggestions for future research.

2. Background

Advertising plays multiple roles (for example, as a signal of quality, to provide information, as a barrier to entry, etc.). Focusing on the information-providing role, a key aspect involves setting quality expectations. Quality expectations influence both initial purchases and, through their role in determining satisfaction, repeat/subsequent purchases. Further, while high initial expectations may lead to initial purchase, inflated expectations lead to dissatisfaction and, hence, decreased future purchases. Consequently, the management of expectations both pre- and postpurchase is a key component of marketing strategy. In this paper, we focus on the use of advertising to set customer quality expectations.

Of course, advertising does not always accurately convey product quality (Jacoby and Szybillo 1995, Johar 1995, Richards 1990). One might expect the largest gap between advertised and actual quality when quality is difficult to observe (Darby and Karni 1973), such as the health and nutritional benefits of certain foods (Greenberg 1996, Pappalardo 1996). Typical analysis assumes that all companies have an incentive to stretch unverifiable claims within the boundaries of the law (Crawford and Sobel 1982, Farrell and Gibbons 1989). Even advertisements for products whose quality can be both observed and measured tend to exaggerate claims. For example, ski resorts routinely overstate the quality of their skiable terrain (*Wall Street Journal* 1992), just as food producers embellish claims of product freshness. Nestle S.A.'s Contadina Fresh refrigerated pasta sauce and Procter & Gamble Company's Citrus Hill Fresh Choice orange juice both conveyed the quality of "freshness" in their packaging. When the two companies removed the word "Fresh" from these products' labels (*Wall Street Journal* 1991), they in effect admitted that they had overrepresented product quality.

Nagler (1993) suggests that companies will advertise deceptively when customers are boundedly rational, i.e., when full rationality entails a cost to the customers. This, however, does not explain why some companies deliberately underrepresent the quality of their products or services. Although it is more difficult to find examples of this, one example was Boeing, whose "sales force ... tend to understate rather than overstate product benefits" (Kotler and Armstrong 1987). Small firms, such as Ben & Jerry's, gained customers' trust and respect with their modest claims (*Advertising Age* 1994). Similarly, some restaurants exaggerate the amount of time to get a table, delivery companies overstate delivery time, and airlines overstate travel time, thus deliberately understating quality. Toyota's understatement of quality in its introduction of Lexus is another example. The objective of underplaying quality is to lead customers to expect less and then pleasantly surprise them when their expectations are exceeded.

Whether under- or overrepresenting, each of the above companies promoted a level of quality that differed from their products' actual quality. Here we examine the conditions under which a firm should overstate or understate quality. This involves considering the effects of actual and advertised quality on customer expectations and satisfaction, and the ensuing impact on demand and profit. Akin to Bloomfield and Kadiyali (2000) and Kopalle and Assunção (2000), we assume advertised claims of quality (unlike advertised prices) do not need to be completely accurate and do not result in additional out-of-pocket costs (as long as the misstatement is not so large as to incur legal liability).

This paper focuses on three marketing-mix variables: the advertised level of product quality, average actual quality, and the price charged. A firm that exaggerates its quality and has high initial sales faces the problem of lower subsequent sales when customers learn that the product has not lived up to their expectations. Alternatively, a firm could understate its quality (and thus have lower sales initially), but build a base of satisfied customers who would subsequently repeat.

3. A Model of Customer and Firm Behavior

This section develops a model for the impact of advertised quality on profits, relying on results established in the choice modeling, advertising, and satisfaction areas. Our model applies to experience goods (Darby and Karni 1973)—products that must be used in order for their quality to be observed. Typically, for such products, experienced (actual) quality varies across customers and over time due to chance variation in quality (see Wadsworth et al. 1986) as well as customer heterogeneity and environmental characteristics. For example, durability of car tires depends on customer driving habits, driving conditions, etc. (*Consumers' Research* 1991). Similarly, customer service time differs across customers and over time (Kumar et al. 1997). Thus, we conceptualize actual quality, Q, as following a distribution, $f(Q)$ with mean, μ, and variance, σ^2. In other words, the actual quality experienced by a given customer in a given period is a random draw from this distribution.

The focus of this paper is on the firm setting customers' quality expectations, taking into consideration their impact on trial, satisfaction, and subsequent purchase. We allow three forms of customer heterogeneity. First is the heterogeneity in experienced quality, as described above. The second and third, described in the next subsection, are heterogeneity in customer expectations about product quality and heterogeneity in customers' sensitivity to the gap between expected quality and experienced quality.

We consider a two-period model. When customers purchase the product in Period 1, they do so based on the information provided by the firm and on general information sources that suggest the average actual quality of the product. Customers then update their expectations about the product's quality based on their experience with the product and make a decision whether to purchase in the second period (and, by implication, subsequent periods).

There is a philosophical issue here. Either one uses a simple model and is then subject to the legitimate criticism that the model is unrealistic and hence the results not dependable, or one uses a complex model, which is then subject to criticism by those who prefer closed-form solutions. We chose the second approach, but show in the appendix that a simpler model produces similar results.

While our model does not explicitly consider competitive actions, their impact appears implicitly in many of the model parameters (for example, price sensitivity). Our analysis of firm behavior is akin to a monopolistic competition framework (Shleifer 1986, Shleifer and Vishny 1988). This is a reasonable assumption for a follower in a multiple-firm industry (such as car tires) where the other firms have already chosen their respective marketing-mix strategies. As suggested by Shugan (2002), monopolistic characterizations are often useful. The context we consider is that of a firm introducing a product in a market new to the firm. The impact of strategic thinking by other firms that led to choices of their own optimal quality, advertised quality, and price are contained in the parameters of the demand equation. In effect, this could be construed as a game where the firm under consideration is the follower and initial positions are "sticky;" i.e., the established market is set and does not react to the new entrant, which is typical for large existing companies faced with a new and, at least initially, small competitor. These companies have stickiness due to their established procedures (e.g., regarding price and quality) and a tendency to initially ignore small entrants (e.g., Christensen 1997). For a paper that focuses on competition in the context of service delivery time, but does not consider the dynamics of expectation formation or advertised quality or price, see Ho and Zheng (2004).

Customer Behavior

Expectations in Period 1. Information provided by advertisements partially determines expectations (Boulding et al. 1993, Kopalle and Lehmann 1995, Oliver and Winer 1987, van Raaij 1991). We assume information about the firm's average actual quality is also available through websites, testing firms, firm reputation, etc. Thus, following Boulding et al. (1993. 1999), customer i's "will" expectation about the quality of a product at the beginning of Period 1 ($\widehat{Q}_{i1}$), which is operationalized as "how long customers expect a product to last," is:[1]

$$\widehat{Q}_{i1} = \alpha_{i1} I + (1 - \alpha_{i1})\mu, \tag{1}$$

where I is the information provided by the firm about the quality of the product, i.e., the advertised level of quality; μ is the average actual product quality, and $0 \le \alpha_{i1} < 1$ determines the portion of the expectation due to advertising. Note that advertised quality (I), average actual quality (μ), and price (P) are firm-level decision variables, and therefore are not heterogeneous across customers. We capture customer heterogeneity in quality expectations in Period 1 via the weight customers place on advertised quality in forming their expectations; i.e., α_{i1} for individual i is a draw from a distribution $g(\alpha_1)$ (independent of f) with mean, $\bar{\alpha}_1$, and variance, σ_1^2.

[1] While "will" expectation is the typical standard in the satisfaction literature (Boulding et al. 1993), in alternative specifications, we allowed for (i) "as-if" expectations (Kopalle and Lehmann 2001) to evaluate satisfaction and (ii) a more general expectation standard that involves customers' maximizing their satisfaction. In both cases, we obtained results similar to those in this paper. To conserve space, we report the simpler and widely accepted "will expectation" formulation in this paper.

Demand in Period 1. We use a binary logit specification for the purchase probability of individual i in Period 1, where the purchase probability is a function of customer expectations (Krishna 1992), i.e., expected quality ($\widehat{Q}_{i1}$) and price, P. Thus, the utility of individual i is:

$$U_{i1} = V_{i1} + e_{i1}, \tag{2}$$

where V_{i1} is the deterministic component of individual i's utility in Period 1; i.e.,

$$V_{i1} = b_0 + b_1 \widehat{Q}_{i1} + b_2 P. \tag{3}$$

In Equation (3), b_0 is the intrinsic utility in purchase (intercept), and $b_1 > 0$ and $b_2 < 0$ are the quality and price coefficients, respectively. The deterministic component of utility varies across customers due to heterogeneity in customer expectations. Following Ben-Akiva and Lerman (1985), the probability of purchase for individual i in Period 1, D_{i1}, is,

$$D_{i1} = \frac{e^{V_{i1}}}{1 + e^{V_{i1}}}. \tag{4}$$

The average demand in Period 1, $\bar{D}_1$, is the average purchase probability across all customers; i.e.,

$$\bar{D}_1 = \int_{\alpha_i} D_{i1}(\alpha_{i1}) g(\alpha_1)\, d\alpha_1. \tag{5}$$

Satisfaction. Disconfirmation (i.e., performance minus expectations) significantly affects satisfaction (Boulding et al. 1993, Oliver 1997, Bolton and Drew 1991, Spreng et al. 1996). Although there has been some debate about its exact impact on service quality (Cronin and Taylor 1992, Parasuraman et al. 1994, Teas 1993), it clearly has a significant effect on satisfaction (Bolton and Drew 1991, Bolton and Lemon 1999, Spreng et al. 1996). According to the disconfirmation or gap model, satisfaction at time t is a function of the difference between realized product quality at time t, and prior expectations about the product's quality at $t-1$.

Kopalle and Lehmann (2001) focus on how customers set their expectations and on disconfirmation sensitivity as an individual trait. Disconfirmation-sensitive customers are defined as those who are more satisfied (or dissatisfied) when products perform better (worse) than expected. They show that for customers whose self-rated disconfirmation sensitivity was higher, the impact of disconfirmation on satisfaction was in fact greater. Therefore, we incorporate an interaction effect of disconfirmation sensitivity and performance minus expectations on satisfaction in the demand function for the product under consideration. We also allow disconfirmation sensitivity (DS) to vary across individuals, i.e., disconfirmation sensitivity of individual i, DS_i, is a draw from a distribution h (independent of f and g) with mean, $\overline{\mathrm{DS}}$, and variance, ρ^2.

Following Boulding et al. (1993), Boulding et al. (1999), Bolton and Drew (1991), Bolton and Lemon (1999), Oliver (1997), Spreng et al. (1996), and Yi (1990), we include the direct effect of actual quality on customer satisfaction. Further, we allow for a nonlinear (diminishing returns) impact of the gap between actual quality and expectations on satisfaction (Anderson and Sullivan 1993, Kopalle and Lehmann 2001, Mittal et al. 1998). Finally, as discussed earlier, realized (experienced) quality in Period 1, Q_1, varies across customers. The realized satisfaction of customer i at the end of Period 1 (S_{i1}) is given by:

$$\begin{aligned} S_{i1} = d_0 &+ [d_1 + d_2 \mathrm{DS}_i](Q_{i1} - \widehat{Q}_{i1}) \\ &+ d_3 Q_{i1} + d_4 (Q_{i1} - \widehat{Q}_{i1})^2, \quad \text{where} \end{aligned} \tag{6}$$

Q_{i1} = realized (or experienced) quality for customer i in Period $1 \sim f(\mu, \sigma^2)$

$\widehat{Q}_{i1}$ = expected quality of customer i in Period 1 (Equation (1))

DS_i = disconfirmation sensitivity of customer $i \sim h(\overline{\mathrm{DS}}, \rho^2)$.

The parameters, $d_1, d_2 > 0$ and $d_4 < 0$, capture the nonlinear effect of disconfirmation on satisfaction, while $d_3 > 0$ is the direct effect of realized quality on satisfaction, and d_0 represents the base level of satisfaction with the firm's product regardless of quality.

Expectations in Period 2. Customers update expectations based on past expectations and the actual quality realized in Period 1 (Boulding et al. 1999, Johnson et al. 1995, Rust et al. 1999). Accordingly, if customer i bought the product in Period 1, expectations of that customer in Period 2 are given by:

$$\widehat{Q}_{i2} = \alpha_2 \widehat{Q}_{i1} + (1 - \alpha_2) Q_{i1}, \tag{7}$$

where $0 \le \alpha_2 < 1$ determines the weight given to prior expectations in the updating process. Because expectations in Period 1, as well as experienced quality in Period 1, vary across customers, the expected quality in Period 2 also varies across customers. To keep the model tractable, we assume α_2 is constant across customers. If a customer i does not buy the product in Period 1, we assume expectations are unchanged; i.e., $\widehat{Q}_{i2} = \widehat{Q}_{i1}$.

Demand in Period 2. In Period 2, the utility of customer i is given by $U_{i2} = V_{i2} + e_{i2}$. If the customer bought the product in Period 1, the deterministic component of utility for customer i, V_{i2}, consists of two components. Similar to V_{i1} in Period 1, the first component is due to price and expected quality, which we term the "normal effect." The second component is the satisfaction component; i.e., the utility in Period 2 increases with the amount of satisfaction derived in Period 1 (Shiv and Huber 2000), consistent with Mittal and Kamakura (2001), who find a significant link between satisfaction and repurchase intent, and between repurchase intent and repurchase behavior. Hence, the satisfaction given by Equation (6) impacts the probability of purchase in Period 2. If customer i buys the product in Period 1, $D_{i2|\text{buy}}$, the purchase probability in Period 2 conditional on Period 1's purchase is given by the following binary logit model,

$$D_{i2|\text{buy}} = \frac{e^{\overbrace{b_0+b_1\hat{Q}_{i2}+b_2P}^{\text{normal effect}} + \overbrace{b_3S_{i1}}^{\text{sat. effect}}}}{1+e^{b_0+b_1\hat{Q}_{i2}+b_2P+b_3S_{i1}}}, \tag{8}$$

where satisfaction in Period 1, S_{i1}, is given by Equation (6), and b_3 captures the impact of satisfaction on purchase.

If customer i does not buy the product in Period 1, the deterministic component of the utility remains unchanged from Period 1; i.e., $V_{i2|\text{no buy}} = V_{i1}$ (Equation (3)). However, the error component in Period 2, e_{i2}, would be different from e_{i1}. Hence, it is possible that an individual who has not bought the product in Period 1 may have a different level of utility in Period 2.[2]

In Period 1, the ex ante probability of purchase in Period 2 for a customer i is:

$$D_{i2} = D_{i1}D_{i2|\text{buy}} + (1-D_{i1})D_{i2|\text{no buy}}, \tag{9a}$$

where D_{i1} is the purchase probability in Period 1 ($=D_{i2|\text{no buy}}$). Substituting Equations (4) and (8) for D_{i2} in Equation (9a) and simplifying, we get

$$D_{i2} = \frac{e^{b_0+b_1\hat{Q}_{i1}+b_2P}}{1+e^{b_0+b_1\hat{Q}_{i1}+b_2P}}\left[\frac{e^{b_0+b_1\hat{Q}_{i2}+b_2P+b_3S_{i1}}}{1+e^{b_0+b_1\hat{Q}_{i2}+b_2P+b_3S_{i1}}} + \frac{1}{1+e^{b_0+b_1\hat{Q}_{i1}+b_2P}}\right], \tag{9b}$$

where S_{i1} is given by Equation (6).

D_{i2} (Equation (9b)) lies between 0 and 1. Because realized quality, Q_1, is a random variable, we integrate over its distribution to arrive at the expected purchase probability in Period 2 for customer i, $E[D_{i2}]$; i.e., $E[D_{i2}]$ is derived by integrating Equation (9b) over Q_1. That is,

$$E[D_{i2}] = \int_{Q_1} [D_{i2}]f(Q_1)\,dQ_1. \tag{10}$$

The average purchase probability across all customers in Period 2, $\bar{D}_2$, is given by integrating $E[D_{i2}]$ over α_1 and DS, i.e.,

$$\bar{D}_2 = \int_{\text{DS}}\int_{\alpha_1} E[D_{i2}]g(\alpha_1)h(\text{DS})\,d\alpha_1\,d\text{DS}. \tag{11}$$

Thus, in our model we incorporate customer-level heterogeneity in $\bar{D}_2$ in several ways. First, we allow quality expectations in Period 1 to vary across customers through the weight each customer places on the information provided by the firm via a distribution g. Second, we allow the experienced quality of the product in Period 1, Q_1, to vary across customers according to a probability distribution f. Note that each of the above two mechanisms cause quality expectations to vary across customers in Period 2, as does the error component of the utility function. We also allow disconfirmation sensitivity, DS, to be customer specific and distributed h (independent of f and g).

Firm Behavior

Consider a firm entering a market new to the company, whose objective is to maximize net discounted profit by setting advertised quality (I), average actual quality (μ), and price (P). We develop a two-period model that incorporates the trade-off between the benefits of immediate sales (from trials), which suggest setting the advertised quality, I, to maximize initial expectations; and future sales (from trials and repeat purchases), which are greater among first-period purchasers who have lower initial expectations.

By allowing the impact of second-period sales to be greater through the use of a multiple (m), the model captures the relatively greater importance of subsequent-period sales. For example, because initial sales are often at a trial level, subsequent per-period purchases are often greater in magnitude than initial ones. The multiplier m represents the discounted value of future earnings from a customer due to repeat purchases from Period 2 forward as a multiplier of that period's revenue (Gupta and Lehmann 2003, Gupta et al. 2004).[3] Thus, the objective function for the firm is

$$\max_{I,\mu,P}[\pi - F] = \max_{I,\mu,P}[(P-v)Ny(\bar{D}_1 + m\bar{D}_2) - F(\mu)], \tag{12}$$

where the purchase probabilities in Periods 1 and 2, $\bar{D}_1$ and $\bar{D}_2$, are given by Equations (5) and (11), respectively, and

π = total profit
v = unit variable cost
F = fixed cost
y = average purchase quantity per customer
N = number of customers.

[2] Because purchase is probabilistic, actual behavior can change even if the purchase probability does not.

[3] Notice that if the average demand stabilizes in Periods 2 through k (and then drops to zero), the average revenue per customer from Periods 2 through k becomes

$$\sum_{t=2}^{k}\left(\frac{1}{1+r}\right)^t (P-v)\bar{D}_2 = \frac{1}{r(1+r)}\left[1-\left(\frac{1}{1+r}\right)^{k-1}\right](P-v)\bar{D}_2,$$

where v is variable cost and r is the discount rate. Therefore, m would be

$$\frac{1}{r(1+r)}\left[1-\left(\frac{1}{1+r}\right)^{k-1}\right].$$

Clearly, the size of market, customer expansion, and defection rate can all change and impact aggregate demand. The formula in this footnote assumes that the net effect of these factors is zero. To the extent that the multiplier varies substantially due to these factors, a more complex formula would apply.

Based on Kopalle and Winer (1996), Lehmann-Grube (1997), and Rosenkranz (1997), we assume that changes in quality impact fixed cost, F, as in cases where investments in new machinery or facilities or R&D are required for quality improvements. The tire industry is a good example of where R&D investments are necessary for quality enhancements (for example, see Quelch and Isaacson 1994). We consider a convex relationship between fixed cost, F, and the average actual quality:

$$F(\mu) = k\mu^2. \tag{13}$$

For $k > 0$, Equation (13) has increasing marginal cost of quality, similar to the functional form used by Schmalensee (1978), and fulfills the criteria for a cost function in Rogerson (1988). We also allowed for variable cost to depend linearly on quality; i.e., $v = a + b\mu$. The nature of our results remains unchanged, so we present only results based on Equations (12) and (13).

To determine optimal advertised quality, average quality, and price, in principle we could substitute Equations (1), (5), (7), (11), and (13) into the profit Equation (12), and simultaneously solve the first-order conditions with respect to advertised quality (I), average quality (μ), and price (P). Given the complexity of the general model, there is no closed-form solution for optimal advertised quality, average actual quality, and price. Therefore, in the next section we describe an empirical application of our model and develop the results. Appendix 1 shows analytical results from a special case that uses linear probability of choice and satisfaction specifications, no customer heterogeneity, and where actual quality and price are given.

4. An Application and Results

Instead of choosing arbitrary parameter values to arrive at model results, we estimated a base set of parameters using data from Kopalle and Lehmann (2001) that focus on tire purchasing. Although the study participants were told that the brand, CAMAC, had been in the tire business for over 50 years, almost all (99%) the study participants indicated that they had not heard of that brand before participating in the study. This means that the product was new to respondents.[4] Based on the estimated parameters, we determined the optimal solution numerically for some base cases. We then conduct simulations, i.e., comparative statics, that vary model parameters to arrive at our results. We also varied the various model parameters (+/−50%) to test the robustness of our results.

We used two additional sets of base case parameters based on Kopalle and Lehmann (2001): One follows their Table 1 and another incorporates the concept of "as if" expectations. In both analyses, we again varied the parameter values +/−50% and developed the results. Because in all analyses the model results continued to hold, we focus on the case where we use Kopalle and Lehmann's (2001) Study 2 to estimate a base set of parameters.

Data and Measures. The data consist of customer expectations (in miles), satisfaction (1–7 scale), and repurchase intention (1–7 scale) measures about car tires from 200 mall intercept respondents, along with their disconfirmation sensitivities (1–7 scale). Car tires are a relatively high-involvement durable good for customers in a mall intercept study, and tread life is a good measure of product quality (*Consumers' Research* 1991). In the study, subjects were told they were driving, and encountered a road hazard which made it necessary to get new tires. At the service station they found that the only brand of tires in their size was a brand they had not heard of, which the store recommended (see Kopalle and Lehmann 2001 for details). Actual quality was manipulated between respondents at five levels (20,000; 30,000; 40,000; 50,000; and 60,000 miles). Both prior and updated (after observing the quality of the product, which was revealed in the experimental setting) expectations were measured in miles.

Estimation. Equation (7) may be rewritten as:

$$\widehat{Q}_{i2} - \widehat{Q}_{i1} = (1 - \alpha_2)(Q_{i1} - \widehat{Q}_{i1}). \tag{14}$$

The impact of the difference between experienced quality and prior expectations on change in expectations was:

$$\text{Change in expectations} = 0.70(Q_{i1} - \widehat{Q}_{i1}); \quad R^2 = 0.67.$$

Thus, $\alpha_2 = 0.30$, which means respondents update their expectations fairly quickly.

Satisfaction in Period 1 (Equation (6)) is determined by actual quality in Period 1, disconfirmation, disconfirmation squared, and disconfirmation sensitivity (Table 1). Disconfirmation sensitivity, as expected, has no significant direct effect on satisfaction, and therefore we drop it from the satisfaction equation in the reduced model.[5] Disconfirmation sensitivity does have a significant impact on satisfaction through an interaction with disconfirmation. The quadratic disconfirmation term is negative and significant, suggesting a diminishing-returns effect of disconfirmation on satisfaction. Comparing the reduced

[4] Kopalle and Lehmann's (2001) paper indicated that CAMAC had been in business in the United States (actually, CAMAC had been in the tire business in Europe, but had not been introduced in the United States). Therefore, there is a question as to whether respondents treated CAMAC as a new entrant in the United States.

[5] The disconfirmation sensitivity variable is mean centered to reduce collinearity between the gap, $Q_{i1} - \widehat{Q}_{i1}$, and the interaction $(\mathrm{DS})(Q_{i1} - \widehat{Q}_{i1})$.

Table 1 Regression Results

Independent variables	Full model: Unstandardized estimates	Full model: Standardized estimates	Reduced model: Unstandardized estimates	Reduced model: Standardized estimates
Intercept	3.34 (9.9)	—	3.40 (9.34)	—
Actual quality, Q_{i1}	0.35 (4.04)	0.26 (4.04)	0.34 (3.93)	0.25 (3.93)
Disconfirmation sensitivity, $(\mathrm{DS}_i - \overline{\mathrm{DS}})$	0.13 (1.13)	0.05 (1.13)	—	—
Gap, $(Q_{i1} - \widehat{Q}_{i1})$	0.95 (9.37)	0.61 (9.44)	0.90 (9.54)	0.62 (9.88)
Gap-squared, $(Q_{i1} - \widehat{Q}_{i1})^2$	−0.14 (−3.39)	−0.18 (−4.88)	−0.15 (−3.46)	−0.17 (−3.46)
Interaction, $(\mathrm{DS}_i - \overline{\mathrm{DS}})(Q_{i1} - \widehat{Q}_{i1})$	0.27 (3.71)	0.17 (3.71)	0.24 (3.55)	0.15 (3.55)
R^2	0.74		0.74	
Sample size	196			

Notes. t-values in parentheses. Dependent variable: Satisfaction.
$\widehat{Q}_1$ = will expectations in Period 1.
$\overline{\mathrm{DS}}$ = mean disconfirmation sensitivity = 5.5 (of a possible 7.0).

model results in Table 1 with Equation (6), we get $d_0 = 3.40$, $d_3 = 0.34$, $d_4 = -0.15$, $d_1 + d_2\mathrm{DS} = 0.90 + 0.24(\mathrm{DS} - \overline{\mathrm{DS}})$; substituting $\overline{\mathrm{DS}} = 5.5$, we get $d_1 = -0.42$ and $d_2 = 0.24$.

Finally, we examine the impact of satisfaction on purchase behavior in Period 2. Because the data consist of stated purchase intentions in Period 2, which tend to overpredict actual buying behavior, we first converted the stated purchase intentions (on a 7-point scale) to estimate purchase probabilities $D_{i2|\mathrm{buy}}$,[6] using the table presented in Lehmann et al. (1998, p. 253) based on Haley and Case (1979). Following Pindyck and Rubinfeld (1998, p. 309), Equation (8) may be rewritten as,

$$\log\left[\frac{D_{i2|\mathrm{buy}}}{1 - D_{i2|\mathrm{buy}}}\right] = b_0 + b_1\widehat{Q}_{i2} + b_2P + b_3S_{i1}. \qquad (15)$$

Thus, we regressed $\log[D_{i2|\mathrm{buy}}/(1 - D_{i2|\mathrm{buy}})]$ on updated expectations and satisfaction. The results (Table 2) suggest that while both updated expectations and satisfaction determine purchase probability, the impact of satisfaction is much stronger (standardized coefficient of 0.8 versus 0.12). In other words, the subjective reaction to past purchase dominates the impact of updated expectations.

Optimal Advertised Quality, Average Actual Quality, and Price

We use the estimated parameters to determine optimal advertised and actual quality and price in an analysis of a base-case scenario and then develop comparative statics. In the numerical analysis, we set $b_0 = 1$ and $b_2 = -1$ because we could not uniquely estimate these parameters based on the available data; using these parameter values, the implied price elasticity is around −1.70 in the first period and −1.63 in the second, within the range reported in Tellis (1988) and close to the average price elasticity of about −1.76 (Tellis 1988). Importantly, varying b_0 and b_2 did not change the qualitative nature of our results; i.e., the model results still hold.

We consider two distributions for $f(Q_1)$, $g(\alpha_1)$, and $h(\mathrm{DS})$. One is uniform with respective means μ (a decision variable), $\bar{\alpha}_1 = 0.5$, and $\overline{\mathrm{DS}} = 5.5$. We vary both $\bar{\alpha}_1$ and $\overline{\mathrm{DS}}$ to examine the impact of these parameters on the optimal solution. In Kopalle and Lehmann (2001), the range for actual quality, Q_{i1}, was 20,000 to 60,000, and disconfirmation sensitivity ranged from 4 to 7 on a 7-point scale. We used the same ranges in this paper. Because we varied $\bar{\alpha}_1$ (which lies between 0 and 1) from 0.2 to 0.8, the range was set at +/−0.2 around $\bar{\alpha}_1$ to keep all values between 0 and 1. The second distribution used for f, g, and h was the normal with the same mean values as in the uniform case. Because actual quality, Q_{i1}, ranged from 20,000 to 60,000, σ for an equivalent normal distribution is approximately given by $40{,}000/6$. Because α_{i1} spans 0 to 1, the corresponding

Table 2 Logistic Regression

Independent variables	Unstandardized coefficients (t-value)	Standardized coefficients (t-value)
Intercept	−5.86 (−36.0)	—
Updated expectations, $\widehat{Q}_{i2}$	0.10 (2.1)	0.12 (2.1)
Satisfaction, S_{i1}	0.66 (25.5)	0.80 (25.5)
R^2	0.81	
Sample size	196	

Notes. S_{i1} = realized satisfaction in Period 1. Also, t-values are in parentheses. Dependent variable: $\log[D_{2|\mathrm{buy}}/(1 - D_{2|\mathrm{buy}})]$.

[6] In the study, all respondents bought the product in Period 1. Ideally, we would have data both on respondents who bought in the first period and those who did not (Anderson and Simester 2004). Therefore, the data do not test the impact of quality claims on actual choice in the first period and repeat in the second. This is an area for future research.

approximate standard deviation for the normal distribution is 1/6. Similarly, the standard deviation for the disconfirmation sensitivity distribution was set at 3/6. Without loss of generality, we consider a single customer segment buying four tires ($y = 4$), with a multiplier effect of $m = 3$. Our choice of the multiplier effect is consistent with Gupta and Lehmann's (2003) analysis, which suggests the customer lifetime value is often about four times the current (initial) period value.

While we report the results of the uniform distribution in this paper, we obtain very similar results with the normal distribution. Our results were also robust to variations in the two cost parameters, v and k, which were varied around the base case values of 1.0 and 0.1. Using the parameter values described above, the optimal levels of average actual quality, advertised quality, and price were 3.75 units, 4.5 units, and 2.5 units, respectively. In other words, for the base case, the corresponding optimal average actual and advertised quality are 37,500 miles and 45,000 miles, respectively, implying about 20% overstatement of quality.

Table 3 describes the effect of the multiplier, m, and advertised quality, I, on purchase probabilities in Periods 1 and 2 and the total profit in both periods (average quality and price were set at their respective optimal levels).

Initial sales increase as advertised quality increases. Further, when the second-period sales "count" the same as first-period sales, profits are greater when advertised quality exceeds average actual quality. However, when future period sales are more important ($m = 3$), profit begins to decrease when advertised quality exceeds its optimal level.

Model Results

We examined how optimal levels of the variables of interest change when the parameters of the model, especially those related to customer characteristics, change. One interesting variable is the "quality claim differential," the difference between advertised and average actual quality; a positive (negative) level indicates overstatement (understatement). In order to develop general results, we varied the following five model parameters: average disconfirmation sensitivity ($\overline{\text{DS}}$) from 1 to 7 in steps of 1, the weight customers place on advertised quality (α_1) from 0.2 to 0.8 in steps of 0.1, the value of future purchases (m) from 1 to 7 in steps of 1, the base level of customer satisfaction with the firm (d_0) from 1 to 7 in steps of 1, and the weight customers place on prior expectations in updating their expectations (α_2) from 0.1 to 0.9 in steps of 0.1.

Table 3 **Impact of Advertised Quality on Demand and Profit**

Adv. quality, I	Average purchase probability, Period 1, $\bar{D}_1$	Average purchase probability, Period 2, $\bar{D}_2$	Total profit $m = 1$	Total profit $m = 3$
2 (20,000)	0.253	0.415	2.61	7.60
3	0.264	0.421	2.70	7.76
4	0.273	0.423	2.77	7.85
5	0.283	0.419	2.81	7.84
6	0.294	0.411	2.82	7.76

The following results 1–3, while not fully predictable ex ante, are intuitive. To some extent they play the role of manipulation checks in experimental research.

Result 1. As disconfirmation sensitivity, $\overline{\text{DS}}$, increases, optimal quality claim differential decreases.

As disconfirmation sensitivity increases, customers will be more satisfied for a given level of realized and expected quality. Firms can enhance satisfaction, and therefore increase sales in Period 2, by lowering advertised quality and thereby lowering expectations. Hence, the optimal quality claim differential decreases as disconfirmation sensitivity increases, exactly as expected. From a managerial practice standpoint, the challenge for firms is in determining how disconfirmation sensitive the customer base is. One way of gauging such a construct is to conduct a survey of current and potential customers and use the disconfirmation sensitivity measure developed by Kopalle and Lehmann (2001).

Result 2. When potential future sales (i.e., the multiplier m) from a customer increases, optimal quality claim differential decreases.

As the relative value of future income from a customer increases, it becomes more important for the firm to increase the likelihood that a customer will buy its product in Period 2. One way to increase this likelihood is to increase satisfaction in Period 1 by lowering the level of advertised quality. Thus, unsurprisingly, it is optimal for the firm to understate quality when future potential is high, because the benefits of future sales resulting from satisfied customers outweigh the advantage of higher initial sales. This is in contrast to the implication some might draw from the customer relationship management literature, which suggests that for valuable, long-run customers—i.e., customers with a large m—a firm would put extra effort into acquiring them, which might include overpromising.

Result 3. As the weight customers place on prior expectations (α_2) increases, the optimal quality claim differential increases.

If customers are slow to update expectations, there is incentive to create higher (false) initial expectations. The negative effect of disconfirmed expectations on Period 2's purchase probability is offset by the positive effect of the still-high expectations on the corresponding purchase probability. If quality is less readily observable—for example, products that have relatively more credence attributes (Darby and Karni 1973)—customers may place more emphasis on prior expectations. On the other hand, for an experience good, customers are likely to update expectations significantly, and hence it is less useful to overstate quality (assuming the product is bought multiple times). Thus, overstatement may vary by product type.

The next two results were not expected a priori and are less intuitive.

Result 4. As the weight customers place on advertised quality (α_I) increases, the optimal quality claim differential decreases.

At the outset, one might expect that the more effective advertising is, the more the firm should overstate quality. Following Equation (1), as customers place more weight on the advertised information provided by the firm (as is the case with firms that are well known), customer expectations increase with advertised quality. However, ceteris paribus, higher expectations lead to lower satisfaction in Period 1, thus lowering future revenue. It is in its best interest for a firm to enhance Period 2's purchase probability without unduly sacrificing Period 1's likelihood of purchase (because Period 2's probability is conditioned on purchase in Period 1). Thus, when customers do not discount what firms say about the quality of their products and use it in evaluating the products for purchase decisions, firms have less incentive to overstate quality. For example, the advertising of well-known firms, at least those with positive brand equity, tends to be more effective. That is, customers place more weight on the ads and discount the claims of a brand with a strong reputation and high credibility (which tend to be well known) less (Goldberg and Hartwick 1990). Result 4 suggests that in such instances there is less need to "hype" quality. Hence, such firms are able to manage customer expectations in such a way that future purchase probability is enhanced without overly sacrificing sales in the first period. By contrast, because customers are more likely to place less emphasis on advertised quality in the case of unknown firms, such firms, in an effort to increase customer expectations (and therefore sales in Period 1), would be more likely to advertise higher quality and thus increase the overstatement of quality. Of course, a well-known brand has more at risk in terms of possible damage to its other products as well, providing another (not modeled) reason not to overstate quality.

Result 5. As the base level of satisfaction with a firm's product (d_0) increases, the optimal quality claim differential increases.

One might expect that as customer satisfaction increases, managers would not overstate quality and hence jeopardize satisfaction levels. However, when customers' base level of satisfaction is higher, they are more satisfied with a firm's product regardless of quality; this, in turn, decreases the relative impact of disconfirmation sensitivity on satisfaction in Period 1 and consequently on Period 2's purchase probability. Hence, the firm is more concerned with increasing sales in Period 1, which can be achieved by increasing optimal advertised quality, which leads to increasing the quality claim differential. In other words, if customers are going to be satisfied with a firm's product regardless of quality, such firms have an incentive to overstate quality.

Additional Analysis

In many situations, a marketing manager does not control quality. Thus, we investigated the special case where average quality is predetermined. In this situation, as the average quality level increases, the percent gap between advertised and average quality decreases. This suggests that firms with higher quality can obtain optimal initial expectations by relying more on the market's information (as driven by $1-\alpha_{i1}$) rather than overstatement (which has negative consequences in Period 2). In other words, there is a "virtuous" reward to high technical quality. For example, high-quality firms such as Vanguard, GE, and Marriott tend not to overstate their quality. Combining this result with Result 5 suggests that firms need to balance the effect of high quality (which decreases the percent claim differential) with that of a high base level of satisfaction (which increases the quality claim differential).

5. Empirical Support

In this section, we examine whether some of the model implications are consistent with observed behavior. We do so via two methods. One is using data from the Federal Trade Commission (FTC) on deceptive advertising practices. The second is a study with MBA students (i.e., soon to be managers) from a top business school.

FTC Study

Results 4 and 5 predict the types of companies that would be most likely to overstate quality. To get a sense of whether these results reflect reality, we collected data on deceptive-advertising cases dealt with by the Federal Trade Commission in the United States from mid-1996 to December 2002. Cases since August 1996 are archived at www.ftc.gov. There were a total of 745 deceptive-advertising cases (in 149 categories, per the North American Industry Classification System (NAICS), http://www.census.gov/epcd/www/naics.html—NAICS replaced the Standard Industrial

Classification (SIC) system a few years ago), of which 627 either were found guilty as charged by the FTC or agreed to a settlement, and 117 were still under trial; there was only one case that did not settle and was found not guilty.[7] Note that neither the data nor the model include legal costs. Further, because these data do not closely match the model and are nonspecific in many cases about how new the products involved were, this analysis should be viewed as potentially interesting and indicative, but far from a strong test. Still, unless "real world" results are generally consistent, there would be serious concerns about the model's validity.

The FTC classifies the severity of deceptive advertising into four categories: (1) *Misrepresentation*, for example, a company could promise customers awards if they purchased their product, but then provide awards worth significantly less than represented; (2) *unsubstantiated claim*, for example, advertising a dietary supplement as a cellulite treatment without substantiating the claim; (3) *false claim*, where a company claims it has evidence establishing their product's efficacy but no such evidence exists; and (4) *scam*, which is fraudulent activity that is intentionally devised to cheat customers. Thirty-six percent of the cases were misrepresentations, while 12%, 13%, and 39% fell in the other three categories, respectively. To get an index of deception, we coded misrepresentation as the mildest form of deceptive advertising, followed by unsubstantiated claims, false claims, and scam, the most severe form of deceptive advertising.[8]

In order to assess the reputation of the companies in each of the above 627 cases, we searched five databases that provide company-level information: Global Business Browser, Lexis-Nexis, Dun & Bradstreet Million Dollar Database, Responsive Database Services, and Thomson Research. Although these databases cover over half a million companies, only 25% of the 627 FTC cases were included in the databases. No company information was available for the rest of the cases. Therefore, we created a dummy variable where 1 indicates the company was known, i.e., mentioned in one of the five databases. If the company was not mentioned in the databases, it was coded as unknown (0). Second, of the "known" companies, for 41 of the cases, we were able to obtain company satisfaction relative to industry satisfaction using the American Consumer Satisfaction Index made available at the website, www.theacsi.org/industry_scores.htm, by the National Quality Research Center at the University of Michigan Business School. The satisfaction measures we used were for the year preceding the FTC case.

Result 4 suggests that when customers rely on advertised quality, which we assume is the case for better-known firms, a firm has less incentive to indulge in overstatement of quality. This appears to be the case: 468 of the 627 cases were against unknown firms, far greater than their percent of gross domestic product and products sold.[9] Moreover, the severity of the FTC charge (which reflects to some degree the extent of overstatement of quality) was negatively correlated with whether the firm was known or not ($r = -0.36$, $p < 0.0001$, with means of 1.74 and 2.84, respectively, for known and unknown firms). Note that this result does not depend on the total number of known or unknown firms. It is also interesting that the most severe form of exaggeration, scam, only occurred for unknown firms.

As suggested by Result 5, when customers are generally more satisfied with a firm—i.e., as customers' base level of satisfaction with a firm increases—the firm has more incentive to overstate quality. Among the known companies in the FTC cases, as expected, the company's base level of satisfaction (measured as company satisfaction relative to industry satisfaction) was positively correlated with overstating quality ($r = 0.44$, $p < 0.005$).[10] Thus, the pattern of actual firm behavior provides some support for the two model implications.

MBA Study

A potentially interesting question is whether managers behave in accordance with the normative model

[7] The high percentage of cases found guilty or settled is not surprising because it turns out that the FTC only deals with those cases that are brought to their attention many times (e.g., number of complaints in the range of 50–100).

[8] We tested the sensitivity of our results to the coding scheme by using another plausible alternative order: unsubstantiated claim, misrepresentation, false claim, and scam, and obtained similar results.

[9] We used ReferenceUSA, an Internet-based reference service (website: http://referenceusa.com), to obtain the total number of firms in the United States in each of the NAICS categories in our data. Note that one of the databases (Global Business Browser) we used to classify the companies as "known" or "unknown" includes companies with five employees or more in its data. ReferenceUSA also provides the number of firms in the United States by number of employees; we used companies with five employees or more as a proxy for whether a firm was "known." The total number of firms was 5.62 million, of which 2.3 million are known. Hence, in the data, 59% (3.32M/5.62M) are unknown firms and they account for a significantly greater ($p < 0.01$) proportion ($71\% = 468/627$) of the FTC cases. Put differently, the probability that an unknown firm would indulge in deceptive advertising is 0.00014 (468/3.32M), higher than 0.000069 (159/2.3M), the corresponding probability for a known firm.

[10] Firm satisfaction is confounded with industry factors such as frequency of purchase, which could also impact overstatement. To determine customers' base level of satisfaction, we use the difference between firm and industry satisfaction levels to control for such industry effects.

Table 4 MBA Study Design

Scenario	Brand	Objective	Rely on	Expectations change	Satisfaction	Average mileage claim
1	Not well known	First year	Ads	Marginally	Satisfied	48,860
2	Not well known	First year	Ads	Substantially	Not satisfied	44,965
3	Not well known	Long-run	Ratings	Marginally	Not satisfied	40,575
4	Not well known	Long-run	Ratings	Substantially	Satisfied	38,669
5	Well known	First year	Ratings	Marginally	Not satisfied	44,568
6	Well known	First year	Ratings	Substantially	Satisfied	42,622
7	Well known	Long-run	Ads	Marginally	Satisfied	43,733
8	Well known	Long-run	Ads	Substantially	Not satisfied	37,278
			Overall average			42,656

implications. To address this, we conducted a survey of MBA students. These future managers had all completed the core marketing course. In addition, they had, on average, four years of work experience, including 1.7 years of work in sales and marketing, and were about 28 years old. Thus, the subjects should be a reasonable proxy for working managers. They were contacted via e-mail and were entered in a lottery with one \$500 and five \$100 prizes as an incentive to participate.

The study introduction described the task as deciding on the level of mileage to advertise for their company's new line of tires. They were told their testing showed the tires would last between 28,000 and 52,000 miles, depending on driving patterns and road conditions. Subjects were told that satisfaction and repeat purchase depend significantly on the difference between expected and realized tire life. The 235 MBAs who were e-mailed the survey were then given eight scenarios representing an orthogonal design of five binary factors (see Table 4 and Appendix 2): (1) Brand: well-known versus not well known, (2) Primary Objective: maximize first-year sales versus maximize long-run sales, (3) What Customers Primarily Rely on in Forming Expectations: company advertising versus independent quality ratings such as *Consumer Reports*, (4) Customer Expectations Updating: marginal versus substantial, and (5) Overall Customer Satisfaction with Tires: satisfied versus not satisfied.

The order of scenarios was rotated across subjects in a Latin square design. Notice that the first variable (Brand) and the last (Customer Satisfaction Level) are the same used in the FTC data analysis to test Results 4 and 5, respectively, and that the objective and updating variables related to other model predictions (Results 2 and 3, respectively). The third factor (reliance on company ads versus independent quality ratings) represents an alternative way to test Result 4. Because disconfirmation sensitivity is a relatively abstract concept, we chose not to test its impact on advertising claims (Result 1) to keep the study as simple as possible.

In all, 111 students completed the study, a response rate of 47.2%. The average mileage claim for the eight scenarios used is shown in Table 4. From this, a few observations are warranted. First, the general tendency was to advertise slightly above the midpoint of the actual mileage range, i.e., to "overstate" because 42,656 is significantly above 40,000 (by 6.6%). Second, as expected, respondents overstated quality the most (48,860) in Scenario 1, where the brand was not well known, the objective was short run, and customers rely on ads, change expectations slowly, and are generally satisfied. By contrast, they actually understated quality (37,278 versus 40,000) for Scenario 8: a well-known brand with a long-run objective facing customers who rely on ads, change expectations substantially, and are generally not satisfied. Encouragingly, clearly false claims were rarely utilized—only 1% of the observations were outside the 28,000 to 52,000 range, and the averages all fall within the tested range of 28,000 to 52,000.

To more formally test the model results, we ran a regression where the quality claim differential (mileage claim minus 40,000, the average actual quality) was the dependent variable. The independent variables were the five study variables. Because we have multiple (eight) observations from each respondent, we take into consideration individual specific effects using the following random-effects regression model (Raudenbush and Bryk 2002, p. 23).

$$\text{ClaimDiff}_{ij} = \beta_0 + \beta_1(\text{Brand}_i) + \beta_2(\text{Obj}_i) + \beta_3(\text{Rely}_i) + \beta_4(\text{EC}_i) + \beta_5(\text{Sat}_i) + \theta_j + \varepsilon_{ij}, \qquad (16)$$

where,

ClaimDiff_{ij} = quality claim differential (mileage claim minus 40,000) in scenario i by subject j;

$\text{Brand}_i = 1$, if brand is well known in scenario i, otherwise 0;

$\text{Obj}_i = 1$, if objective is to maximize long-run sales in scenario i, otherwise 0;

$\text{Rely}_i = 1$, if customers rely on company ads in scenario i, otherwise 0;

$\mathrm{EC}_i = 1$, if customer expectations change substantially in scenario i, otherwise 0;

$\mathrm{Sat}_i = 1$, if customers are satisfied in scenario i, otherwise 0;

θ_j = Subject j's specific effect in mileage $\sim$ Normal$(0, \tau_1^2)$;

$\varepsilon_{ij} = \text{error} \sim \text{Normal}(0, \tau_2^2)$.

Per Results 4 and 5 and based on the FTC study, we respectively expect $\beta_1 < 0$ and $\beta_5 > 0$ in Equation (16). Results 2 and 3, respectively, suggest that $\beta_2 < 0$ and $\beta_4 < 0$. Result 4 also implies that $\beta_3 < 0$. We test model significance by constructing a null model that includes the intercept (β_0) and the respondent-specific effects (θ_j); the corresponding log-likelihood test (Raudenbush and Bryk 2002, p. 58) shows that the full model performs significantly better than the corresponding null model. The results are given in Table 5. Equivalent results are obtained from OLS regression, which (i) takes into consideration subject-level heterogeneity in other ways, i.e., either via 110 dummies for the 111 participants or by including the mean response for each subject across the eight scenarios, and (ii) includes the five factor dummies.

Most of the results were consistent with the model. First, respondents advertised lower quality (tire life) when they had a well-known brand or when the customers were not satisfied with the tires they bought, consistent with Results 4 and 5 as well as with the results of the FTC study. Interestingly, the "future managers" made higher-quality claims when they believed customers would, in general, be satisfied, consistent with the model predictions. The respondents also advertised lower quality when they expected customers would update their expectations substantially (e.g., for an experiential good) or when they were concerned primarily about long-run sales, as expected in Results 2 and 3.

Table 5 MBA Study: Random Effects Regression Results

Independent variables	Coefficient
Intercept	9,505 miles (89.3)
Brand is well known versus not well known	−1,222 miles (−3.4)
Objective is maximize long-run sales versus first-year sales	−5,195 miles (−14.3)
Rely on ads versus independent rating services	2,096 miles (5.8)
Expectations change substantially versus marginally	−3,556 miles (−9.8)
Customers are satisfied versus not satisfied	1,630 miles (4.5)
Fit statistics	
Sample size	880
−2 log likelihood	5,677.1
AIC (Akaike information criterion)	5,681.1
BIC (Bayesian information criterion)	5,686.6
−2 log likelihood of the null model	5,976.7
Chi-square statistic (p-value)	299.6 (<0.001)

Note. Dependent variable: Mileage claim minus 40,000 (t-values in parentheses).

One result contradicted model predictions. Subjects made lower mileage claims when they believed customers relied more heavily on independent quality ratings such as customer reports vis-à-vis ads. This suggests they would make high ad claims only when they thought such ads were effective in shaping customer expectations. When customers largely ignore ad claims, while we expected a "why not" attitude to making high claims (i.e., because they expect customers to discount the ad claims), a "why bother" response appears to be stronger.

6. Discussion

A firm's decisions with respect to quality, price, and in particular advertised quality (which may differ from average actual quality), are critical for the long-run success of a new product. Here we modeled the impact of advertised quality on initial and subsequent sales incorporating customer expectations and satisfaction. A fairly complex (and hopefully realistic) model was developed, a set of base parameters estimated based on a field study, and its propositions examined via numerical methods across a broad range of conditions. Note that it is not "necessary" to include heterogeneity to get our results. To demonstrate that, we removed the three types of heterogeneity and re-derived the results, which are essentially unchanged. However, heterogeneity almost certainly exists in terms of individuals' reliance on advertising, their level of disconfirmation sensitivity, as well as the performance they experience. We include heterogeneity in the more general model because (a) we believe it exists and (b) to guard against the (legitimate) potential criticism that, had we not included it, our results would be suspect.

Several results emerge. In the intuitive category, the difference between optimal advertised quality and average quality decreases when customers are more sensitive to the difference between expected and experienced quality, potential future earnings from customers increase, and when customers place less weight on prior expectations (i.e., place more weight on actual experience). In the "novel" or less intuitive category, optimal overstatement of quality decreases when customers (i) place more weight on advertised quality, and (ii) the base level of satisfaction with a firm decreases. Note that we employed three very different methods that produced similar results, thus giving us confidence that the results are not an artifact of any of the three methods. Specifically, (1) the data used to estimate a base set of model parameters for the analytical model were "forced choice" of a product new to the customers. We then varied these parameters in subsequent simulations. We also used (2) FTC data on firms that advertised at such a level as to lead to a complaint that the FTC chose to hear, and (3) a survey of the quality level that managers would advertise in different scenarios.

To reiterate, the main purpose of this paper is analytical. The empirical analyses were included to (a) help choose parameter values for the model to be used in optimization (the tire study) and extend the results of the simple model without heterogeneity (see appendix) to a more general specification and (b) show that the model conclusions were not wildly at variance with what actually happens (the FTC data provide some "circumstantial" evidence in this regard) and what managers do (which the survey does).

Our results suggest that when customers accept a company's "word" (i.e., believe its claims), overstatement of quality should be reduced. This suggests that well-established, high-quality companies have less incentive to overstate quality. However, when customers are generally satisfied (e.g., in the case of brand extensions or ego-expressive products), there is more reason to overstate quality. These results were consistent with our analysis of deceptive advertising cases at the FTC. Both (1) unknown companies and (2) companies whose customers' are generally more satisfied (relative to industry satisfaction) seem to indulge in more deceptive advertising. Thus, while Sauer and Leffler's (1990) evidence suggests that adoption of the FTC advertising substantiation program increased the credibility of advertising, firms have incentives to overstate quality. In summary, our results have implications for customers (i.e., when to believe advertising claims), managers (i.e., when not to overstate quality), as well as public policy makers (i.e., when to, and when not to, regulate).

It is also interesting that all but one of the four model results tested were directionally consistent with the tendencies of soon-to-be managers. The one exception was that managers would not "bother" to advertise high quality if they thought customers would not weight ads heavily whereas the model indicates it would be optimal to do so. This suggests that managerial instinct is not always optimal and that model prescriptions should at least be considered in making decisions.

Of course, the results reported here depend on both the model and the data. Generalization to other data sets and product categories is clearly desirable. One may also investigate other model forms, in particular a dynamic, multiperiod model that includes multiple updating of expectations. Other possibilities include developing equilibrium properties under strategic competition, incorporating measures of key constructs such as whether a firm is known and/or examining the link between the weight customers place on advertising and how well known a firm is. Further, while we include a continuous form of heterogeneity in terms of the weight customers place on advertised quality, variation in actual quality, and disconfirmation sensitivity, it might be interesting to study discrete forms of customer heterogeneity.

Other extensions could deal with a number of interesting aspects, such as: (i) the impact of warranties; (ii) explicit feedback effects to the brand's other products (which would tend to decrease the overstatement of quality), particularly when network effects exist (Sun et al. 2004); (iii) discounting of claims by customers before combining them with quality ratings (which could actually increase overstatement); (iv) allowing the firm to use other methods (e.g., promotions) to induce trial; (v) allowing disconfirmation sensitivity to influence experienced quality; (vi) allowing the satisfaction of those who bought in Period 1 to impact the next-period purchase likelihood of those customers who did not buy in Period 1, i.e., an information-cascading type of behavior in a diffusion setting (Golder and Tellis 2004); (vii) explicitly including legal costs; and (viii) investigating other reasons for overstating quality (e.g., positioning).

Still, the results here are encouraging. As an example of the implications, Table 6 suggests some categories may be more prone to quality overstatement.

Table 6 Five Questions to Help Determine When Overstatement of Quality Will Be Greater

	When should quality overstatement be greater?		Where more quality overstatement is expected
1. What is the inherent level of *satisfaction* with the firm?	Low	High ✓	Vacations, beer
2. To what extent will customers *accept the company's* "*word*" at face value versus discount it?	Accept	Discount ✓	Unknown company
3. How rapidly do customers *update expectations* based on personal experience?	Slow ✓	Fast	Quality hard to observe—long-term medical care
4. How important are *future versus initial sales*?	Initial ✓	Future	Movies
5. How *disconfirmation sensitive* are the customers?	Not ✓	Very	

This suggests which industries are more likely to require regulatory scrutiny, i.e., how to prioritize enforcement in a resource-constrained world.

One other interesting implication also emerges from our modeling effort. The results suggest that decisions about price, quality, and advertising need to be integrated, yet in practice these decisions are often made by different organizational units and individuals. These results clearly imply that making decisions separately for the various elements of the marketing mix is likely to be noticeably less than optimal. Hopefully, future research and practice will incorporate the more integrative perspective.

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Appendix 1. Deriving Analytical Results for a Simple Model
We derive analytical results for a simplified model. The purpose is to demonstrate that complex model results hold under a set of (reasonable) simplifying assumptions. This model has the following simplifications: (1) We simplify Equation (6) by setting $d_3, d_4 = 0$; i.e., we use a simple gap model of satisfaction; (2) the probability of purchase is linear rather than logit; (3) there is no customer heterogeneity either in α_1 or in quality realization (Q) or in disconfirmation sensitivity; i.e., customers are homogeneous and everyone realizes actual quality, μ; and (4) price and quality are exogenously set (i.e., given). The model and results thus become:

Expectations in Period 1. $\widehat{Q}_1 = \alpha_1 I + (1-\alpha_1)\mu$.

Probability of purchase for a customer: $D_1 = b_0 + b_1\widehat{Q}_1 + b_2 P$.

Satisfaction (S_1) in Period 1: $S_1 = d_0 + [d_1 + d_2\text{DS}](\mu - \widehat{Q}_1)$.

Expectations in Period 2. $\widehat{Q}_2 = \alpha_2\widehat{Q}_1 + (1-\alpha_2)\mu$.

Probability of purchase in Period 2:

$$D_{2|\text{buy}} = \overbrace{b_0 + b_1\widehat{Q}_2 + b_2 P}^{\text{normal effect}} + \overbrace{[d_0 + (d_1 + d_2\text{DS})(Q_1 - \mu)]}^{\text{satisfaction effect}},$$

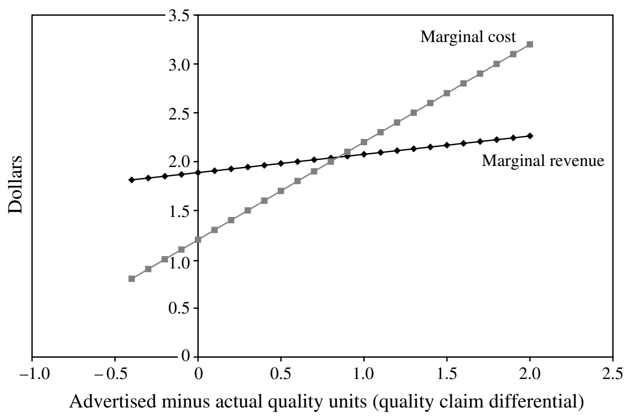
$$D_{2|\text{no buy}} = b_0 + b_1\widehat{Q}_1 + b_2 P,$$

$$D_2 = D_1 D_{2|\text{buy}} + (1 - D_1) D_{2|\text{no buy}}.$$

Firm Behavior

$$\max_I[\pi - F] = \max_I[(P - v)Ny(D_1 + mD_2) - F]. \qquad \text{(A1)}$$

Before we develop optimal advertised quality and the corresponding proposition, we analyze marginal revenue and marginal costs to shed light on the intuition behind overstating, versus understating, quality.[11] We obtain the following graph with the parameter values, $b_0 + b_2 P = 1$, $\mu = 0.5$, $\alpha_1 = 0.5$, $d_0 = 0.1$, $d_1 = 1$, $d_2 = 0$, $\text{DS} = 0$, $F = 0$, $N = y = 1$:



When the marginal revenue and marginal cost curves intersect to the left of the y-axis, the solution is to understate quality. For example, this is the case when the value of future sales (multiplier m) is high or when customers weight advertising heavily. On the other hand, when the marginal revenue and cost curves intersect to the right (for example, when customers are slow to update their expectations, or when the base level of satisfaction is high), it is optimal to overstate quality.

We conducted a simple thought experiment in the above framework to include legal costs. If legal costs are high, the marginal cost function will be discontinuous. Hence, when overstatement exceeds a threshold that leads to legal action, the solution is then more likely to understate quality.

Optimal Advertised Quality
Taking the derivative with respect to the advertised quality, I, in the firm's objective equation (A1), setting it to zero, rearranging the terms, and simplifying, we get optimal advertised quality

$$I^* = \frac{\mu}{2} + \frac{1+m(1+d_0)}{2\alpha_1 m(b_1(1-\alpha_2)+d_1+d_2\text{DS})} - \frac{b_0+\mu b_1(1-\alpha_1)+b_2P}{2\alpha_1 b_1}$$
$$= \underbrace{\mu\left(1-\frac{1}{2\alpha_1}\right)}_{\text{quality effect}} - \underbrace{\frac{b_0+b_2P}{2\alpha_1 b_1}}_{\text{price effect}} + \underbrace{\frac{1+m(1+d_0)}{2\alpha_1 m(b_1(1-\alpha_2)+d_1+d_2\text{DS})}}_{\text{disconfirmation sensitivity effect}}.$$

Propositions
The optimal quality claim differential (difference between optimal advertised quality and average quality) is given by

$$I^* - \mu = \frac{1+m(1+d_0)}{2\alpha_1 m(b_1(1-\alpha_2)+d_1+d_2\text{DS})} - \frac{b_0+\mu b_1+b_2P}{2\alpha_1 b_1}. \qquad \text{(A2)}$$

[11] We thank an anonymous *Marketing Science* reviewer for this suggestion.

Proposition 1. *The optimal quality claim differential decreases with customer disconfirmation sensitivity, DS.*

Proof. Taking the partial derivative of Equation (A2) with respect to disconfirmation sensitivity, DS, and simplifying, we obtain

$$\frac{\partial(I^*-\mu)}{\partial(\mathrm{DS})}=\frac{-d_2(1+m(1+d_0))}{2\alpha_1 m(b_1(1-\alpha_2)+d_1+d_2\mathrm{DS})^2},$$

which will be negative if $d_0>0$. Because $d_2>0$, $m>0$, α_1 and $\alpha_2>0$, $\partial(I^*-\mu)/\partial(\mathrm{DS})<0$. □

Proposition 2. *The optimal quality claim differential decreases with the potential future earnings from a customer, i.e., the multiplier, m.*

Proof. Taking the partial derivative of Equation (A2) with respect to the multiplier, m, and simplifying, we have

$$\frac{\partial(I^*-\mu)}{\partial m}=\frac{-1}{2\alpha_1 m^2(b_1(1-\alpha_2)+d_1+d_2\mathrm{DS})}<0.$$

Because α_1, m, d_1, d_2, and DS are greater than zero, and $\alpha_2<1$, the derivative is negative. □

Proposition 3. *The optimal quality claim differential increases with α_2, the weight customers place on prior expectations in forming their updated expectations.*

Proof. Taking the partial derivative of Equation (A2) with respect to α_2, and simplifying, we get

$$\frac{\partial(I^*-\mu)}{\partial\alpha_2}=\frac{b_1(1+m(1+d_0))}{2\alpha_1 m(b_1(\alpha_2-1)-d_1-d_2\mathrm{DS})^2}>0.$$

Because α_1, b_1, and $m>0$, and with $d_0>0$, the above derivative is positive. □

Proposition 4. *The optimal quality claim differential decreases with α_1 (the weight customers place on advertised quality in forming their expectations) if $b_1(1/m+d_0+\alpha_2)>d_1+d_2DS$.*

Proof. Taking the partial derivative of Equation (A2) with respect to α_1, the weight placed on advertised quality, and simplifying the terms, we have

$$\frac{\partial(I^*-\mu)}{\partial\alpha_1}=\frac{1}{2\alpha_1^2}\left[\frac{-(1+m(1+d_0))}{m(b_1(1-\alpha_2)+d_1+d_2\mathrm{DS})}+\frac{(b_0+b_1\mu+b_2P)}{b_1}\right].$$

Because $b_0+b_1\mu+b_2P$ is a special case of purchase probability in Period 1, D_1, we have $0\le b_0+b_1\mu+b_2P\le 1$. However, $(1+m(1+d_0))>1$ for $d_0>0$. Therefore, $\partial(I^*-\mu)/\partial\alpha_1$ will be <0 if

$$\frac{1+m(1+d_0)}{m(b_1(1-\alpha_2)+d_1+d_2\mathrm{DS})}>\frac{1}{b_1},$$

i.e., cross multiplying, rearranging the terms, and simplifying, we get $b_1(1/m+d_0+\alpha_2)>d_1+d_2\mathrm{DS}$. This condition is satisfied either when the average disconfirmation sensitivity is low or when the quality sensitivity is high, or both. In a field study of car tires (§4), we find that this condition is indeed satisfied. □

Proposition 5. *As the base level of satisfaction with the firm (d_0) increases, the optimal quality claim differential also increases.*

Proof. Taking the partial derivative of Equation (A2) with respect to d_0, the base level of satisfaction with the firm's product, and simplifying the terms, we have

$$\frac{\partial(I^*-\mu)}{\partial d_0}=\frac{1}{2\alpha_1(b_1(1-\alpha_2)+d_1+d_2\mathrm{DS})}>0.$$

Because $\alpha_1, d_1, d_2, \mathrm{DS}>0$, and $\alpha_2<1$, the derivative is positive. □

Proposition 6. *As average actual quality (μ) increases, the difference between optimal advertised quality and average actual quality decreases.*

Proof. Taking the partial derivative of Equation (A2) w.r.t. μ, the average actual quality, we get $\partial(I^*-\mu)/\partial\mu=-1/2\alpha_1<0$. Because $\alpha_1>0$, the derivative is negative. □

Appendix 2

Instructions to Participants:

Please note that there are no right or wrong answers. Individual responses will be kept absolutely confidential and used only for statistical analysis. Please do not discuss this exercise with others—the quality of the research we do depends on your confidentiality. We will provide you with a debrief once the analysis is complete.

This study will require about five minutes of your time and concerns managerial decisions about how to market a new product. We will enter each participant's name in two raffles: (i) one cash prize of $500.00 and (ii) five cash prizes of $100 each.

This study is designed to assess how managers make decisions when introducing new products. Specifically we are interested in what specific advertising claims they make about their products.

Imagine you are in charge of managing the introduction of a new line of car tires marketed under your company's existing brand. The product will be sold through standard channels, i.e., tire distributors, gas stations, etc. Your job is to determine what level of quality, i.e., how long (in miles) a tire lasts, to claim for the product in its advertising and product information.

Your company tests indicate that a set of your tires will last between 28,000 miles and 52,000 miles depending on customer driving patterns and road conditions. Car tire industry research shows that customer satisfaction and repeat purchase depend, to a significant extent, on the difference between how long tires actually last and how long customers expect the tires to last prior to purchase.

What mileage would you use when describing your tires in each of the following situations?

Format for the Eight Scenarios:

Your company's brand is **not well known (well known)**. Your primary objective is to maximize **first-year (long-run) sales**. Market research has provided the following insights:

- Customers **rely mainly on company advertising** rather than on **independent quality-rating services (such as *Consumer Reports*)** in forming expectations about how long tires last.
- Once formed, customer **expectations change only marginally (substantially)** based on personal experience.
- Most customers are **satisfied (not satisfied)** with tires that they buy.

Mileage claim in advertising and product information: —— (miles).

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