How Does Objective Quality Affect Perceived Quality?
Short-Term Effects, Long-Term Effects, and Asymmetries

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Abstract

We examine the relationship between objective and perceived quality for 241 products in 46 product categories over a period of 12 years. On average, we find that the effect of a change in objective quality is not fully reflected in customer perceptions of quality until after about 6 years. In the first year after a quality change, only about 20% of the total effect over time is realized. These effects are significantly larger and quicker for a decrease in quality relative to an equivalent increase. Interestingly, we also find that brand reputation has a "double" advantage. High reputation brands are rewarded 3 years quicker for an increase in quality and punished 1 year slower for a decrease in quality compared to low reputation brands. These differences in response time are a meaningful measure of brand equity. Finally, we examine the differences in quality effects across several product and category-specific variables and discuss the implications of our findings.

(Quality, quality perception, lagged effects, carryover duration, brand management, reputation effects, consumer learning, product management)

INTRODUCTION

Quality may be the most important factor underlying the long-term success of products and firms. The business press routinely cites quality as the cause of firm success and failure (*Fortune* 1998; *New York Times* 2003; *Wall Street Journal* 2004b). However, it is now well established that it is not quality *per se* but customers' perceptions of quality that drive preferences and consequently satisfaction, loyalty, sales, and profitability (e.g., Aaker and Jacobson 1994; Anderson and Sullivan 1993; Anderson, Fornell, and Lehman 1994; Bolton and Drew 1991b; Rust et al. 1995; Zeithaml 1988). Yet, numerous anecdotes suggest that customer perceptions of quality do not reflect objective quality. For example,

> "General Motors has surged on quality ...(but) despite improvements, it still suffers from negative perceptions. 'There is a perception gap between what we are actually doing in terms of vehicle quality and where the customer perceives us to be' claims GM's spokesman." (*Wall Street Journal*, Mar 9, 2004, D4).

> "The web traffic numbers are unlikely to stray much irrespective of Yahoo's (improved) quality…people have their favorite search engine…and go to that site all the time" (*money.cnn.com*, May 25, 2004).

Still many researchers believe that customer perceptions of quality do respond to changes in quality, albeit slowly, and that quality changes "become noticeable (to customers) only in the long run" (Bolton and Drew 1991a, p. 7). For example, while Toyota is currently reaping the benefits of higher perceived quality, it took many years for customers to recognize its quality advantage over U.S. automakers (Mannering and Winston 1991). Similarly in the case of search engines, it took Google three years after launch to be perceived as the superior search engine (see http://www.google.com/corporate/timeline.html).

To understand such long-term aspects of the business environment, researchers have often called for more longitudinal studies (Aaker and Day 1986; Golder 2000; MSI Research Priorities 2002-2004). In fact, there is a growing body of literature that seeks to understand the long-term effects of marketing variables (Dekimpe and Hanssens 1999; Jedidi et al. 2000; Lal and Padmanabhan 1995; Mela et al. 1997). But these studies tend to focus on price, promotion, and advertising. The few longitudinal studies examining quality consider relatively short-term effects or they are based on single-company or experimental data (Bolton and Drew 1991a; Prabhu and Tellis 2000; Tellis and Gaeth 1990). Thus, there are no large sample studies on the effects of quality, the duration of these effects, and how they change by product and category-level characteristics (Fornell 1995). Yet, it is critically important for managers to know about these effects for their own products as well as competing products. Such information can help them make better decisions about the amount and timing of investments in quality and new product development, as well as about pricing and promotions.

In this paper, we address the limitations of previous longitudinal studies of quality by collecting and analyzing time-series of quality and perceptions of quality across many product categories. We also collect additional data on price, advertising, and market share to address the following specific and related questions. Answers to these questions make unique contributions to the marketing literature.

- What is the relationship between quality and customer perceptions of quality over time?
- What are the sizes and durations of short-term and long-term effects for increases and decreases in quality on customer perceptions of quality?
- Are the sizes and durations of these effects different for high-reputation products and lower-reputation products?
- Are there asymmetries between increases and decreases in quality, or on their effects with high-reputation versus lower-reputation products?
- What are the roles of other category-specific variables on the relationship between quality and customer perceptions of quality?

The remainder of the paper is organized as follows. First, we present the definitions of key terms. Second, we draw on the quality literature to develop a conceptual framework of the quality perception process. We then use this framework to develop our hypotheses on the short-term and long-term effects of quality on perceptions of quality. Third, we present our model and estimation procedures. Fourth, we describe our extensive data set and operationalize the variables. Fifth, we present our results and analyses of their robustness. Finally, we conclude with a discussion of our key findings, their implications, and directions for future research.

DEFINITIONS

We begin by defining the key terms in our study. ***Objective quality*** is the aggregate performance of all vector product attributes (i.e., those attributes for which customers prefer either a higher or a lower magnitude). Similar to previous research (Curry and Riesz 1988; Lichtenstein and Burton 1989; Riesz 1978; Tellis 1989), we measure objective quality through a composite of instrument and expert ratings. For example, a personal computer's objective quality attributes include processing speed, hard disk capacity, reliability, and features like DVD drive and modem. Objective quality does not include intangible attributes like aesthetics and extrinsic attributes like brand image or salesperson behavior. It is similar to earlier concepts like "observed quality" or "performance" for physical products (Olshavsky and Miller 1972; Kopalle and Lehman 1995) and "delivered service," "service change," or "personnel and equipment effort" for service products (Bolton and Drew 1991a; Boulding et al. 1993; Kamakura et al. 2002). In this paper, *objective quality* and *quality* alone are synonymous.

Perceived quality is the overall subjective judgment of quality relative to the expectation of quality. These expectations are based on one's own and others' experiences, plus various other sources including brand reputation, price, and advertising (Zeithaml 1988; Dodds et al. 1991; Boulding et al. 1993; Johnson et al. 1995). Thus, it is not necessary to use or examine a product to form perceptions of quality. In this paper, *perceived quality* is the perception of the customer; hence, we use it interchangeably with *customer perceptions of quality*.

Similar to previous studies (Clarke 1976; Mela et al. 1997; Tellis et al. 2000), we characterize the effects of objective quality on customer perceptions of quality as follows. The ***contemporaneous effect*** is the impact of objective quality on perceived quality in the current time period (in this study, the same year). Previous longitudinal studies of quality find a positive, though not large, contemporaneous effect (Boulding et al. 1993; 2000; Bolton and Drew 1991b; Kamakura et al. 2002). The ***short-term effect*** is the impact of objective quality on perceived quality in the current and subsequent time period (i.e., same year plus one year later in this study). ***Short-term carryover*** refers to the difference between the short-term effect and the contemporaneous effect. The relative size of the contemporaneous effect versus the short-term carryover determines whether the overall effect is monotonic or non-monotonic over time. Only a few studies have examined short-term effects (Bolton and Drew 1991a; Boulding et al. 1993; 2000). ***The long-term effect*** is the cumulative effect of objective quality on perceived quality over an infinite time horizon. ***Long-term carryover*** is the difference between the long-term effect and the short-term effect. Only one study has examined the long-term effect of quality based on experimental data (Prabhu and Tellis 2000). ***Carryover Duration*** is the time needed to reach a pre-specified percentage of the long-term effect. All else equal, it takes a longer time to reach a higher percentage of the long-term effect. Typically studies report the 90% carryover duration (Clarke 1976; Mela et al. 1997).

CONCEPTUAL FRAMEWORK

In this section, we describe the conceptual framework relating objective quality and perceived quality. Then, we develop testable hypotheses based on our framework.

Effects of Objective Quality on Perceived Quality

Most marketing studies on brand choice assume that quality is constant over time (Jedidi et al. 1999; Mela et al. 1997). However, "there are many instances in which a producer can affect quality" so as to influence the customers' product experience (Tirole 1998, p. 121; Ferrier, Smith, and Grimm 1999; Willard and Cooper 1985). Some analytical models in the industrial organization literature allow firms to select quality in each period and evaluate its effect on the price premium required to maintain its quality "reputation" (Allen 1984; Klein and Leffler 1981; Shapiro 1983). These studies assume a fixed "one time-period" information lag for customers while acknowledging the impact of varying lengths of this lag.[1]

On the other hand, there is a rich tradition in the marketing literature that studies this reputation-building process through the determinants and dynamics of perceived quality. According to this literature, perceived quality is determined primarily by objective quality and prior expectations of quality (Boulding et al. 1993, 1999; Olshavsky and Miller, 1972; Parasuraman et al. 1985).[2] In Figure 1, we present the relationships among these variables. Based on this dynamic framework, objective quality is linked to perceived quality in two ways. The first is the direct contemporaneous link. The second is the indirect lagged link through the updated prior expectations of quality (Bolton and Lemon 1999; Boulding et al. 1993, 1999; Nerlove 1958). This latter link leads to the carryover or delayed effect of objective quality on perceived quality. Because of the uncertainty about objective quality and the cognitive effort

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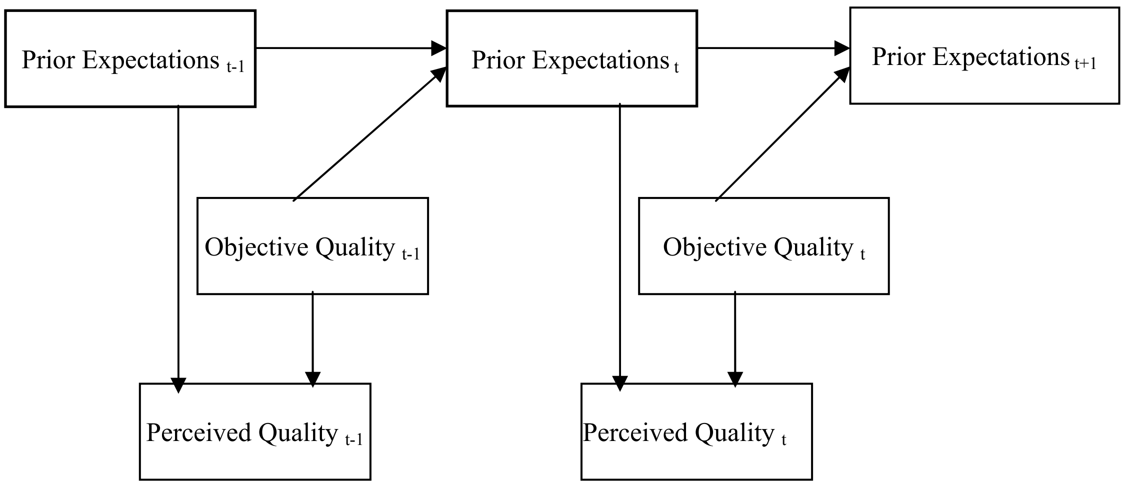
[1] For example, "[as the information lag increases] the quality premium must increase to keep the firm from milking its reputation" (Tirole 1998, p. 123).

[2] In different contexts, objective quality is referred to through different terms like observed quality (Kopalle and Lehman 1995), performance (Parasuraman et al. 1985; Johnson et al. 1995), delivered service (Boulding et al. 1993), service change (Bolton and Drew 1991a), personnel/ equipment effort (Kamakura et al. 2002), or just quality improvement (Rust et al. 2002).

required to update expectations, changes in perceived quality may occur slowly (Akerlof 1970; Johnson et al. 1995; Camerer 1992; Lucas 1986).

Figure 1: The Conceptual Framework



Next, we relate existing literature to our framework and develop our hypotheses.

Short-Term and Long-Term Effects

Contemporaneous Effect: There are two groups of studies in the marketing literature on the dynamic effects of quality. The first group of studies provides empirical estimates of the contemporaneous effect of objective quality on perceived quality. In three experimental studies, the effect ranges between 9% and 22% of the change in objective quality (Boulding et al. 1993, 1999; Prabhu and Tellis 2000).[3] Similarly, in two field studies, one for telephone service and another for banking service, the effect ranges from 3% and 22% of the change in objective quality (Bolton and Drew 1991; Kamakura et al. 2002).[4] A second group of studies demonstrates how individuals do not properly incorporate all relevant information because of

[3] Coefficient of "delivered service" was calculated after adjusting both "delivered service" and "perceived service" to the same scale in Boulding et al. (1993) and Boulding et al. (1999).

[4] After incorporating the objective quality variables in the "quality" equation and adjusting both variables to the same scale in Bolton and Drew (1991).

limited effort, time, memory, and cognitive ability, plus the salience of recent experiences, overconfidence, and several other biases and heuristics (Bettman, Johnson and Payne 1991; Hoyer and Brown 1990; Kahneman and Tversky 1979; Tellis and Gaeth 1988). These studies suggest that the contemporaneous effect of objective quality on perceived may not be significant.

In spite of individual inefficiencies, we still expect the market-level contemporaneous effect to be positive. Thus, our first hypothesis is a replication test of previous research.

H1a: There is a significant positive contemporaneous effect of objective quality on perceived quality.

Short-term Carryover: There is scant empirical evidence on the effects of quality in a subsequent time period. Bolton and Drew (1991) find a significant effect of quality on perceived quality in a subsequent time period, although this effect is smaller than the contemporaneous effect. Some studies find a significant effect of one-period-lagged quality on the market share of automobiles and on the price of Bordeaux wines (Mannering and Winston 1991; Landon and Smith 1998). Other studies do not directly examine the short-term carryover of quality but indirectly support its significance. For example, three different studies find (i) a significant effect of 'actual' quality on expectations, (ii) a significant effect of expectations on same-period perceived quality and (iii) a significant effect of expectations on next-period expectations (Boulding et al. 1993, 1999; Kopalle 2001; Rust et al. 1999). Although previous empirical studies only consider a single category or an experimental context, this limited evidence still leads us to expect a significant short-term carryover of quality on perceived quality.

H1b: There is a significant positive short-term carryover of objective quality on perceived quality.

Long-Term Carryover: There are many potential reasons why consumer perceptions may not fully reflect objective quality in the short run. These include uncertainty and lack of knowledge about objective quality, high cognitive efforts required for adjusting prior expectations, low involvement, and long inter-purchase frequencies. Yet, over time, market-level perceptions of quality are likely to move toward objective quality (Camerer 1992). Thus, there will be a long-term carryover of objective quality on perceived quality. Surprisingly, there are no empirical studies and only one experimental study that examine this long-term carryover for more than three periods. In their lab study of airline choice, Prabhu and Tellis (2000) do not find significant carryover (learning, as they term it) at the aggregate level, but they do find significant long-term carryover effects for some segments of subjects. A few other studies provide suggestive evidence for long-term carryover effects. Anderson and Salisbury (2003) find a significant dynamic effect of current-period perceived quality on next-period expectations. Two other studies find that it takes between 5 and 10 years for actual quality initiatives to translate into higher profits (Easton and Jarrell 1998; Hendricks and Singhal 2001). Overall, these studies lead us to expect that we will find a significant long-term carryover of quality on perceived quality. In addition, as discussed earlier, previous studies have found small contemporaneous and short-term carryover effects (e.g., Bolton and Drew 1991). Thus, the long-term carryover is likely to be larger than the short-term effects (i.e. contemporaneous effect plus short-term carryover effect).

H2a: There is a significant long-term carryover of objective quality on perceived quality.
H2b: The long-term carryover of quality is larger than the short-term effect of quality on customer perceptions of quality.

Asymmetries in Carryover

Based on our conceptual framework, the carryover effects of quality are moderated by prior expectations of quality. Thus, a similar change in objective quality may have different effects on perceptions of quality across categories and products.[5] In this section, we discuss variables that may lead to asymmetries in quality carryover.

Increases and Decreases in Objective Quality

We expect asymmetric effects from increases and decreases in quality based on the extensive literature on prospect theory (Kahneman and Tversky 1979). According to this theory, customers have a greater change in utility for losses than for equally-sized gains. Research on individual level processes of perception and satisfaction formation supports such asymmetric effects (Kopalle and Lehmann 1995; Mittal et al. 1998). Therefore, we expect that decreases in quality will have a greater impact on customer perceptions of quality than equivalent increases in quality. Moreover, previous research has found that bad news diffuses more than good news because of stronger word-of-mouth effects (Richins 1983). Thus, decreases in quality are likely to have a greater impact on perceived quality both in terms of short-term effect and long-term carryover.

H3a: The short-term effect of objective quality on perceived quality is larger for a decrease in quality than for an equivalent increase.
H3b: The long-term carryover of objective quality on perceived quality is larger for a decrease in quality than for an equivalent increase.

Prior Brand Reputation

Brand reputation is formed through advertising, word-of-mouth, and personal experience. Previous research has found that customers are more likely to incorporate information that is consistent with their beliefs (Boulding et al. 1999). This effect can be attributed to the 'confirmatory' bias of many customers (Hoch and Ha 1986; Lord et al. 1979). Therefore,

[5] Effects will be different across individuals as well. However, in this study we focus on the aggregate market.

customers will more easily incorporate the quality increase of a high-reputation brand than a similar increase of a low-reputation brand. Conversely, a quality decrease of the high-reputation brand will be less negatively perceived than a similar decrease by a low-reputation brand. Thus:

H4a: The short-term effect of an increase in objective quality is larger for high-reputation brands than for low-reputation brands.

H5a: The short-term effect of a decrease in objective quality is larger for low-reputation brands than for high-reputation brands.

However, over the long term, information about changes in quality should diffuse among customers through media reports and word-of-mouth (Rogers 1995). Under these circumstances, we believe the initial "confirmatory bias" will gradually diminish. Thus,

H4b: The long-term carryover of an increase in objective quality is smaller for high-reputation brands than for low-reputation brands.

H5b: The long-term carryover of a decrease in objective quality is larger for high-reputation brands than for low-reputation brands.

Product Category Effects

In order to control for some of the differences across categories, we consider three category-level variables: average quality variance, purchase frequency, and search costs. Although current theory seems insufficient to develop hypotheses on the short-term effects, long-term effects, and carryover effects of these variables, we will report their impact on the relationship between objective quality and perceived quality.

MODEL

Based on our conceptual framework, objective quality is linked to perceived quality in two ways. The first is a direct, contemporaneous link:

$$PQ_{jt} = \alpha_{0j} + \alpha_{1j}EX_{jt} + \alpha_{2j}OQ_{jt} + e_{jt} \tag{1}$$

where perceived quality (PQ) of product 'j' at time period 't' is based on objective quality (OQ) of product j at time 't' and prior expectations of quality (EX) of product j at time 't'.

The second link is an indirect one caused by updating prior expectations (Bolton and Lemon 1999; Boulding et al. 1993, 1999; Nerlove 1958). Since attitudes shift in the direction that reduces inconsistencies (Osgood and Tannenbaum 1955; Festinger 1957), we expect the change in expectations to be proportional to, but less than, the difference between prior expectations and prior objective quality (Kopalle and Lehmann 1995, 2001; Boulding et al. 1993). Therefore,

$$EX_{jt} - EX_{j(t-1)} = \lambda(OQ_{j(t-1)} - EX_{j(t-1)}), \text{ where } 0 < \lambda < 1 \qquad (2)$$

This second link combined with the role of expectations in (1) leads to the carryover or delayed effect of objective quality on perceived quality. The size and duration of this carryover effect is determined by the relative impact on perceived quality from objective quality (α_{2j}) and expectations (α_{1j}), plus the adjustment rate of expectations (λ). Most consumers will have substantial delays in updating their perceptions because of the uncertainty surrounding objective quality and the cognitive effort required to adjust expectations (Akerlof 1970; Anderson and Salisbury 2003; Camerer 1992; Lucas 1986; Prabhu and Tellis 2000).

By combining the two impacts on perceived quality (equations 1 and 2), we obtain:

$$PQ_{jt} = \alpha_{0j}\lambda + (1-\lambda)PQ_{jt-1} + \alpha_{2j}OQ_{jt} + [\lambda\alpha_{1j} - (1-\lambda)\alpha_{2j}]OQ_{jt-1} + [e_{jt} - (1-\lambda)e_{jt-1}] \qquad (3)$$

which is of the following form:

$$PQ_{jt} = a_{0j} + a_{1j}PQ_{j(t-1)} + a_{2j}OQ_{jt} + a_{3j}OQ_{j(t-1)} + \varepsilon_{jt} \qquad (4)$$

Equation (4) is similar to a partial adjustment model, which has been frequently used to study long-term effects of advertising and promotion (Clarke 1971; Mela et al. 1997, 1998; Tellis et al. 2000; van Heerde et al. 2004). The model in equation (4) has several important features. First, the model parameters can be used to compute the short-term and long-term effects of objective quality on perceived quality. The contemporaneous effect of objective quality on perceived quality is given by:

$$E_i = a_{2j} \quad (5a);$$

the short-term effect is:

$$E_s = (a_{2j} + a_{3j}) \quad (5b);$$

the long-term effect is:

$$E_l = (a_{2j} + a_{3j})/(1 - a_{1j}) \quad (5c);$$

the short-term carryover is:

$$C_s = E_s - E_i = a_{3j} \quad (6a);$$

and the long-term carryover is:

$$C_l = E_l - E_s = a_{1j}\,(a_{2j} + a_{3j})/(1 - a_{1j}) \quad (6b).$$

We can also test for the significance of E_i, E_s, E_l, C_s, and C_l based on the covariance matrix of the parameters. Further, we can compute the duration of the carryover of objective quality.

$$\text{p\% carryover duration} = 1 + \left[\frac{\ln(1-p) - \ln\left[\dfrac{a_{3j} + a_{1j}a_{2j}}{a_{2j} + a_{3j}}\right]}{\ln a_{1j}}\right] \quad (7)$$

The p % carryover duration denotes the time during which p % of the cumulative effects are realized (See Clarke 1976 for details).

A second benefit of Equation (4) is that the extra lagged objective quality term can account for non-monotonic carryover structures. A third benefit is that this lagged term has been shown to reduce data interval bias in this class of models (Russell 1988).

Finally, it has been established that the behavioral process that leads to a distributed lag model is a rational response to the uncertainty in the causal variable (McLaren 1979; Lutkepohl

1984). In our case, a distributed lag model is credible because the causal variable, objective quality, is not known by customers with certainty.

Empirical Models and Estimation

In this section, we present our approach for empirically evaluating our hypotheses and estimating our models. Hypotheses 1 and 2 are based on aggregate results, while Hypotheses 3, 4, and 5 are based on the heterogeneity in short-term and long-term effects. Thus, we begin by our discussing our aggregate-level model, and then introduce the necessary heterogeneity.

Aggregate Model

To test hypotheses 1 and 2, we use an aggregate version of (4) with homogeneous slope parameters:

$$PQ_{jt} = a_0 + a_1 PQ_{j(t-1)} + a_2 OQ_{jt} + a_3 OQ_{j(t-1)} + \varepsilon_{jt} \quad (8)$$

$$\varepsilon_{jt} = u_j + v_t + e_{jt}$$

where u_j and v_t are random variables that partition the error in terms of the product and time period respectively and e_{jt} is a classical error term with zero mean and homoscedastic covariance structure.

We estimate (8) with a time-series, cross-sectional regression method because we have cross-sectional data of many products over time. We use a two-way random effects model such that the error structure is a combination of the cross-section (product) and the time-series (year) to which the data belong. The estimation also accounts for the possibility of autocorrelation and heteroscedasticity in the data. Later, in the robustness section, we examine the model results after correcting for possible non-stationarity and specification bias.

We use the RANTWO option in TSCSREG procedure of SAS to estimate (8). This procedure employs an Estimated Generalized Least Squares method in arriving at the parameter estimates. We choose a random effects model for two reasons. First, the fixed effects model assumes that all products are independent, thus introducing a bias in the estimation (Nickell 1981). On the other hand, a random effects model is appropriate for panel data of many products that are “drawn from a large population” of products in different categories (Greene 1990, p. 485). Second, a random initial value of perceived quality at time t = 0 has been found to produce consistent estimates of the model parameters when the data contain a limited number of time periods and a large number of products (Anderson and Hsiao 1982).

Disaggregate Models

For Hypotheses 3 to 5, plus the three product category variables, we introduce heterogeneity in the parameters of (8) through a 3-level hierarchical model that is simultaneously estimated (Bryk and Raudenbush 1992). This approach has been usefully applied in many social science disciplines, as well as at least two marketing studies (Anderson and Salisbury 2003; Steenkamp et al. 1999).

At the first level, we estimate equation (8) for an individual product j in category i over time t.

$$PQ_{ijt} = b_0 + b_{ij1}PQ_{ijt-1} + b_{ij2}OQ_{ijt} + b_{ij3}OQ_{ijt-1} + \varepsilon_{ijt} \qquad \varepsilon_{ijt} \sim N(0, \sigma^2) \tag{9.1}$$

At the second level, we estimate the parameters of the first-level model as a function of several product-specific variables, plus control for average (over time) relative price and relative advertising. First, we use only a subset of the data for products with increasing and decreasing quality to test for any differences in the first-level regression parameters (Hypotheses 3a and b).

$$\begin{aligned}
b_{ij1} &= \beta_{i01} + \beta_{11}{*}Increase_{ij} + \beta_{41}{*}P_{ij} + \beta_{51}{*}Ad_{ij} + r_{ij1} && r_{ij1} \sim N(0, \tau_1^2) \\
b_{ij2} &= \beta_{i02} + \beta_{12}{*}Increase_{ij} + \beta_{42}{*}P_{ij} + \beta_{52}{*}Ad_{ij} + r_{ij2} && r_{ij2} \sim N(0, \tau_2^2) \\
b_{ij3} &= \beta_{03} + r_{ij3} && r_{ij3} \sim N(0, \tau_3^2)
\end{aligned} \tag{9.2a}$$

Second, for only those products that have increasing quality, we examine the effects of a higher brand reputation (Hypotheses 4a and 4b).

$$\begin{aligned}
b_{ij1} &= \beta_{i01} + \beta_{21}{*}\,HR_{ij} + \beta_{41}{*}P_{ij} + \beta_{51}{*}Ad_{ij} + r_{ij1} && r_{ij1} \sim N(0, \tau_1^2) \\
b_{ij2} &= \beta_{i02} + \beta_{22}{*}\,HR_{ij} + \beta_{42}{*}P_{ij} + \beta_{52}{*}Ad_{ij} + r_{ij2} && r_{ij2} \sim N(0, \tau_2^2) \\
b_{ij3} &= \beta_{03} + r_{ij3} && r_{ij3} \sim N(0, \tau_3^2)
\end{aligned} \tag{9.2b}$$

Third, for those products that have decreasing quality, we examine the effects of a higher brand reputation (Hypotheses 5a and 5b).

$$b_{ij1} = \beta_{i01} + \beta_{31}{*}\, HR_{ij} + \beta_{41}{*}P_{ij} + \beta_{51}{*}Ad_{ij} + r_{ij1} \qquad r_{ij1} \sim N(0, \tau_1^2)$$
$$b_{ij2} = \beta_{i02} + \beta_{32}{*}\, HR_{ij} + \beta_{42}{*}P_{ij} + \beta_{52}{*}Ad_{ij} + r_{ij2} \qquad r_{ij2} \sim N(0, \tau_2^2)$$
$$b_{ij3} = \beta_{03} + r_{ij3} \qquad r_{ij3} \sim N(0, \tau_3^2) \qquad (9.2c)$$

Finally, at the third level, we model the intercept parameters of the second-level model using the category-specific control variables, i.e., quality variance, purchase frequency, and search cost.

$$\beta_{i01} = \eta_{001} + \eta_{101}QV_i + \eta_{201}PF_i + \eta_{301}S_i + u_{i01} \qquad u_{i01} \sim N(0, \nu_1^2)$$
$$\beta_{i02} = \eta_{002} + \eta_{102}QV_i + \eta_{202}PF_i + \eta_{302}S_i + u_{i02} \qquad u_{i02} \sim N(0, \nu_2^2) \qquad (9.3)$$

We estimate the disaggregate models (Equations 9.1, 9.2, and 9.3) with the HLM 5 program developed by Raudenbush, Bryk and Congdon. This program applies a maximum likelihood procedure to generate parameter estimates through an iterative EM algorithm. Since our hypotheses are on short-term effects and long-term carryover, their evaluation involves combining two or more estimated parameters of the hierarchical model. In the appendix we derive the hypothesis conditions in terms of the combination of parameters estimated by the HLM procedure (see Appendix for details). As in earlier studies, we use Cramer's theorem to derive the variance of these combinations of parameters (Mela et al. 1997; van Heerde et al. 2004). This approach allows us to evaluate our hypotheses with significance tests.

DATA

The lack of suitable data has probably been the biggest obstacle preventing research on quality. In our case, this obstacle is even larger since we need longitudinal data on objective quality and perceived quality for multiple products across multiple categories. After collecting data from multiple sources and manually compiling them into a common dataset, we believe that our data are sufficient for providing insights on the short-term, long-term, and asymmetric effects of quality. Next, we elaborate on the data collection and discuss the operationalization of variables.

Sources and Data Collection

Our initial goal was to collect relevant data for as many consumer product categories as possible. We used multiple sources to compile our data. For perceived quality, we use the *Equitrends* data of Total Research Corporation (TRC). These data have been collected for many years, are well known in industry, and have been used in previous research (Aaker and Jacobson 1994; Helloffs and Jacobson 1999). Each year TRC surveys over 30,000 people, 15 years of age and older. Each respondent evaluates the quality of products on a 0-10 scale ranging from poor quality to outstanding quality. The perceived quality of each product is calculated as the average quality rating given by those customers who had an opinion about the product. The data include ratings on 280 products between 1989 and 1994 and 1000 products between 1995 and 2000. When there are gaps in the perceived quality data, we use an average of the two nearest data points.[6] This process seems reasonable because perceived quality changes tend to occur smoothly over time. Overall, we filled 187 gaps constituting less than 10% of our data.

For objective quality, we use quality ratings from *Consumer Reports*. Quality is measured on 100-point scales. These quality ratings have been commonly used in the academic literature (e.g., Tellis and Wernerfelt 1987; Caves and Green 1996; Curry and Riesz 1988). Several factors contribute to the objectivity of *Consumer Reports* quality ratings including rigorous laboratory tests conducted by experts. These tests constitute one of the most elaborate quality rating systems in the world (Thorelli and Thorelli 1977). Also *Consumer Reports* has no

[6] Later, we check the robustness of the results using alternate methods of data interpolation.

allegiance to any business organization, accepts no sponsors or advertisements, and discourages use of its ratings in advertising. As a result, these ratings represent the most trusted objective quality information for consumers (Curry and Faulds 1986; Tellis and Wernerfelt 1987). Since *Consumer Reports* does not test all products every year, we identified those product categories that have been tested more frequently. We found 53 product categories that were tested 4 or more times between the years 1989 (the first year when perceived quality data is available) and 2000. 21 of these product categories were tested 8 or more times during this period. We use the same objective quality rating for each year in our data until a new rating becomes available. In addition, for some product categories, model-level quality is reported. For these products, we collected the rating of the best model for a product as well as the average rating for all models of a product.[7]

In addition to our data on quality, we collected annual, product-level data for price, advertising, and market share, so that we can examine differences in carryover size and duration for different categories and products. For price, we use the retail price as reported in *Consumer Reports*. For advertising data we use *Leading National Advertisers*, which reports annual, product-level advertising expenditures based on audits of seven media - magazines, newspapers, newspaper supplements, network television, spot television, network radio, outdoor, and cable TV. We use *Market Share Reporter* to collect average market share data during the same period.

Variables

Our model's dependent variable is perceived quality and its independent variables are lagged perceived quality, objective quality, and lagged objective quality. Because rating scales

[7] Since these measures are highly correlated ($\rho = 0.87$), we use the best model ratings to represent the objective quality of a product.

and other factors may differ across categories and data sources, we use relative measures for all the variables rather than absolute measures. Since our data contain different numbers of products with different market shares in different categories, simple averages across products (for which data are available) within a category will not be comparable across categories.[8] Thus, the relative measures we use for each variable are the ratio of the variable divided by the average value of the same variable for the two highest market share products in the category. We use the average of the two highest market share products as our reference to be consistent across categories. This approach is in line with earlier research on PIMS data which use an average of three highest market share products.[9] For example, let the objective quality ratings in a particular year for products A, B, C, and D within a category be 60, 40, 50 and 90 respectively. If A and B are the two highest market share products, then the relative objective quality figure for A is 60/50, i.e. 1.2. Similarly, the measures for B, C, and D are 0.80, 1.0, and 1.80 respectively. We compute similar relative measures for perceived quality, price, and advertising.

We operationalize products with a "Quality Increase" or "Quality Decrease" as follows. First, we compute the average change in objective quality across years for each product. Second, we compute the number of times a product has increased or decreased its quality. We use the products in the top quartile and bottom quartile of both measures to arrive at 54 "Quality Increase" products and 49 "Quality Decrease" products.

We identify the "high-reputation brand" products in our data set based on the BusinessWeek rankings of top 100 brands during the years 2000 and 2001. The BusinessWeek

[8] For example, for some categories brands included in our data have a very high cumulative market share (e.g. 87% for diapers) while for others it can be low (e.g., 31% for toilet soaps).

[9] We also used alternate relative measures - market share weighted average, and average of 3 highest market share brands. The correlation of the relative measures for the different variables using these references with the one used average of two highest market share brands in category) range between 0.78 and 0.91 and do not yield any significant differences in terms of aggregate model results.

rankings represent the “economic value of brand reputation” through an asset valuation method that is based on “how much extra a brand is likely to earn going forward” solely on account of its reputation (BusinessWeek Aug 6, 2001, p. 60). Since this measure is only available from 2000, we validate it by using a one-third split of the average (over time) perceived quality ratings. Thus, we arrive at a set of 52 “high-reputation brand” products in our data set.

For “Quality Variance” of a product category, we first calculate the variance of objective quality (over time) for every product in the category. We operationalize “Quality Variance” as the average variance of objective quality across all the products in the category. For “Search Cost” we use an interaction between category-level average price and a dummy variable, which is 0 for ‘unpacked’ goods that can be experienced and evaluated prior to buying at no cost, and 1 otherwise. Therefore, a low “Search Cost” product category will include high-priced products that can be experienced before purchasing (e.g., television) as well as very low-priced product categories that can be experienced at low cost (e.g., dishwashing liquid). We operationalize purchase frequency using an ordinal scale with six levels: once every five or more years, once every two to five years, once every one to two years, once a year, once a month, and weekly or more frequently.

Our overall data set contains annual observations for relative perceived quality and relative objective quality from 1989-2000. In addition, we have average relative price, average relative advertising, and average market share at the product level during the same period. We have dummy variables for “Quality Increase,” “Quality Decrease,” and “High-Brand Reputation” products. We also have time-invariant category-specific variables for quality variance, search cost, and purchase frequency. We include in our data set only products with objective quality and

perceived quality ratings for 4 or more years spanning a period of at least 6 years. This leaves us with a time-series of 241 products in 46 product categories for periods ranging from 6 to 12 years. Overall the data include 1926 observations on objective quality and perceived quality, plus several other important variables.

RESULTS

We begin by presenting descriptive results of our data. Next, we discuss the model results and our findings on each hypothesis. Afterwards, we examine the robustness of our results to certain modeling and data assumptions.

Descriptive Results

Prior research has examined the correlation between price and quality. Although correlations cannot be used to draw inferences about learning, in Table 1 we present these correlations as a point of comparison with previous research.

TABLE 1: Average Cross-Category Correlations
(standard deviations in parentheses)

	OQ - Price Correlation	PQ - Price Correlation	OQ – PQ Correlation
AVG. PRODUCT	0.16 (0.21)	0.31 (0.12)	0.21 (0.14)
AVG. DURABLE PRODUCT	0.20 (0.28)	0.39 (0.11)	0.18 (0.10)
AVG. NON-DURABLE PRODUCT	0.07 (0.13)	0.11 (0.15)	0.29 (0.21)

Across products in all categories, we find that the price-objective quality correlation is 0.16. The correlation for durable products in our data is 0.20 and that for non-durables is 0.07. These findings are similar to results from many previous studies (Morris and Bronson 1969; Oxenfeldt 1950; Riesz 1978; Sproles 1977). In these studies, correlations range from 0.26 to 0.29 for durable goods and 0.01 to 0.09 for non-durable goods. In addition to the results in Table 1, we compute price-objective quality correlations at the product category level for all categories with 6 brands or more. We find negative correlations in 9 of 23 categories (6 durables, 3 non-durables). These results are consistent with previous findings of negative price-objective quality correlations in some categories (Lichtenstein and Burton 1989; Tellis and Wernerfelt 1987).

We also compute the correlation between price and perceived quality. Many studies in consumer behavior find the existence of a "price-quality schema" among individuals (Peterson and Wilson 1985; Rao and Monroe 1988). This suggests that the correlation of price with perceived quality should be higher than that with objective quality. As expected, based on our data, we find a correlation of 0.31 between price and perceived quality, which is indeed higher than the price-objective quality correlation of 0.16. Curiously, this overestimation is higher for durables (0.39 vs. 0.20) than for non-durables (0.11 vs. 0.07). We also find a correlation of 0.21 between objective quality and perceived quality, which is similar to that of earlier studies (Bolton and Drew 1991a; Lichtenstein and Burton 1989).

Changes in Objective Quality and Perceived Quality

Although many earlier studies assumed quality to be constant over time, we find significant changes in objective quality in our data. A paired difference test between the objective quality in the first and last years of our data shows that the change is significantly different from zero ($p<0.01$).

Also, we find that the variance of objective quality is significantly higher than the variance in perceived quality ($p<0.01$). It might be argued that even though we use relative measures, this result might be partially driven by the raw scales that are 0-100 for objective quality and 0-10 for perceived quality. Thus we count the number of times there is a change in ranks of products for objective quality versus the same for perceived quality in our data set. The total number of transitions for objective quality is 121 versus only 34 for perceived quality, thus indicating more variance in perceived quality. The smaller variance in perceived quality is further evidence of delay in updating perceptions of quality.

Model Results

Short-term and Long-term Effects

In the third column of Table 3, we report the estimates of our aggregate model.

Table 2: Aggregate Model Estimates

Variables	Parameters	Base Model (Equation 8)	Heteroscedasticity adjusted	Random Effects with Autocorrelation (ARMA) [2]
Intercept	a_0	-0.018*	NS	NS
PQ_{t-1}	a_1	0.69***	0.69***	0.60***[1]
OQ_t	a_2	0.086*	0.067*	0.16***[1]
OQ_{t-1}	a_3	0.16***	0.14**	0.052*[1]
No. of observations		1685	1602	1361
Adj. R^2		0.39	0.41	0.23

Contemporaneous Effects[3]	0.086*	0.067**	0.16***
Short-Term Effects[3]	0.25***	0.21**	0.21***
Long-Term Effects[3]	0.80**	0.67**	0.53**
Carryover Duration[3]	7.99 years	8.02 years	5.14 years

[1] Parameters obtained are for instrumental variables
[2] For this model $\rho = 0.22$
[3] See Equations 5 and 7
* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$

Since the Goldfeld-Quandt test of heteroscedasticity rejects the homoscedastic null hypothesis for the aggregate model, we use jackknifing techniques to identify products with large average residuals (Sayrs 1989). We isolate these products sequentially and repeat the Goldfeld-Quandt test till the homoscedastic null is accepted. Thus, we re-estimate Equation 8 without 11 such products and report the results in the fourth column. Overall, these estimates are quite consistent with the base model estimates. Next, we examine the auto-correlation function and partial autocorrelation function of the error term in the heteroscedasticity adjusted model.[10] We find a single-peaked PACF indicating a one-period lag effect. Thus, we use a first-order ARMA variation in the error structure:

$v_t = \rho v_{t-1} + \xi_t$, where v_t is as defined in (8), distributed $N(0,\sigma^2{}_v\varphi)$, and $\sigma^2{}_v = \sigma^2{}_\xi / (1-\rho^2)$.

We present the estimates of this EGLS-ARMA model in the last column of Table 2. Compared to the base model, the parameter for objective quality is lower and the parameter for lagged objective quality is higher.

Across the three estimations, we find statistically significant comtemporaneous effects, short-term effects, and long-term effects. These results support H1a, H1b, and H2a. The significant parameter for lagged objective quality indicates non-monotonic carryover effects. Overall, we find that the contemporaneous effect is about 10% of the change in objective quality and constitutes, on average, 19% of the long-term effect. Also, the short-term effect constitutes about 35% of the long-term effect resulting in a carryover duration that is between 5 and 8 years. This means, the size of the long-term carryover (given by the difference between long-term effects and short-term effects) is greater than the size of the short-term effects. This result supports H2b.

Increase and Decrease in Quality

We now report results for the 54 "Quality Increase" products and 49 "Quality Decrease" products (as described in the Data section). The third column of Table 3 contains the estimation results of the hierarchical linear model for Equations 9.1, 9.2a, and 9.3.

Table 3: Disaggregate Model Estimates: Product and Category Effects

Variable	Para-meter	Quality Increase vs. Quality Decrease (9.1, 9.2a, 9.3)	Quality Increase (High Reputation vs. Low reputation) (9.1, 9.2b, 9.3)	Quality Decrease (High Reputation vs. Low reputation) (9.1, 9.2c, 9.3)
Intercept	b_0	-0.013*	NS	-0.0081*
PQ_{t-1}	η_{001}	0.67***	0.79***	0.55***
OQ_t	η_{002}	0.16**	0.031*	0.17***
OQ_{t-1}	β_{03}	0.10***	0.083***	0.11*
Increase	β_{11}	NS	-	-
	β_{12}	-0.096***	-	-
Increase*HR	β_{21}	-	-0.13*	-
	β_{22}	-	0.058***	-
Decrease*HR	β_{31}	-	-	0.091**
	β_{32}	-	-	NS
Avg. Relative Price	β_{41}	NS	NS	NS
	β_{42}	-0.040*	-0.064**	NS
Avg. Relative Advertising	β_{51}	NS	NS	NS
	β_{52}	NS	NS	NS
Quality Variance	η_{101}	-0.022*	NS	-0.019**
	η_{102}	0.011**	0.014***	0.0088*
Purchase Frequency	η_{201}	-0.0034*	NS	-0.0071***
	η_{202}	NS	NS	NS
Search Cost	η_{301}	NS	NS	NS
	η_{302}	NS	NS	NS
No. of observations		759	422	337

* $p \le 0.10$, ** $p \le 0.05$, *** $p \le 0.01$

Based on the model estimates in Tables 2 and 3, we compute the mean and variance of the function of parameters that depict our hypotheses (see Appendix for details). In Table 4, we present these results:

[10] We cannot use the Durbin Watson d statistic because of lagged variables in the model.

TABLE 4: Summary of Hypotheses Conditions and Results[1,2]

H1a	$a_2 > 0$	0.16***	**H1b**	$a_3 > 0$	0.05*
H2a	$(a_2 + a_3)/(1 - a_1) > 0$	0.53**	**H2b**	$a_1 > 0.5$	0.69***
H3a	$\beta_{12} < 0$	-0.10***	**H3b**	$\eta_{001}\beta_{12} + \eta_{002}\beta_{11} + \beta_{11}\beta_{12} + \beta_{11}\beta_{03} - \eta^2_{001}\beta_{12} - \beta_{11}\beta_{12}\eta_{001} < 0$	NS
H4a	$\beta_{22} > 0$	0.06***	**H4b**	$\eta_{001}\beta_{22} + \eta_{002}\beta_{21} + \beta_{21}\beta_{22} + \beta_{21}\beta_{03} - \eta^2_{001}\beta_{22} - \beta_{21}\beta_{22}\eta_{001} < 0$	-0.007**
H5a	$\beta_{32} < 0$	NS	**H5b**	$\eta_{001}\beta_{32} + \eta_{002}\beta_{31} + \beta_{31}\beta_{32} + \beta_{31}\beta_{03} - \eta^2_{001}\beta_{32} - \beta_{31}\beta_{32}\eta_{001} > 0$	0.012*

[1] Aggregate results based on ARMA model
[2] See Appendix for derivation of these conditions
* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$

These results indicate that a relative decrease in quality has a larger short-term effect than a relative increase in quality ($\beta_{12} = -0.096$ with $p<0.01$), thus supporting H3a. The mean size of the short-term effect for a relative decrease in quality is 1.6 times that of an equivalent increase. In terms of the long-term carryover of a decrease in quality, even though the computed parameter has the right sign, the effect is not significant. Thus, we do not find support for H3b.[11] Overall, we find that customers disproportionately lower their perceptions for decreases in quality in the short term. Since firms will generally promote increases in quality, but not decreases, these results underscore the importance of word-of-mouth and media reports.

Brand Reputation

Now, we report results for the 52 “high-reputation” products in our data (as described in the Data section). Based on our hypotheses, we examine these reputation effects with both “Increasing Quality” and “Decreasing Quality” products. The HLM estimates of equations 9.1, 9.2b, 9.2c, and 9.3 are reported in the fourth and fifth columns of Table 4.

For increasing quality, we find a significantly positive short-term effect for high-reputation products ($\beta_{22} > 0$ at $p<0.01$), thus supporting H4a. We also find that the long-term carryover is significantly smaller ($p<0.05$) for high-reputation brands that are increasing in quality, thus supporting H4b.

For decreasing quality, we do not find a significant short-term effect for high-reputation products. Thus, we do not find support for H5a. However, we do find that the long-term carryover is marginally larger ($p<0.1$) for high-reputation brands that are decreasing in quality, thus supporting H5b.

Overall, our findings provide support for an important asymmetry between high-reputation products and lower-reputation products. High-reputation products have larger short-term returns for increases in quality, but are not penalized more for decreases in quality in the short-term. Such asymmetry is also reflected in the carryover duration. High-reputation products are rewarded 3 years sooner for an increase in quality and penalized 1 year later for a decrease in quality. This difference provides an additional 4 years of reaction time for the high-reputation products in our data.

Role of Price and Category Characteristics

In addition to the asymmetry in reputation effects, we have several interesting findings on price and two of the three category characteristics – quality variance and purchase frequency. First, we find that lower-priced products have significantly larger short-term effects, particularly when quality is increasing ($\beta_{42} < 0$ at $p<0.05$). The results also indicate that for product categories with high quality variance, the short-term effects are significantly larger ($\eta_{102}>0$ at $p<0.05$) and the long-term carryover is significantly smaller ($\eta_{101}<0$ at $p<0.1$) Also for more frequently purchased product categories, the long-term carryover is significantly smaller ($\eta_{201}<0$ at $p<0.1$). These results indicate that the adjustment in perceptions is relatively faster in categories with higher quality variance and higher purchase frequency. Therefore, markets, on the aggregate, act as a learning organization on both counts. For example, the potential of long-

[11] One reason that the difference in long-term carryover is not significant may be because of the operationalization

term adjustment in perceptions is relatively smaller in frequently purchased categories in which short-term learning potential is high. Similarly, higher quality variance denotes higher uncertainty in the long-term that may lead to markets being more responsive to changes in quality in the short-term.

Robustness of the Results

The longitudinal nature of our study, the large number of product categories, and the different data sources present potential challenges in identifying robust results. Although we do control for certain biases like autocorrelation and heteroscedasticity, other potential estimation-related and data-related concerns remain. These include non-stationarity, data interval bias, omitted variables, and measurement bias.

In fact, a Levin and Lin panel data unit root test on the objective quality data is unable to reject the non-stationary null hypothesis (Levin and Lin 1992). Even though Levin and Lin is an extremely conservative test,[12] we estimated the following first-difference model to evaluate the robustness of our estimated parameters.

$$PQ_{jt} - PQ_{jt-1} = a_1 * IV(PQ_{jt-1} - PQ_{jt-2}) + a_2 * (OQ_{jt} - OQ_{jt-1}) + a_3 * IV(OQ_{jt-1} - OQ_{jt-2}) + (\varepsilon_{jt} - \varepsilon_{jt-1})$$

We use PQ_{jt-2} and OQ_{jt-2} as instruments for $(PQ_{jt-1} - PQ_{jt-2})$ and $(OQ_{jt-1} - OQ_{jt-2})$ respectively (Arellano 1989). While the significance of the parameters are reduced, the results of this model show that that any possible non-stationarity of objective quality is not affecting our estimates of short-term and long-term effects. For example, both the short-term effects (0.21 with $p<0.1$) and long-term effects (0.89 with $p<0.05$) fall within one standard error of the estimates of the random

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of the decrease in quality as a relative measure.

[12] A major limitation of the Levin and Lin test is that "the alternative (hypothesis) is too strong to be held in any interesting empirical cases… and rarely of practical significance" (Maddala and Wu 1999).

effects model in Table 2. These results are consistent with Pesaran and Shin (1999) and Binder et al. (2000), who show that as the number of cross-sections increase, autoregressive distributed lag models yield asymptotically consistent parameter estimates irrespective of stationary or non-stationary regressors.

To account for non-autocorrelated unobservable factors, we use lagged values of the regressors, based on the obvious assumption that the future cannot cause the past (Jacobson 1990). Therefore, we estimate:

$$PQ_{jt} = a_0 + a_1 PQ_{jt-2} + a_2 OQ_{jt-1} + a_3 OQ_{jt-2} + u_j + v_t + \hat{e}_{jt}$$

The estimated short-term effect in this model (0.17) is virtually identical with the ARMA model reported in Table 2 (0.16). The long-term effect in this model (0.82) is within one standard error of the ARMA model (0.53).

Studies that examine longitudinal effects are also prone to data interval bias. Specifically, the parameter estimates are biased upwards or downwards depending on the interval in which changes in quality actually take place and the interval data is collected (Clarke 1976). One way of examining the extent of data interval bias is through data aggregation, i.e., estimating the model based on 2-year-interval data, 3-year-interval data, and so on. Because of our relatively short time-series, we first aggregate our data to evaluate a 2-year interval. Then, we expand our data set through interpolation to evaluate a 6-month interval. Since interpolation is based on existing data, we use three different kinds of 6-month interpolations – quick change, average change, and slow change. In the quick change interpolation, the interpolated data point is equal to the later actual data point. In the slow change, the interpolated data point is equal to the earlier actual data point. The average interpolation is based on the average of the earlier and later actual data points. Based on the estimates of the 2-year interval and 6-month interval models, we find that the short-term effect ranges between 0.17 and 0.24, while the long-term carryover ranges between 0.69 and 0.84. These estimates provide a reasonable range for the magnitude of the short-term and long-term effects of quality.

To evaluate other potential data concerns, we conduct three additional tests. First, our model assumes that perceived quality is caused by objective quality. Although this assumption is based on previous research, it is possible that expert ratings may, in fact, be based on prior perceptions of quality (Zeithaml 1988). Therefore, we use Granger tests to examine causality in our data. Based on the double pre-whitening method, we find that a higher cross-correlation exists between the residuals of perceived quality and objective quality at a positive lag (Hanssens and Parsons 1993). This result is consistent with objective quality causing perceived quality.

Second, we use alternate methods to complete gaps in the objective quality data to see if the results are sensitive to these changes. Specifically, we use the fits from a linear regression to complete the gaps and re-estimate the random effects model. None of the parameters in (8) are significantly different from our original estimates.

Third, if there are systematic errors in measuring objective quality, the error term will not be independent of objective quality, thus leading to biased estimates. Therefore, we use the Durbin method of using ranks as instrumental variables for objective quality. The parameter of the lagged perceived quality variable in this model is not significantly different from (8). This result leads us to conclude that measurement error in objective quality is not a significant problem in our data.

Overall, the stability of the parameter estimates under all these different conditions leads us to believe that our results are fairly robust.

DISCUSSION

We conclude by summarizing our primary findings, discussing their implications, and suggesting directions for future research.

After an extensive data collection effort, we have the objective quality, perceived quality, price, advertising, and market share data for 241 products in 46 product categories over a period of 12 years. These data provide the basis for our empirical results. In particular, we find that:

- There is a significant long-term carryover effect of quality on customer perceptions of quality that is more than twice the short-term effect and five times the contemporaneous effect. On average, we find that the effect of a change in objective quality on customer perceptions of quality persists over a period as long as five to seven years.
- The effect of quality is asymmetric in terms of increases and decreases in quality. A decrease in quality has larger short-term and long-term effects and is more quickly perceived than an equivalent increase.
- With high-reputation products, the short-term effect of an increase in quality is larger and the long-term carryover is smaller relative to lower-reputation products. But for a decrease in quality, we do not find significant differences in the short-term although the long-term carryover is larger for higher-reputation products.
- There are significant differences in the size and duration of quality effects for different products depending on category-level quality variance and purchase frequency. We also find that lower-priced products have larger short-term effects with increasing quality.

We believe that these asymmetries in our data are likely to be even stronger in practice because the lower-reputation products are all fairly well-known national or regional brands. As such, less well-known brands would likely extend the lower bound of our reputation measure. Similarly, quality is a relative measure in our study. Thus, some of our declines in quality are only because other brands increased quality. If we could isolate absolute quality decreases, we expect our effects would be even stronger.

Implications

Our findings have several implications for managers and researchers. First, our study demonstrates the importance of objective quality in driving customer perceptions of quality. It also provides estimates of how long it takes for objective quality to impact perceived quality. To provide some additional insights, we estimate Equation (8) using OLS for all categories in which we have data for at least four products over a time period of eight years or more. In Table 6, we report the effect sizes and carryover durations for the ‘average’ product in each category.

TABLE 5: Quality Carryover in Product Categories

Product Category	Short-Term Effects[a]	Long-Term Carryover[a]	Carryover Duration[a]
Auto Tire	0.06	0.39	9.5 years
Clothes Washer	0.30	0.51	5.4 years
Color Television	0.27	0.69	5.7 years
Dishwasher Detergent	0.27	0.54	5.1 years
Dishwashing Liquid	0.31	0.49	3.3 years
Disposable Diaper	0.41	0.86	3.1 years
Laundry Detergent	0.11	0.34	5.9 years
Personal Computer	0.42	0.67	3.3 years
Refrigerator	0.21	0.56	7.1 years
Room Air conditioner	0.37	0.81	5.0 years
Sneaker	0.09	0.36	4.0 years
Toothpaste	0.38	0.85	3.9 years
Vacuum Cleaner	0.39	0.72	4.6 years

[a] Refer to equations 5, 6, and 7

While providing rough benchmarks, these results also confirm that there are substantial differences among product categories in effect sizes and carryover durations. Some of these category-level differences may be partly responsible for the differences in the shape of the product life cycle and in the number of products in different product categories (Bohlmann, Golder, and Mitra 2002; Golder and Tellis 2004; Villas-Boas 2004).

Similarly, with adequate data, carryover duration can be computed at the product level. For example, there is speculation about a change in perceived quality for Mercedes Benz cars in the context of the recent quality problems. An auto analyst comments, “…your (their) brand cachet would only begin to suffer if you (they) maintained a (quality) position below average over an extended period …” (New York Times July 8, 2003). Our study provides strong rationale for managers to track both objective quality and perceived quality over time to better understand the duration of this period.

Second, the asymmetry of time lags between different brands throws new light on the differential advantage of brand reputation. Our results show that there are extra benefits for high-reputation brands in terms of the dynamics of customer perceptions. Estimates of this time advantage can be one way of operationalizing the "resilience" component of brand equity and can be used to determine optimal competitive response time (Bowman and Gatignon 1995; Keller 1993). Some companies may already understand the effect of this duration asymmetry. For example, "companies like Cisco, Intel, and Microsoft do not need to be first or best anymore, it's enough (for them) to be observant and nimble" (Wall Street Journal August 8, 2003).

Third, the quality strategy of a product must be integrated with its marketing strategy. The same improvement in quality that is profitable for one product may be unprofitable for another product because of a different lag structure. Though not conclusive, our results also indicate that price itself may have a significant impact on the size and duration of the effects of quality. In particular, lower-priced products have relatively higher short-term effects of quality than higher-priced products, particularly for increases in quality. This result has significant implications for the management of store brands and national brands (Pauwels and Srinivasan 2004).

Fourth, we find that significant changes in quality have occurred during the period of our study. It appears that customers are learning about past changes in quality even as current changes are taking place. Thus, even though at no point in time do the customers behave efficiently, the very fact that customers do learn creates a force promoting quality competition

(Moorman 1998). As a result, low correlations between price and quality that have been reported by many studies may not be indicative of market inefficiency, at least in the long term.

The fifth implication of our study is about the evolution of products. Earlier studies found that about 30% of products in "mature" categories have evolving market shares even though they do not have evolving marketing expenditures (Lal and Padmanabhan 1995). Our results suggest that such evolution may be due to continuous changes in quality.

Sixth, our study has important implications regarding the sustainability of competitive advantages in the strategy area. In particular, there is a question about whether any advantage can be sustained in a fast-changing world (Barney 1991; D'Aveni 1994; Lippman and Rumelt 1982; Wernerfelt 1984). This study shows that at least limited sustainability can be achieved through asymmetries and lags in customer perceptions of quality. Smart companies can build on this sustainability by using their time advantage to attack as well as defend.

Finally, our results on the short-term and long-term effects of quality can be extended to settings other than physical products. For example, we examined quality in the context of business schools and airlines. The carryover duration for airlines (about 4 years) is shorter while that for business schools is much longer (about 13 years) than the average product in our study.

Directions for Future Research

Our study's findings as well as its limitations provide several opportunities for future research. First, we use a market-level aggregate model to understand the effects of quality. While this approach enables us to look at several product and category-level effects, future research can use panel data to examine the long-term effects of quality at the individual level. In particular, it will be interesting to examine the role of quality on the price-sensitivity and advertising sensitivity of individuals (Mela et al. 1997; Parsons 1975; Simon 1979).

Second, future researchers could use alternative measures of objective quality. A disaggregated measure of quality at the attribute level may reveal important differences in the lag structures for different quality attributes. Another possibility is to compute objective hedonic prices of attributes that could also be combined to arrive at the product-level objective quality measure (Bajic 1993; Combris et al. 1997; Griliches 1971). This approach could also alleviate the problem of using ratings from different data sources across different time periods. Thus, we can understand the effect of a "true" decrease in quality versus that of a "relative" decrease in quality as reported in this study.

Third, as in other longitudinal studies, our results may suffer from data interval bias. Both more frequent measures and longer data series would help to evaluate this potential problem. However, in our study, including the lagged independent variable (lagged objective quality) is a simple method of adjusting for this bias (Russell 1988). Also, since quality improvements are unlikely to occur more frequently than a year, data interval bias is less likely to create a positive bias in our case (Clarke 1976). Finally, our analysis of different intervals suggests that the results are fairly robust to this potential problem.

Finally, future studies should use additional reputation measures in order to decompose the asymmetric effects on perception into brand size and brand reputation components. Unfortunately, in spite of the strategic importance of reputation, longitudinal data are hard to find. For example, the broad measure of reputation used in this study is positively correlated with market share (0.38). Yet, the relative effects of reputation and size on perceptions of quality are not identical – particularly for decreases in quality.[13] These results call for empirical research on both the determinants and measurement of brand reputation. One way to understand reputation is to conduct archival studies on the evolution of different brands in a product category. Such studies could potentially provide a link between the literature on long-term market leadership and our findings on asymmetric carryover effects.

[13] When market share is used instead of reputation in equations 9.2b and 9.2c, we find that large market share brands have a higher short-term effect for an increase as well as a decrease in quality, which contrasts with the results for high reputation brands.

APPENDIX: Derivation of Hypotheses Conditions

For Hypothesis 1a, $a_2 > 0$

For Hypothesis 1b, $a_3 > 0$

For Hypothesis 2a, $(a_2 + a_3)/(1 - a_1) > 0$ (A)

For Hypothesis 2b,
Long-Term Carryover > Short-Term Effects
$a_1 (a_2 + a_3)/(1 - a_1) > (a_2 + a_3)$
i.e., $a_1 /(1 - a_1) > 1$
i.e., $a_1 > 0.5$

For Hypothesis 3a,
$(\eta_{002} + \beta_{03} + \beta_{12}) < (\eta_{002} + \beta_{03})$
i.e., $\beta_{12} < 0$

For Hypothesis 3b,
$(\eta_{001} + \beta_{11}) (\eta_{002} + \beta_{03} + \beta_{12}) / [1 - (\eta_{001} + \beta_{11})] < \eta_{001} (\eta_{002} + \beta_{03}) / [1 - \eta_{001}]$
i.e., $[(\eta_{001} + \beta_{11}) (\eta_{002} + \beta_{03} + \beta_{12}) / [1 - (\eta_{001} + \beta_{11})]] - \eta_{001} (\eta_{002} + \beta_{03}) / [1 - \eta_{001}] < 0$
Simplifying,
$\eta_{001}\beta_{12} + \eta_{002}\beta_{11} + \beta_{11}\beta_{12} + \beta_{11}\beta_{03} - \eta^2_{001} \beta_{12} - \beta_{11}\beta_{12}\eta_{001} < 0$ (B)

For Hypothesis 4a,
$(\eta_{002} + \beta_{03} + \beta_{22}) > (\eta_{002} + \beta_{03})$
i.e., $\beta_{22} > 0$

For Hypothesis 5a,
$(\eta_{002} + \beta_{03} + \beta_{32}) < (\eta_{002} + \beta_{03})$
i.e., $\beta_{32} < 0$

For Hypothesis 4b,
$(\eta_{001} + \beta_{21}) (\eta_{002} + \beta_{03} + \beta_{22}) / [1 - (\eta_{001} + \beta_{21})] < \eta_{001} (\eta_{002} + \beta_{03}) / [1 - \eta_{001}]$
i.e., $[(\eta_{001} + \beta_{21}) (\eta_{002} + \beta_{03} + \beta_{22}) / [1 - (\eta_{001} + \beta_{21})]] - \eta_{001} (\eta_{002} + \beta_{03}) / [1 - \eta_{001}] < 0$
Simplifying,
$\eta_{001}\beta_{22} + \eta_{002}\beta_{21} + \beta_{21}\beta_{22} + \beta_{21}\beta_{03} - \eta^2_{001} \beta_{22} - \beta_{21}\beta_{22}\eta_{001} < 0$ (C)

For Hypothesis 5b,
$(\eta_{001} + \beta_{31}) (\eta_{002} + \beta_{03} + \beta_{32}) / [1 - (\eta_{001} + \beta_{31})] > \eta_{001} (\eta_{002} + \beta_{03}) / [1 - \eta_{001}]$
i.e., $[(\eta_{001} + \beta_{31}) (\eta_{002} + \beta_{03} + \beta_{32}) / [1 - (\eta_{001} + \beta_{31})]] - \eta_{001} (\eta_{002} + \beta_{03}) / [1 - \eta_{001}] > 0$
Simplifying,
$\eta_{001}\beta_{32} + \eta_{002}\beta_{31} + \beta_{31}\beta_{32} + \beta_{31}\beta_{03} - \eta^2_{001} \beta_{32} - \beta_{31}\beta_{32}\eta_{001} > 0$ (D)

For deriving the variance of the functions of the parameters as in A-D, we use Cramer's theorem:
If $\phi = g(.)$
$\text{Var}(\phi) = \dot{g}' \sum \dot{g}$,
where $\dot{g}$ = row vector of the first partial derivatives of function g,
$\dot{g}'$ = column vector of the first partial derivatives of function g, and
$\sum$ = variance covariance matrix of the parameters

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