The Formation of Market-Level Expectations and Its Covariates

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A formal model of market-level expectations is developed and used to identify testable hypotheses. The empirical findings indicate that market-level expectations are more adaptive in nature than previously thought. The study also provides the first systematic investigation of cross-industry variation in the formation of market-level expectations. Several factors, including advertising, word-of-mouth, market growth, and purchase frequency, are found to have a significant moderating influence on the adaptation rate. Finally, we find that market-level expectations adjust faster when perceived quality declines, suggesting that negativity biases manifest at a macrolevel—a phenomenon that has not been previously observed.

Auto manufacturers in the United States continue to express concern over how long it takes public perception to catch up with objective improvements. Government agencies wonder when efforts to improve customer service will translate into greater public confidence in the quality of service they provide. Airlines engaged in reducing service levels in order to control costs must consider how long it will take passengers’ expectations about service quality to depreciate.

The rate at which the market’s expectations adapt has important implications for firms considering investments in quality, as well as for managers assessing the ramifications of a drop in quality for their firm’s future. Empirical findings on the formation of market-level expectations—the aggregate expectations of consumers for a particular good or service provider—suggest relatively little weight is placed on recent information about product or service quality (Anderson, Fornell, and Lehmann 1994; Johnson, Anderson, and Fornell 1995). Yet, it seems intuitive that recent information about quality should often be given considerable weight, such as when a market is evolving rapidly or quality is declining precipitously.

The purpose of this study is to provide the first systematic theoretical and empirical investigation of the formation of market-level expectations and its covariates. In doing so, it builds on and extends previous work in several ways. First, we develop a formal model of the formation of market-level expectations and use it to identify potential moderating factors. Second, we apply a more appropriate methodology accounting for firm- and industry-level heterogeneity and find that the rate at which market-level expectations adapt is roughly twice as great as indicated by Anderson et al. (1994) and Johnson et al. (1995). Hence, whereas they conclude that the formation of market-level expectations is largely rational and stable, we find the process to be significantly more adaptive in nature. Third, we find that several factors—market growth, advertising and word-of-mouth levels, and frequency of experience with current quality—have a significant moderating influence on the adaptation rate. Finally, we find that greater weight is placed on recent experience when perceived quality declines, suggesting that negativity biases manifest at a macrolevel.

BACKGROUND ON MARKET-LEVEL EXPECTATIONS

The formation and revision of expectations is a central theoretical issue for consumer research (Oliver and Winer 1987). For a complete review of the expectations literature, readers are encouraged to see Oliver and Winer’s (1987) comprehensive review of the area, as well as Johnson et al.’s (1995) discussion of market-level expectations. In this section, we briefly review individual- and market-level expectations.

In consumer research, the most frequent context in which expectations are studied is pricing (e.g., Krishna 1992; Winer 1986). Expectations are also found to play a role in other
consumer evaluations such as expected promotion size (Blattberg et al. 1978), promotion frequency (Krishna, Currin, and Shoemaker 1991), purchase quantity (Neslin, Henderson, and Quelch 1985), message order (Hautvedt and Wegener 1994), product quality (Meyer 1981), and service quality (Boulding et al. 1993). The ubiquitous role of expectations in consumer evaluations and choice is not surprising, given that consumer evaluations and choice are inherently tied to reference points and context (Bettman 1979; Howard and Sheth 1969). Beyond consumer research, reference points and their formation play roles in a broad range of human decision-making behavior (Hogarth and Einhorn 1992).

There is increasing interest in market-level expectations in consumer research. Anderson et al. (1994) posit that the market should consider all available information concerning quality and update market-level expectations based on both past experience and external sources of information. Further, the updating process should be as efficient as possible, given imperfections (e.g., uncertainty, costs) that impede the flow of information. Hence, market-level expectations should exhibit a small, adaptive component. Johnson et al. (1995) test the adaptive hypothesis against a series of alternative specifications for modeling expectations. Both studies find that expectations adjust over time in an adaptive manner as hypothesized.

The focal unit of analysis throughout this study is market-level expectations. Johnson et al. (1995) provide an extensive discussion of the rationale for pursuing market-level analysis, arguing that there is much to gain from augmenting existing individual-level studies. Attitudes and behavior of individuals are often driven by situational and contextual factors that make it challenging to establish useful empirical generalizations. Aggregation may improve reliability by averaging out those individual-level errors and biases that are random. For example, individual-level, time-series studies often find little or no relationship between attitudes and subsequent behavior, yet such relationships are relatively clear and appear robust in aggregate, cross-sectional analyses (Katona 1979).

In moving to a market-level unit of analysis, however, it is important to be aware of potential theoretical and empirical pitfalls inherent in such a transition. In particular, one must avoid incorrectly anthropomorphizing collective activities, which is the misattribution of individual human characteristics and processes to higher-level units of analysis, such as segments and markets. Aggregation requires assuming homogeneity regarding the object evaluated and requires that important systematic differences across individuals are not masked. For example, average leadership style works as a measurable construct if a leader’s style is assumed to be constant across all group members (Rousseau 1985). Applying this criterion to the current study, it seems reasonable to aggregate over individuals to measure overall quality perceptions, given that a firm’s offering can be considered constant at any point in time although individual customer perception may, of course, vary.

### A MODEL OF MARKET-LEVEL EXPECTATIONS

We employ a Bayesian approach to modeling market-level expectations. Bayesian decision theory has proven useful in modeling expectations at the individual level (Anderson and Sullivan 1990, 1993; Rust et al. 1999), and we posit that the same approach should also provide an informative model of the underlying mechanism at the market level for several reasons. First, preexisting expectations about quality are modeled as a prior distribution, $N(E_{t-1}, \tau^2_{t-1})$. This captures the market’s historical experience with quality in a way that provides both a mean for expectations, $E_{t-1}$, and an estimate of the expected variance in future quality, $\tau^2_{t-1}$ (Anderson and Sullivan 1990, 1993). Hence, throughout this section, expectations is a random variable described by the mean and variance of a prior and posterior distribution.

Second, recent quality information is modeled as a likelihood, $N(Q_{t-1}, s^2_{t-1})$. The likelihood captures variation in production and consumption (Anderson 1994; Anderson and Sullivan 1990, 1993; Rust et al. 1999), as well as nonexperiential information (e.g., advertising, word-of-mouth, etc.). For example, on the production side, if a good or service is difficult to standardize, variance in perceived quality is likely to be greater. Similarly, on the consumption side, if consumers use a good or service in a variety of different contexts, variance may increase.

Finally, the revised expectation is represented by the posterior distribution, $N(E_{t}, \tau^2_{t})$. It also allows a role for nonexperiential information, such as advertising, word-of-mouth, or media reports regarding quality (Rust et al. 1999). The standard equations for updating the posterior mean—or expected value for expectations—and variance of expectations are written as follows:

$$E_t = \frac{(1/\tau^2_{t-1})E_{t-1} + (1/s^2_{t-1})Q_{t-1}}{(1/\tau^2_{t-1}) + (1/s^2_{t-1})};$$  \hspace{1cm} (1)

$$\frac{1}{\tau^2_t} = \frac{1}{\tau^2_{t-1}} + \frac{1}{s^2_{t-1}}.$$  \hspace{1cm} (2)

Equation 1 represents the updating process for the expected value of expectations. Other information about quality is captured in the manner depicted by equation 2, which provides the updating formula for the variance of expectations expressed as the posterior precision. This expression captures the precision associated with the posterior expected value of expectations. In effect, it represents the confidence with which expectations are held, and we will refer to it as such throughout the remainder of the article.

Taken together, these two expressions serve to formalize our approach to the question of when the prior expected value, $E_{t-1}$, should be expected to dominate the formation of posterior expectations and when recent experience,
$Q_{t-1}$, should matter more. To see this, define the coefficient of adaptation, $\pi$, as follows:

$$\pi = \frac{(1/s_{t-1}^2)}{(1/\tau_{t-1}^2) + (1/s_{t-1}^2)}.$$ (3)

Substituting the above expression into the expression for expectations formation given in equation 1 yields an expression in the familiar form of the classic updating equation:

$$E_t = (1 - \pi)E_{t-1} + \pi Q_{t-1}.$$ (4)

Hence, equations 3 and 4 provide insight into when greater weight should be placed on recent experience with quality, $Q_{t-1}$, as opposed to the preexisting mean of expectations, $E_{t-1}$. The weight placed on the prior mean ($E_{t-1}$) is determined by the relative confidence with whichprior expectations are held ($1/\tau_{t-1}^2$) versus confidence regarding recent experience with observed quality ($1/s_{t-1}^2$). As confidence in prior expectations increases (or confidence in current information falls), the prior mean should dominate, and the weight placed on current experience should decrease ($\pi \downarrow$). As confidence in current quality information increases or confidence in prior expectations decreases, current perceived quality should receive greater weight ($\pi \uparrow$).

We formalize the above reasoning in the following proposition:

**Proposition 1.** As confidence in prior expectations increases (decreases) relative to confidence in current experience, the formation of expectations will place greater (less) weight on prior expectations.

**Proof.** As confidence in prior expectations increases ($1/\tau_{t-1}^2$), the size of the coefficient of adaptation is decreasing everywhere, $d\pi/d(1/\tau_{t-1}^2) < 0$. Q.E.D.

**HYPOTHESES**

What factors might lead to greater weight being placed on prior expectations as suggested by proposition 1? Under what conditions might we expect greater weight to be placed on current experience with quality? Figure 1 illustrates our theoretical framework. As shown, prior expectations and recent experience are integrated to form current expectations.

The model’s proposition and its proof suggest that the weighting of current experience versus preexisting expectations should be influenced by the degree of confidence with which prior expectations are held. Greater confidence in prior expectations should result in the market placing greater weight on prior expectations and less weight on the most recent information. As confidence in preexisting expectations decreases, the market should put greater weight on recent experience and less weight on prior expectations. Hence, the coefficient of adaptation should be smaller (larger) when confidence in prior expectations is greater (smaller).

As illustrated in figure 1, we identify six sources of heterogeneity we expect to moderate the market’s degree of
confidence in prior expectations: ease of evaluating quality, the rate of sales growth, research and development (R&D) intensity, advertising intensity, word-of-mouth, and frequency of current experience. In the remainder of this section, we explore the implications of the theoretical framework and develop testable hypotheses.

We expect all sources of covariation to vary considerably across industries. Confidence in prior expectations should be lower when quality is difficult to evaluate, change is rapid, or the frequency of experience is high. One naturally expects all these influences to vary considerably across industries. Similarly, nonexperiential information, via both media and private sources, should be expected to vary considerably across industries (e.g., automobiles vs. canned fruit).

Given that we expect extensive heterogeneity across industries in terms of confidence in prior expectations, we naturally expect considerable heterogeneity in the weighting of current experience relative to prior expectations across industries. We formalize this prediction as:

H1: The coefficient of adaptation should exhibit significant heterogeneity across industries.

In terms of covariates representing sources of heterogeneity, we begin by drawing on the literature pertaining to the economics of information (Stigler 1961). Nelson (1970) categorizes goods and services on the basis of the ease of evaluating quality as either search, for which quality is observable prior to purchase, or experience, for which quality can only be evaluated after purchase, if at all (Darby and Karni 1973). When it is relatively easy to judge quality, we argue that the market should exhibit greater confidence in past experience. Hence, we predict that industries exhibiting search qualities will tend to place greater weight on prior expectations. Conversely, industries where quality is more difficult to judge should place greater weight on current experience relative to previous expectations. We summarize these arguments in hypothesizing the following interaction between perceived quality and ease of evaluating quality:

H2: As the ease of evaluating quality for an industry increases, the coefficient of adaptation should decrease.

Less stable markets—such as those that are relatively new or rapidly changing—should have less confidence in past experience and, therefore, place less weight on such information and greater relative weight on current quality. Fast-evolving markets will naturally have less confidence in prior expectations than markets with greater prior experience with a widely adopted and/or stable good or service. High growth markets will also have a greater proportion of consumers with less experience to rely on in forming expectations. Overall, current experience is likely to be viewed as more relevant and salient (Anderson 1981). Consequently, we expect to observe greater weight placed on current quality in higher growth industries and the size of the coefficient of adaptation should increase. The expected interaction between industry growth and perceived quality can be stated as follows:

H3: As the industry rate of growth increases, the size of the coefficient of adaptation should increase.

A similar argument can be advanced with regard to innovation. Industries with relatively higher R&D spending are likely to have more new product and service offerings. With new products and services, the market is likely to have greater confidence in current experience. Moreover, high R&D industries will have relatively more customers experiencing products and services for the first time than industries with relatively lower R&D spending. This suggests that industries with relatively higher R&D spending should exhibit a higher coefficient of adaptation due to placing greater weight on current quality. The interaction between R&D intensity and perceived quality is formalized in the following hypothesis:

H4: As industry R&D intensity increases, the size of the coefficient of adaptation should increase.

Advertising intensity should be a strong indicator of the degree to which consumers can easily gather product or service information prior to purchase. Information acquisition through advertising is incorporated into consumers’ prior expectations before purchase, presumably as a means of lowering search cost. The result should be increased confidence in prior expectations. As a result, industries with relatively higher advertising spending levels are expected to place less weight on current experience, and we should observe a lower coefficient of adaptation. The hypothesized interaction between advertising and perceived quality is formalized as follows:

H5: As industry advertising intensity increases, the size of the coefficient of adaptation should decrease.

A fifth source of industry heterogeneity is word-of-mouth communications. Word-of-mouth encompasses informal interpersonal communications between consumers about products and services. Any word-of-mouth communication received by a consumer acts as information upon which the consumer can base his or her expectations regarding performance quality. To the extent that new information received via word-of-mouth communications is incorporated into expectation levels, confidence in expectations should be relatively greater and the coefficient of adaptation should be relatively smaller for industries with a higher degree of word-of-mouth communication. Stating the proposed interaction as a formal hypothesis:

H6: As the average level of word-of-mouth for an industry increases, the coefficient of adaptation should decrease.

A final source of industry heterogeneity is the frequency with which the served market experiences the quality of a supplier’s current output. In our model, the number of occasions to experience quality in a given time period increases.
the confidence with which current quality information is viewed. Hence, we naturally predict relatively less weight will be put on prior expectations and greater weight placed on current experience for more frequently purchased goods and services. For example, we expect the market to place greater weight on current quality for telephony, as opposed to items for which current quality is experienced less frequently such as insurance. Stating this final proposed interaction as a formal hypothesis:

**H7:** As purchase frequency increases, the coefficient of adaptation should increase.

For our final hypothesis, we argue that market-level expectations should be more sensitive to decreases in perceived quality, as opposed to increases in perceived quality. A decrease in market-level perceived quality reflects a relatively higher proportion of individuals experiencing decreased quality and/or having a negative quality experience. Under these conditions, we expect two underlying mechanisms to influence the degree to which current quality perceptions are integrated into revised market-level expectations: (1) heavier weighting of lower quality experiences in the updating of expectations at the individual level and (2) greater emphasis on negative quality experiences in public and private communications.

At the individual level, it has long been observed that consumers are more sensitive to losses than to gains (Kahneman and Tversky 1979). Accordingly, we expect consumers to be more sensitive to decreases in perceived quality (losses) than to increases in perceived quality (gains) when updating expectations. At the individual level, negative information is more likely to be diagnostic and accessible (Skowronski and Carlston 1989) and so should be more readily integrated when expectations are formed. As the portion of the served market experiencing lower quality increases, this effect should manifest in the aggregate at the market level.

In addition, we expect bad news from the portion of the served market that has a negative quality experience to travel faster in terms of both private and public communications. At the individual level, a decrease in quality is not only more likely to be recalled (Skowronski and Carlston 1989) but also more likely to be selected for communication and received. In terms of private communications, there may be greater motivation to engage in word-of-mouth when dissatisfied in order to vent hostility (Jung 1959), as well as to reduce anxiety, warn others, or seek vengeance (Allport and Postman 1947; Knapp 1944; Richins 1984). It also seems plausible that public media are more likely to convey information about lower quality, to the extent that they believe their own markets are more sensitive to such communications. Finally, members of the served market are likely to be more receptive to such negative information as it is often viewed as more salient (Taylor 1991), as well as relatively scarce (Lutz 1975).

We formalize the preceding arguments as follows:

**H8:** The coefficient of adaptation should be greater for decreases in perceived quality relative to increases in perceived quality.

**METHODOLOGY**

To test the hypotheses, we require an approach that allows us to incorporate industry heterogeneity into a model of adaptive expectations and to analyze whether there are systematic factors that explain industry heterogeneity in the formation of expectations. A straightforward method for testing the heterogeneity hypothesis is a classic pooled versus un pooled test of the basic updating equation (eq. 4) to determine whether the coefficient of adaptation varies significantly across j firms operating in i industries. However, this standard approach is not viable for several reasons. First, unpooling to the firm level is impractical given the very limited number of data points per firm available to us (four time periods). Second, even pooling to the industry level, the median number of firms per industry is just four, and many are smaller, so industry-level parameters from a simple OLS analysis are not statistically stable. Third, we wish to partition the variance into firm-level, between-firm, and between-industry variances. Ordinary least squares does not allow us to do so. Fourth, we wish to use the set of covariates identified in the process of hypotheses development to explain variance across industries.

Although a random-coefficient model is the most parsimonious methodology that allows us to address the first two issues, and would allow us to partition variance into within and between firms, it does not allow for additional partitions of the variance and, most importantly, it provides no basis for incorporating covariates into the analysis. Hence, we are forced to reject both OLS and random coefficient approaches to testing our hypotheses.

An approach that satisfies our requirements is a Hierarchical Linear Model, or HLM (Bryk and Raudenbush 1992, chap. 2). Hierarchical Linear Model is a method that provides the benefits of pooling without giving up the requirement of estimates of parameters for each industry and firm. From an intuitive standpoint, HLM operates by borrowing information from across firms to improve firm-level estimates of the coefficient of adaptation. In the process, it provides a method of separating variance associated with industry-level differences from variance within industries or within firms, as well as a means of introducing covariates. It is worth noting that HLM subsumes both OLS and random coefficient approaches as special cases. A single level hierarchical model with one common variance component is equivalent to OLS. A two-level hierarchical model with variance partitioned into within- and between-group variance is equivalent to a random coefficients model.

Our hierarchical model of expectations is specified as follows.

$$E_{i,j,t} - E_{i,j,t-1} = \pi_{i0} + \pi_{i1}(Q_{i,j,t-1} - E_{i,j,t-1}) + \epsilon_{i,j,t} \quad \epsilon_{i,j,t} \sim N(0, \sigma^2)$$  (5.1.1)
\[ \pi_{ijt} = \beta_{ij} + r_{ijt} \quad r_{ijt} \sim N(0, \tau_{ij0}); \] (5.2.1)

\[ \pi_{ij} = \beta_{i1} + r_{ij} \quad r_{ij} \sim N(0, \tau_{i1}); \] (5.2.2)

\[ \beta_{ii} = \gamma_{i0} + \mu_{ii} \quad \mu_{ii} \sim N(0, \tau_{ii0}); \] (5.3.1)

\[ \beta_{ij} = \gamma_{ij} + \beta_{ij1}F_{i,high} + \gamma_{ij2}F_{i,moderate} + u_{ij} \quad u_{ij} \sim N(0, \tau_{ij1}). \] (5.3.2)

The level-1 within-firm equation 5.1.1 captures the formation of firm-level expectations as specified in our modeling effort. The level-1 dependent variable, \( E_{ijt} \), represents the market’s expectations for firm \( j \) in industry \( i \) during period \( t \). The first term on the right-hand side of the level-1 equation represents the firm-specific constant. Lagged expectations (\( E_{ij(t-1)} \)) and performance quality \( (Q_{ijt}) \) are the independent variables in the expectations model. The coefficient of adaptation is \( \pi_{ijt} \) and within-firm variation in expectations is represented by the white noise term, \( \epsilon_{ijt} \sim N(0, \sigma_{ij}^2) \).

The level-2 equations represent variation between firms within each industry. In equation 5.2.1, the first term, \( \beta_{ij} \), represents the industry-specific fixed effect. The error term, \( r_{ijt} \), is the unique firm-specific fixed effect for firm \( j \) relative to the mean of industry \( i \). \( \beta_{ij0} \). The second equation (eq. 5.2.2) at this level models within-industry heterogeneity in the coefficient of adaptation. The second term, \( r_{ij} \), represents the unique firm-specific effect on the coefficient of adaptation. Within-industry variation in the coefficient of adaptation is represented by \( \tau_{i1} \).

Level 3 captures heterogeneity between industries. Cross-industry heterogeneity in the relative weighting of prior expectations and most recent perceived quality is incorporated into the model at level 3. The coefficient of adaptation for industry \( i \) is \( \beta_{ij} \), is assumed to have a common fixed effect, \( \gamma_{ij} \) and unexplained variation represented by \( u_{ij} \).

We empirically model the effect of industry characteristics on the coefficient of adaptation by introducing six industry covariates into the level-three between-industry equation 5.3.2. The variable \( G_i \) represents percent annual sales growth in industry \( i \); \( R \) denotes R&D spending as a percent of gross sales for industry \( i \); \( A \) represents advertising spending as a percent of gross sales for industry \( i \); \( J \) represents customers’ overall ease of judging quality within industry \( i \); and \( W \) reflects the level of word-of-mouth within industry \( i \). Finally, \( F_{i,high} \) and \( F_{i,moderate} \) are binary indicator measures of purchase frequency for industry \( i \).

**DATA**

Measures of firm-level expectations, \( E_{ijt} \), and perceived quality, \( Q_{ijt} \), are assembled from the American Customer Satisfaction Index (ACSI) database. The ACSI was developed in 1994 by the University of Michigan Business School’s National Quality Research Center with support from the American Society for Quality. The ACSI measures customer satisfaction and related constructs, such as expectations and perceived quality, on an annual basis for more than 200 firms operating in six major economic sectors: retail, finance/real estate/insurance, durable manufacturing, transportation/communications/utilities, nondurable manufacturing, and basic services. In 1998, sales by these firms amounted to 43% of U.S. GNP.

For the purposes of this study, data from 25 industries were suitable: beer, soft drinks, food processing, personal care, automobiles, appliances, utilities, parcel delivery, airlines, local telephone service, long distance telephone service, department stores, discount stores, gas stations, fast food, supermarkets, commercial banks, property insurance, life insurance, hotels, consumer electronics, personal computers, tobacco, apparel, and athletic shoes. A total of 156 firms are represented across the 25 industries. The span of the data is from 1994 to 1998. Once lagged independent variables and the addition of new firms during the data span are taken into account, the data set consists of 613 usable observations.

Fornell et al. (1996) provide a detailed description of the process through which the indices are produced. The expectation index is based on three manifest variables: overall expectations of quality, expectations regarding how well the product fits the customer’s requirements, and expectations regarding reliability, or how often things would have gone wrong. The manifest variables for perceived quality are analogous to those for expectations and include an overall quality evaluation, an evaluation of how well the product fits the customer’s requirements, and an evaluation of reliability. The expectation and quality measures used in our model are the mean annual indices for each firm, calculated by averaging the customer indices for each firm in the data set. The resulting data set is a panel at the firm level. That is, for each of the 156 firms in the data set, we have three or more observations over time.

The industry-level covariates are operationalized using measures from both the ACSI database and Standard and Poor’s COMPUSTAT database of financial, statistical, and market information. Industry sales growth, advertising spending, and R&D spending measures come from the COMPUSTAT database for the years 1993–98. Sales growth is measured as an annual percent increase or decrease. Average annual sales growth indicates the annualized percent increase or decrease in gross sales for an industry over the five-year period. Advertising and R&D spending are measured as a percent of industry sales. Advertising spending is operationalized as the ratio of advertising expense divided by gross sales. Advertising expense represents the cost of advertising media (radio, television, newspapers, and periodicals) and promotional expenses. Research and development spending is operationalized as the ratio of R&D expense divided by gross sales.
### TABLE 1

SUMMARY OF ESTIMATION RESULTS FOR EACH SPECIFICATION

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>(1) Without heterogeneity (eq. 4)</th>
<th>(2) With heterogeneity</th>
<th>Industry characteristics (eq. 5.1.1–5.3.2)</th>
<th>Industry characteristics (constrained)</th>
<th>(5) Asymmetric response</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>$\gamma_{00}$</td>
<td>$-0.483^*$</td>
<td>$-0.632^*$</td>
<td>$-0.617^*$</td>
<td>$-0.619^*$</td>
</tr>
<tr>
<td>Coefficient of adaptation</td>
<td>$\gamma_{10}$</td>
<td>$0.132^*$</td>
<td>$0.236^*$</td>
<td>$0.086$</td>
<td>$0.127^*$</td>
</tr>
<tr>
<td>Coefficient of adaptation covariates:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ease of evaluating quality</td>
<td>$\gamma_{11}$</td>
<td>$0.032$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sales growth rate</td>
<td>$\gamma_{12}$</td>
<td>$0.010^{**}$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R&amp;D/sales</td>
<td>$\gamma_{13}$</td>
<td>$-0.005$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Advertising/sales</td>
<td>$\gamma_{14}$</td>
<td>$-0.037^{**}$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Degree of word-of-mouth</td>
<td>$\gamma_{15}$</td>
<td>$-0.002^{***}$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Purchase frequency—high</td>
<td>$\gamma_{16}$</td>
<td>$0.258^{**}$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Purchase frequency—moderate</td>
<td>$\gamma_{17}$</td>
<td>$0.060$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Difference in coefficient of adaptation when quality decreases</td>
<td>$\gamma_{20}$</td>
<td></td>
<td></td>
<td></td>
<td>$0.226^{***}$</td>
</tr>
<tr>
<td>Sources of variation:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Within firm</td>
<td>$\sigma^2$</td>
<td>$4.557$</td>
<td>$4.274$</td>
<td>$4.283$</td>
<td>$4.290$</td>
</tr>
<tr>
<td>Between firms within an industry</td>
<td>$\tau_{000}$</td>
<td>$0.0005^*$</td>
<td>$0.005^*$</td>
<td>$0.0005^*$</td>
<td>$0.0006^*$</td>
</tr>
<tr>
<td>Between industries</td>
<td>$\tau_{011}$</td>
<td>$0.0001^*$</td>
<td>$0.001^*$</td>
<td>$0.0001^*$</td>
<td>$0.0001^*$</td>
</tr>
<tr>
<td></td>
<td>$\tau_{001}$</td>
<td>$0.1524^*$</td>
<td>$0.0892^*$</td>
<td>$0.0877^*$</td>
<td>$0.0374^{***}$</td>
</tr>
<tr>
<td></td>
<td>$\tau_{022}$</td>
<td>$0.0255^*$</td>
<td>$0.0002^{**}$</td>
<td>$0.0002^{**}$</td>
<td>$0.0773^*$</td>
</tr>
</tbody>
</table>

**Note:** Ease of evaluating quality range is 1–10. Expectations, perceived quality, and word-of-mouth ranges are 0–100.
*Significant at $p < .01$.
**Significant at $p < .05$.
***Significant at $p < .10$.

Expense represents the estimated costs incurred, by the industry segment, for the development of new products or services that were paid by the companies and were not reimbursed by a customer.

Ease of evaluating quality and word-of-mouth communications are measures from the ACSI database. The ACSI respondents are asked to evaluate the degree to which it is difficult or easy to evaluate quality (1 = very difficult and 10 = very easy). Word-of-mouth communications is operationalized as the percent of consumers surveyed who say they have told at least one person about their experience. Firm-level ease of judging quality and word-of-mouth are averaged within industries to form the industry measures.

Frequency of experience with current quality is operationalized through the creation of two indicator variables. The first reflects whether or not purchase frequency is high (weekly or more often), the second indicator variable denotes more moderate levels of frequency of experience (weekly to every six months), while infrequently purchased goods and services (six months or greater) are treated as the base case.

### FINDINGS

To test for heterogeneity (hypothesis 1), we estimate an OLS regression model without heterogeneity (eq. 4) and compare the results with those when allowing for heterogeneity. If there is a significant improvement in fit when allowing for heterogeneity, then we reject the null hypothesis that the coefficient of adaptation is homogeneous across industries.

A summary of parameter estimates for the two specifications is presented in the first two columns of table 1. For the simple model without heterogeneity (model 1)—without heterogeneity), the coefficient of adaptation is 0.132 ($p < .001$). When heterogeneity is allowed (model 2—with heterogeneity), the mean coefficient of adaptation is 0.236 ($p < .001$). This figure is nearly double the size of the estimate for the simple model with no heterogeneity. Hence, allowing for firm and industry heterogeneity in the coefficient of adaptation suggests that market-level expectations place greater weight on current information than previously thought.

A likelihood ratio test provides a basis for model comparison (Bryk and Raudenbush 1992). Model 2 explains significantly more variance than model 1 ($\chi^2 = 24.01, df = 8, p < .01$). Hence, we conclude that the model with heterogeneity (model 2) is superior to the model without heterogeneity (model 1). In addition, it is worth noting the relative size of the between-firm variation ($\tau_{p11} = 0.0001, p < .001$) and between-industry variation ($\tau_{p11} = 0.0255, p < .01$) in the coefficient, indicating that variation due to industry differences is 255 times greater than the variation due to firm differences within an industry. Hence, industry characteristics not only influence the relative weight placed on current perceptions versus preexisting expectations, but...
these industry-level effects appear to dominate firm-level effects by a considerable margin.

In light of our findings with regard to industry heterogeneity in the updating of market-level expectations, we reexamine the findings of Anderson et al. (1994) and Johnson et al. (1995). Both studies use data from the Swedish
Customer Satisfaction Barometer and find the coefficient of adaptation to be 0.094 (p < .01). Reexamining the data from those studies using HLM and allowing for heterogeneity within and across industries yields a new coefficient of adaptation of 0.195 (p < .001). As for the U.S.-based ACSI analysis above, this figure is roughly double the size of the estimate without allowing for heterogeneity.

Examining the variance components for the SCSB also reveals a pattern similar to that found in the ACSI. Decomposing the coefficient of adaptation, we again find that between-industry variation (τ_{ij1} = 0.0244, p < .01) is far greater than between-firm variation (τ_{i1} = 0.0015, p < .001). Hence, as in the ACSI, industry-level effects found in the SCSB data dominate firm-level effects. In addition, the pattern of industry differences in the coefficient of adaptation is similar across the two data sets. For industries that appear in both ACSI and SCSB—airlines, automobiles, banks, department stores, life insurance, property insurance, personal computers, service stations, and supermarkets—the correlation between the U.S. and Swedish estimates of the coefficient of adaptation is 0.63. Taken together, the findings based on the ACSI and SCSB strongly support the heterogeneity hypothesis. Moreover, the fact that the relative size of the findings themselves is highly convergent is encouraging.

The industry characteristics specification estimates the model described in equations 5.1.1 through 5.3.2 with all industry covariates included. A likelihood ratio test for the baseline model (model 2) versus the industry characteristics model (model 3) indicates that the characteristics model does not quite provide a statistically significant improvement in model fit relative to the baseline model (χ^2 = 10.29, df = 7, p = .17). Accordingly, we reestimate the industry characteristics model constraining the insignificant effects of ease of evaluating quality, R&D intensity, and one of the purchase frequency indicator variables to be zero. The resulting model, shown as model 4 of table 1, is a significant improvement over model 2 (χ^2 = 9.39, df = 4, p = .05). In addition, the estimated between-industry (unexplained) variation in the coefficient of adaptation drops substantially, from τ_{ij1} = 0.0255 in model 2 to τ_{i1} = 0.0002 in the characteristics model. Hence, the characteristics model accounts for further variation between industries via the industry covariates.

The findings indicate that as industry sales growth increases, the coefficient of adaptation increases (γ_{12} = 0.010, p < .05). This supports the hypothesis that the relative weight placed on current experience versus prior expectations increases in industries characterized by greater sales growth. Model 4 also shows that the coefficient of adaptation decreases as advertising spending increases (γ_{14} = −0.033, p < .01). Hence, industries with relatively higher advertising spending levels place less weight on current experience relative to prior expectations. The findings also indicate that increased word-of-mouth communication is accompanied by a decrease in the coefficient of adaptation (γ_{15} = −0.003, p < .05). Hence, word-of-mouth communications moderate the formation of expectations such that less weight is placed on current quality in industries with higher degrees of word-of-mouth communications. Finally, the model results suggest that the coefficient of adaptation increases as consumers’ frequency of purchase increases (γ_{16} = 0.203, p < .05).

In summary, four of the six hypotheses regarding industry characteristics are supported by the empirical model results. The findings support the predictions that industry growth rate and frequency of experience with current quality are positively related to the size of the coefficient of adaptation, while advertising intensity and word-of-mouth communications are negatively related to coefficient of adaptation size. Two industry characteristics are not empirically supported: R&D intensity and ease of evaluating quality. Research and development intensity (measured as a percent of sales) is strongly correlated with sales growth (r = −.422) and word-of-mouth (r = .496), both of which are significant in our model. We expect that may contribute to its insignificance result. The ease of evaluating quality measure used in our study has relatively low variation (M = 7.97, SD = 0.55), which we expect may contribute to its insignificance.

We test the asymmetric response hypothesis by creating an indicator variable, N_{ij1−1}, to denote when the change in perceived quality from one period to the next is positive (equals zero) or negative (equals one). We multiply this indicator variable by the difference between perceived quality and expectations, Q_{ij} − E_{ij1−1}, and incorporate it into equation 5.1.1. This new term represents the difference in the coefficient of adaptation when quality decreases.

A summary of the estimation results when allowing for asymmetric effects appears in column 5 of table 1. As shown, the difference in the coefficient of adaptation for decreases in perceived quality is 0.226. Given that there are only 24 degrees of freedom at the industry level where this coefficient is estimated, the p-value of 0.08 (two-tailed test) indicates that the difference is significant. Hence, the coefficient of adaptation given perceived quality decreases is 0.248, but only 0.022 (NS) when quality improves. This finding suggests support for the asymmetric response hypothesis.

**GENERAL DISCUSSION**

We believe this research extends the existing literature on market-level expectations in several ways. First, we reinvestigate the formation of market-level expectations with a more appropriate methodology and a more representative database. In doing so, we find market-level expectations are far more adaptive than previously thought. Whereas Anderson et al. (1994) and Johnson et al. (1995) find the adaptive coefficient of market-level expectations to be fairly
small, our findings suggest that—on average—it is roughly twice as large when one accounts for industry- and firm-level heterogeneity.

Second, in terms of factors moderating the formation of expectations across industries, we find that industry characteristics play an important role. Specifically, we find that recent experience is given greater weight when industry growth and purchase frequency are greater and less weight when advertising intensity and word-of-mouth are greater. Thus, we find that factors reflecting degree of confidence in prior expectations about quality moderate the size of the coefficient of adaptation as illustrated in figure 1. Generally, we find that the rate at which market-level expectations update based on recent experience increases when information uncertainty is high and information availability is low. Conversely, the served market’s expectations will be more heavily anchored on prior expectations when uncertainty about quality is low and the availability of information about quality is high. Hence, our research helps both researchers and managers recognize conditions under which expectations should be expected to adjust more rapidly or more slowly. For example, information about current quality should be integrated more rapidly in relatively turbulent markets with limited information flow.

Finally, we find that drop-offs in perceived quality have a much stronger impact on expectations than improvements in perceived quality. Hence, we expect markets as a whole to adjust more rapidly to bad news, just as we expect individuals to adjust more rapidly to negative information. While the existence of a negativity bias at the individual level has been well known for many years, this study is the first to offer a theoretical and empirical examination of this phenomenon for groups of consumers (markets).

Several potential limitations of our study should be noted. Although the reexamination of Anderson et al. (1994) and Johnson et al. (1995) suggests that our findings regarding the size and heterogeneity of the updating coefficient may generalize, the other findings in the article should be viewed with some caution in this regard. First, in terms of whether the findings generalize geographically, the limited availability of background data for firms in the SCSB prohibits a complete replication of the moderating influences found in the ACSI. There may also be some concern regarding the sample of industries in the ACSI and whether the findings will generalize well beyond this context. Another potential limitation of our work is the annual nature of the ACSI data-collection process. Annual measurement of expectations may not be the best periodic measurement across all industries. In addition, some of our measures—such as that for purchase frequency—are coarse and based on expert judgments. Future work may wish to investigate whether more accurate measurement or controlling for potential sources of measurement error would affect our substantive conclusions.

From a theoretical standpoint, we believe there is a rich opportunity for further investigation of the nomological network within which market-level expectations are embedded. First, not all of our theoretical predictions were supported by the data. For example, we predicted that confidence in preexisting expectations should be greater when ease of evaluating quality is greater. However, we found the effect to be insignificant. Future research may wish to examine whether this is due to ease of evaluating quality increasing confidence in both current experience and preexisting expectations simultaneously, thus creating a countervailing effect that masks the predicted one. In addition, research is needed to further explicate the constructs comprising this network and the associations between them. For example, what sources of information are drawn on to form market-level expectations and what are the processes by which these different sources of information are integrated? While this study focuses on market-level expectations and perceived quality, these constructs might be fruitfully augmented or decomposed into different sources of expectations and information about perceived quality.

Whichever direction future research selects, we hope that this study provides a useful foundation for subsequent work regarding how market-level expectations are formed and adapt over time.

[David Glen Mick served as editor and Donald R. Lehmann served as associate editor for this article.]

REFERENCES

Fornell, Claes, Michael D. Johnson, Eugene W. Anderson, Jaesung Cha, and Barbara Everitt Bryant (1996), “The American Cus-


