Disentangling the Market Value of Customer Satisfaction: Evidence from Market Reaction to the Unanticipated Component of ACSI Announcements*

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ABSTRACT

By now, there is a rich literature that examines the impact of customer satisfaction on market value. Surprisingly, the short-run market impact of customer satisfaction has been found to be either insignificant or limited in scope. To address this shortcoming, we introduce the notion that investors form expectations about customer satisfaction and they respond only to deviations from these expectations (i.e., “surprise”). We consider two “expectations” models: a naïve model that utilizes last year’s scores and a model that includes firm characteristics and marketing investments to proxy for prior resources allocated to customer satisfaction. In our empirical work, we find that the market does indeed respond in the short-run to the surprise in customer satisfaction with more pronounced effects for our latter expectations model. Overall, our research offers two distinct contributions. First, it refines the extant conceptualization of customer satisfaction by explicitly introducing the notion of investor expectations. Second, we employ this refined conceptualization to unequivocally demonstrate the short-run impact of customer satisfaction investments.
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1. INTRODUCTION

1.1 Motivation

By now, there is a rich literature that examines the impact of customer satisfaction on important outcomes in the financial market. As is worthy of a major field of inquiry, the extant works have examined various elements of this association. Some studies, such as those of Fornell, Mithas, Morgeson, and Krishnan (2006), Ittner and Larcker (1998), Ittner, Larcker and Taylor (2009) investigate the immediate, short-run market impact of customer satisfaction announcements via event studies. Surprisingly, these researchers report effects that are either insignificant or limited in scope. Specifically, across two separate event studies, Ittner and Larcker (1998) and Fornell, Mithas, Morgeson, and Krishnan (2006) find no short-run impact of customer satisfaction announcements on stock prices. More recently, Ittner, Larcker and Taylor (2009) also employ the event-study methodology. They find that investors respond to customer satisfaction announcements but only for relatively large positive changes over previous years’ levels.

Other studies investigate the long-run market impact of customer satisfaction. Within this stream, Anderson, Fornell, and Mazvancheryl (2004), for example, find a positive association between customer satisfaction and shareholder value as measured by Tobin’s Q. In effect, they demonstrate that customer satisfaction is value-relevant in the
long-run: higher levels of customer satisfaction predict higher values of Tobin’s Q, even after accounting for fixed, random, and unobservable factors.

Yet other works have focused on the mispricing of customer satisfaction by the financial markets. Within this stream, Fornell, Mithas, Morgeson, and Krishnan (2006) show that customer satisfaction helps predict long-run changes in equity prices. Specifically, portfolios of firms composed on the basis of high customer satisfaction scores outperform the market even after accounting for trading costs. This particular finding pertaining to the ability of portfolios of high customer satisfaction firms to obtain abnormal returns has subsequently been subject to additional scrutiny in a series of articles. In particular, Jacobson and Mizik (2009a) conclude that the mispricing reported in the extant literature is due to a small group of satisfaction leaders in the computer and internet sectors. This conclusion is further echoed by Ittner, Larcker, and Taylor (2009). Similarly, O’Sullivan, Hutchinson, and O’Connell (2009) correct for three interlinking issues, namely, risk-adjustment, abnormal risk adjustment, and portfolio aggregation and find no evidence of mispricing. However, in their commentary, Fornell, Mithas, Morgeson (2009) present new analysis that updates the findings in Fornell, Mithas, Morgeson, and Krishnan (2006). They report that the above-market returns reported in Fornell, Mithas, Morgeson, and Krishnan (2006) persist; moreover, they are both economically and statistically significant.¹

Clearly, the fundamental question of interest to marketing scholars and practitioners in all of these investigations is to better understand the market value of customer satisfaction. Indeed, the chain of effects leading from customer satisfaction to

¹ We clarify that in all of the aforementioned studies and in our research endeavor, the conceptual development is around the general construct of customer satisfaction; however, the actual measure of customer satisfaction utilized is the ACSI metric provided by ACSI LLC.
favorable customer behaviors followed by enhanced firm performance and culminating in positive stock market response has received substantial attention in the marketing literature. As summarized by Anderson and Mansi (2009), the relationship between customer satisfaction and a host of favorable customer behaviors such as acquisition costs, retention, word-of-mouth, willingness to pay, usage, cross-selling opportunities, reduced complaints, and lower payment defaults now appears to be widely accepted and credibly established (Anderson, Fornell, and Lehmann 1994; Bearden and Teel 1983; Bolton 1998; Bolton and Drew 1991; Bolton and Lemon 1999; Fornell 1992; Homburg, Koschate, and Hoyer 2005). Next, the relationship between customer satisfaction and enhanced firm performance, stemming from the aforementioned favorable customer behaviors, has been reported in a growing number of studies (Bolton 1998; Gruca and Rego 2005; Mittal and Kamakura 2001; Rust, Zahorik, and Keiningham 1994). However, in contrast to the substantial support documented for the first two links in the chain, empirical findings pertaining to the association between customer satisfaction and the response of financial markets are “more mixed” (Anderson and Mansi 2009, p. 704). In particular, this is manifested in the lack of a consistent short-run market reaction to customer satisfaction announcements (Fornell, Mithas, MORGeson, and Krishnan (2006), Ittner and Larcker (1998), Ittner, Larcker and Taylor (2009)). Given that customer satisfaction has demonstrated positive impacts on customer behavior, and subsequently, firm performance, the lack of a consistent short-run market response to customer satisfaction announcements is puzzling.
1.2 Research Conceptualization

To resolve this conundrum, we propose that investors form expectations with respect to customer satisfaction and they respond only to deviations from such expectations. Such a premise is well-grounded in the extant literature. Srinivasan, Pauwels, Silva-Risso, and Hanssens (2009) conceptualize and find that investors respond to deviations from expectations for a wide range of marketing investments and actions (e.g., innovation, advertising, price promotions, competitive promotions, consumer liking, and quality). Similarly, Joshi and Hanssens (2009) report that post-launch performance of studio stock price is strongly influenced by expectations of performance built up prior to release. Our premise that the stock market responds only to new information is also consistent with research in the finance and accounting literatures. For example, in their seminal empirical analysis of market reaction to earnings announcements, Ball and Brown (1968) show that the market responds to the unexpected component of earnings announcements (earnings surprise). Specifically, they demonstrate that the market reacts in the same direction as the difference between actual income and expected earnings. Subsequent researchers (Freeman and Tse 1992; Kinney, Burgstahler, and Martin 2002) have also documented the market response to earnings surprises. They find an S-shaped response with steeply sloped market responses for small absolute surprises and approximately flat market reaction for large absolute surprises.\(^2\)

At this point, the question arises: How do investors form expectations about the level of customer satisfaction? We posit that expectations of customer satisfaction in the current period are influenced by customer satisfaction in the prior period augmented by

\(^2\) Strictly speaking, this body of research does not require individual investors to form expectations; rather, what is required is that, in the aggregate, investors act as though they respond to deviations from expectations.
marketing investments allocated to customer satisfaction in the prior period. Although marketing investments allocated to customer satisfaction in the prior period are not directly observable, we further posit that variables associated with the firm’s environment and its overall marketing investments in the prior period can potentially proxy for these investments in customer satisfaction. For example, firms that face high growth prospects are more likely to invest in customer satisfaction because of the potential to leverage such investments across new opportunities. Similarly, firms investing in advertising in previous periods will likely exhibit higher levels of customer satisfaction because of advertising’s utility enhancing effects.

Accordingly, we posit that prior to the release of new customer satisfaction numbers, investors have their own private forecasts of the realization of customer satisfaction at a particular firm. Moreover, we further predict that the pre-announcement stock price is influenced by these private forecasts. In other words, it is as though some underlying consensus view of all investors is reflected in the pre-announcement stock price.

Next, we hypothesize that the response to customer satisfaction announcements is as follows. Firms that report numbers that are above the underlying consensus forecast earn significantly positive abnormal returns. Conversely, firms that report numbers that are below the underlying consensus forecast earn significantly negative abnormal returns. In effect, the market only responds to the “surprise” or “new” information in the customer satisfaction announcement. Indeed, Ittner, Larcker, and Taylor (2009) take an important first step in this direction when they look at the market reaction to changes (year-over-year) in customer satisfaction. However, as argued by Jacobson and Mizik
(2009b, p. 842) it is also important to allow market participants to “use other information to adjust their expectations” about customer satisfaction. *It is in this way that we build, and extend, the extant literature to better understand the short-run market reaction to customer satisfaction announcements.*

1.3 Alternative Conceptualizations

Of course, there are alternative conceptualizations for the lack of a consistent, short-term response of the financial markets to announcements of customer satisfaction. It may well be that investors are simply not aware of customer satisfaction announcements. A related view is that investors may be aware of the customer satisfaction metric but ignorant of the many positive impacts of customer satisfaction. For either of these reasons, investors may thus come to disregard customer satisfaction thereby leading to the observed lack of market reaction.

A second conceptualization is that investors react to the information contained in customer satisfaction *before* the announcement because they are able to track other marketing indicators prior to the announcement. In this regard, Ngobo, Casta, and Ramond (2011) propose that investors do care about customer satisfaction but they can obtain information on customer satisfaction/dissatisfaction well before customer satisfaction scores are publicly announced. For example, as in Tellis and Johnson (2007), investors may respond positively to reviews of product quality; consequently, announcements of improved customer satisfaction stemming from improved quality provide no additional information.
Finally, a third conceptualization is that investors react to the information contained in customer satisfaction only after the announcement when the positive chain of effects emanating from customer satisfaction has, in fact, materialized. Relatedly, investors may wait for customer satisfaction to be filtered through analysts before responding to it. In this connection, Luo, Homburg, and Wieseke (2010) show that customer satisfaction leads to lower analysts’ forecast errors. Since investors generally find it costly to process information surrounding a customer satisfaction announcement it is thus worthwhile for them to wait for analysts’ forecast before responding.

We respond to the first of these alternative conceptualizations by providing three distinct sets of empirical evidence that demonstrates that market participants do indeed care about customer satisfaction. The first set of empirical evidence includes the fact that many prominent industry associations, investment websites, and companies choose to broadcast information about measured customer satisfaction. The second set of empirical evidence pertains to the increased volume of web searches for customer satisfaction around scheduled customer satisfaction announcements. Finally, the third set of empirical evidence pertains to increased trading volume around customer satisfaction announcements. Taken together, these three sets of empirical evidence refute the notion that market participants do not care about customer satisfaction.

Our response to the other alternative conceptualizations – investors may respond either before or after the announcement - is somewhat different. Indeed, it is highly likely that some of the response to customer satisfaction may precede the announcement. It is also highly likely that some of the response to customer satisfaction will follow the announcement. However, we argue that these effects should only hamper our efforts to
find any effect at the time of announcement. As such, any effects that we find in our paper can be considered conservative.

The remainder of the paper is organized in the following manner. Given the alternative conceptualization that investors may simply disregard customer satisfaction, we first provide three sets of empirical evidence to demonstrate that investors do indeed follow our empirical metric of customer satisfaction, namely the American Customer Satisfaction Index (ACSI). We then develop our conceptual model of customer satisfaction expectations. Subsequently, we describe our data, variables, and summary statistics. Then, we present findings pertaining to two expectations models: a naïve model where expected customer satisfaction is simply last year’s customer satisfaction and a model that includes firm characteristics and marketing investments to proxy for prior resources allocated to customer satisfaction. Finally, examining the market reaction to customer satisfaction announcements, we find that the market does indeed respond to the “surprise” in customer satisfaction announcements with more pronounced effects for our latter model of expectations. We conclude with a summary and discussion of contributions and limitations.

2. ARE ACSI ANNOUNCEMENTS FOLLOWED BY INVESTORS?

An important question to resolve before we proceed is: Do investors follow ACSI announcements? Accordingly, we provide three distinct sets of empirical evidence. First, we note that ACSI announcements are immediately highlighted and re-broadcast by leading industry associations, investment websites, and companies. For example, among
food processing companies, Progressive Grocer routinely summarizes changes in ACSI scores. In particular, a recent announcement highlights the following improvements: “Sara Lee Corporation showed the biggest improvements in its ACSI score,” “Mars Inc., Nestle, General Mills Inc. and ConAgra Foods all posted scores of 83,” and “Hershey Foods Corporation edged up a point.”³ Similar reports are provided by American Banker in the banking industry, Wards Auto in the automobile industry, Nation’s Restaurant News in the restaurant industry, PC Mag for the computer industry, and Insurance Networking News in the insurance industry. In like fashion, ACSI announcements are also highlighted and re-broadcast by several investments websites. For example, Seeking Alpha, a popular investment website recently headlined: “Heinz Ranks Number One in Customer Satisfaction Among All 225 Companies in the American Customer Satisfaction Index.”⁴ Similarly, istockanalyst.com, another investing website, also provides updates on ACSI scores. Finally, companies themselves are not shy about providing press releases about improvements in customer satisfaction. For example, in a conference call held by Comcast Corporation, Brian Roberts, Chairman and CEO, reiterates his goal of providing a superior customer satisfaction experience while noting a 9% improvement in ACSI scores.⁵ Similarly, following an ACSI score announcement in which Yahoo obtained higher scores than Google, a Yahoo spokesperson stated that: “Yahoo is pleased with the results of this year’s ACSI study which reflect our continued efforts to enhance the consumer experience for more than 500 million users of Yahoo

³ http://www.progressivegrocer.com/print/topstory/index-customer-satisfaction-is-up-despite-low-consumer-confidence/7066/
⁵ http://files.shareholder.com/downloads/CMCSA/0x0x313122/1421ccbc-96ee-4a79-b5a6-c38a9eed6394/cmcs%20transcript.pdf
branded properties around the world." Finally, Sprint Corporation recently highlighted its strong showing in customer satisfaction via press releases and full-page ads in the Wall Street Journal with the ACSI logo prominently displayed in tandem with the with the tag line: “The real reward is making customers happy.”

Second, we examine the intensity of online search for the term “american customer satisfaction index” on Google, the search engine with the highest market share. A number of recent studies (Da, Engelberg and Gao 2011; Joseph, Wintoki and Zhang 2011) have demonstrated that online search intensity serves as a valid proxy for investor attention. Moreover, this proxy reliably predicts stock returns and trading volume. Using data from Google Insights where such data are archived, we examine the intensity of search for the term “american customer satisfaction index” over the period 2004 to 2006 (the time period over which the availability of Google search data overlaps that of our sample). Notably, we find that Google searches for the term “american customer satisfaction index” are seven times higher in the week of ACSI score announcements than in other weeks over the period. To further illustrate our point, Figure 1 displays the level of public interest in ACSI scores by plotting weekly search intensity for the term “american customer satisfaction index” during the year 2006. The displayed search intensity is normalized by an unknown factor for privacy and other reasons; consequently, the absolute value displayed is not meaningful. Nevertheless, the figure clearly shows that Google searches for the term spike in the week of, and weeks around,

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6 http://www.informationweek.com/news/201800197
the announcement of ACSI scores. We interpret this as evidence that ACSI announcements are followed by at least some investors.

Third, we also examine changes in trading volume around ACSI announcements. If trading volume increases around ACSI announcement, we can conclude heightened investor attention. To examine this we calculate the average daily volume for each of our sample firms, and for the market, during a “non-announcement window”. This window includes a stretch from fifty days before the ACSI announcement \((t – 50)\) to fifteen days before the ACSI announcement \((t – 15)\), and another stretch from fifteen days after the announcement \((t + 15)\) to fifty days after the announcement \((t + 50)\), where \(t\) is the date of the ACSI score announcement. We find the average volume is 2.8% higher in a ten-day period \((-5 \leq t \leq 5)\) around ACSI announcements than during the “non-announcement” window, relative to the market.\(^8\)

Based on these three sets of empirical evidence, we thus conclude that customer satisfaction, as manifested by the ACSI metric, is closely followed by at least some investors. We next discuss the development of our conceptual model of customer satisfaction expectations.

### 3. MODEL OF CUSTOMER SATISFACTION EXPECTATIONS

As suggested previously, we posit that expectations of the level of customer satisfaction at time \(t\), \(E[CS_t]\), are influenced both by the level of customer satisfaction in

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\(^8\) The market is defined as the entire Center for Research in Security Prices (CRSP) database. The 2.8\% increase in volume is significant at a 10\% level using a two-tailed \(t\)-test.
period $t - 1$, $CS_{t-1}$, as well as investments in customer satisfaction during period $t - 1$, $I_{t-1}$.

Formally, we have:

$$E[CS_t] = \alpha CS_{t-1} + \beta I_{t-1}$$  \hspace{1cm} (1)

Equation (1) suggests that there is some carry-over of the goodwill inherent in customer satisfaction from period-to-period. This is augmented by an increase in customer satisfaction on account of prior investments in customer satisfaction, $I_{t-1}$.

Now, in forming expectations of customer satisfaction in period $t$, $E[CS_t]$, investors cannot observe all the myriad investments devoted to customer satisfaction during period $t - 1$, $I_{t-1}$. Nevertheless, investors have some beliefs about $I_{t-1}$ based on publicly observed firm characteristics and marketing investments at time $t - 1$. We therefore employ publicly observable firm characteristics and marketing investments at time $t - 1$ to serve as proxy for resources allocated to customer satisfaction at time $t - 1$.

What variables will investors employ in estimating $I_{t-1}$? We consider seven variables: growth opportunities, number of segments served, market concentration, efficiency in converting inputs to outputs, firm size, advertising and R&D. We next develop our logic associated with employing these seven variables.\(^9\)

With respect to growth opportunities, investors believe that firm’s with high growth prospects are likely to invest more in customer satisfaction at time $t - 1$ because

\(^9\) More generally, it is common practice in the finance and accounting literature to predict expected levels of key marketing investments by employing observable firm characteristics. Lou (2011), for example, employs an expected model for advertising investments by utilizing such firm characteristics as market-to-book, firm size, sales, assets, and capital expenditures. Bushee (1998) employs market-to-book, firm size, and leverage as control variables in a model that predicts changes in R&D investments. Publicly available information is also often used to predict outcomes related to the firm. For example, Frankel and Lee (1998) and Hughes, Liu, and Su (2008) utilize firm characteristics to predict analyst forecast errors. The essential idea is that these firm characteristics are reflective of the information set available to the investors.
they can potentially recoup these investments over the new opportunities. High levels of customer satisfaction in current businesses can be gainfully leveraged to enter new businesses via lower acquisition costs (Anderson, Fornell, or Lehmann 1994) or benefit from higher receptivity to cross-selling initiatives (Bolton 1998). Relatedly, firms operating in multiple segments will likely invest more in customer satisfaction because of spillover benefits. In this regard, Chai and Ding (2009) provide empirical evidence for such spillovers with respect to customer satisfaction in the mobile phone industry (between handset manufacturers and network operators). Next, since market concentration is a proxy for entry barriers (Powell 1996), it follows that firms operating in concentrated industries will have greater incentives to invest in customer satisfaction because such firms can appropriate more of the value associated with their investments.

In straightforward fashion, we expect efficiency in converting inputs to outputs and firm size to also impact investments in customer satisfaction. Highly efficient firms will see more benefit from such investments whereas large firms will choose to invest less on account of the heterogeneous customers they are likely to serve (Anderson, Fornell, and Lehmann 1994). Finally, we expect firms’ investments in advertising and R&D to positively impact expectations of customer satisfaction. As demonstrated by Erdem and Sun (2002), advertising can increase the mean and decrease the variance of customers’ utility, thereby increasing surplus and customer satisfaction. Similarly, we expect investments in R&D also to allow the firm to provide greater differentiation in its products (Chauvin and Hirschey 1993; Veliyath and Ferris 1997). This positive differentiation should also enhance utility and increase customer satisfaction.
Clearly, these seven variables do not exhaust all of the influences on the firm’s investment level in customer satisfaction. Rather, we make the more modest claim that as a group, they capture important aspects of the decision to invest in customer satisfaction and also serve as good proxies for the information available to investors. Growth opportunities and number of segments served reflect the trajectory and depth of market demand for the firm’s product and are therefore intimately related to future payoffs from customer satisfaction investments. Concentration incorporates the influence of the competitive environment in that it reflects the ability of the firm to appropriate the value it creates through customer satisfaction investments. Efficiency of converting inputs to outputs and firm size pertain to the firm’s productivity in utilizing its resources. Finally, advertising and R&D expenditures capture firms’ direct investments towards customer satisfaction.

We also do not claim that any or all of these variables are exogenous with respect to customer satisfaction. For example, managerial ability could affect both the expected level of customer satisfaction and the market’s assessment of growth opportunities between customer satisfaction announcements. Since this firm-specific effect is not completely observable, failing to address it may introduce an omitted variable bias into the regression estimates. Simultaneity between customer satisfaction and any of the firm characteristics we propose is another issue we acknowledge. For example, in our subsequent empirical analysis, we use market-to-book as proxy for growth opportunities. An increase in growth opportunities at time \( t - 1 \) may cause investors to increase their expectations with regards to what customer satisfaction will be at time \( t \). However, the reverse could also be true. If investors expect customer satisfaction to be higher next
period, investors would bid up the market value of the firm, thus increasing the firm’s market-to-book ratio.

Finally, we acknowledge the dynamic endogeneity, or reverse causality from customer satisfaction to our firm characteristics. So, for example, firms with high growth opportunities are likely to be firms that have had positive shocks to customer satisfaction in the past. In our subsequent empirical analysis we are careful to account for all these sources of endogeneity as best we can in our empirical estimation of expected customer satisfaction.

Given the arguments we have presented in this section, we write our model of customer expectations as:

\[ E[CS_t] = \alpha CS_{t-1} + \beta X_{t-1} \]  \hspace{1cm} (2)

where the vector X encapsulates the seven variables just described. Then, announcements of customer satisfaction in period \( t, CS_t \), lead to investor response that is proportional to \( CS_t - E[CS_t] \).

4. DATA, VARIABLES, AND SUMMARY STATISTICS

4.1 Data

We conduct our analysis within the sample of firms for which there is satisfaction (ACSI) data between 1995 and 2006. As described in Anderson, Fornell, and Mazvancheryl (2004), the ACSI methodology provides a "uniform, independent,
customer-based, firm-level satisfaction measure for nearly 200 companies in 40 industries and in seven sectors of the US economy” (p. 176).

Since our explanatory variables (described below) are from the COMPUSTAT database, we merge the ACSI data with COMPUSTAT. This leaves us with a working sample consisting of 116 firms and 1,109 firm-years over the 12-year period from 1995 – 2006.

4.2 Variables

We construct proxies for our independent variables as follows. With respect to an empirical proxy for future growth, we note that it is quite common in the finance literature to employ market-to-book ratio as a measure of the growth opportunity associated with the firm (e.g. Denis 1994; p. 162). We compute market-to-book value as the market value of assets divided by the book value of assets, where the market value of assets is computed as book value of assets (COMPUSTAT item: “at”) plus the market value of common stock (the product of COMPUSTAT items: common shares outstanding, “csho” and fiscal year end stock price, “prcc_f”) less the sum of the book value of common stock (COMPUSTAT item: “ceq”) and balance sheet deferred taxes (COMPUSTAT item: “txdb”). Next, the number of business segments is obtained by counting the number of business segments from the COMPUSTAT Segments database. With respect to concentration, we use the Herfindahl index (sum of square-market shares) to obtain a continuous measure of industry concentration. Market share, in turn, is
computed via sales revenue (COMPUSTAT item: “sale”) reported at the 2-digit SIC code level for all COMPUSTAT companies with the same 2-digit SIC code.\textsuperscript{10}

To measure efficiency, we employ return on assets and this is computed as operating income before depreciation (COMPUSTAT item: “oibdp”) divided by the book value of assets (COMPUSTAT item: “at”). The proxy for firm size is the log of firm assets, represented by book value of assets. Finally, advertising is the ratio of advertising expenses (COMPUSTAT item: “xad”) to sales (COMPUSTAT item: “sale”) and R&D is the ratio of R&D expense (COMPUSTAT item: “xrd”) to sales. As is conventional, we set R&D expense to zero if it is missing or not reported since SEC has long required all publicly traded firms to report any “material” R&D expenditure (Bound et al. 1984). Similarly, we set advertising expense to zero if it is missing or not reported. Firms generally do not have much latitude with respect to disclosing R&D and advertising; Generally Accepted Accounting Principles (GAAP) require all firms with “material” R&D or advertising expenditure to recognize and disclose these items on their financial statements. Financial Accounting Standards Board (FASB) Statement No. 2: “Accounting for Research and Development Costs” (1974) sets the standards for R&D accounting; FASB Statement of Position (SOP) 93-7 (1993): “Reporting on Advertising Costs” sets the standards for advertising accounting. This leads us to believe that missing values for R&D and advertising are indeed zero or close to zero.

Of course, it is possible that some firms may have advertising expense which they do not recognize; the aforementioned standards do have some exceptions and the very definition of “material” may, on the margin, be subject to auditor judgment. This may

\textsuperscript{10} The Herfindahl Index is widely utilized as a proxy for industry concentration (Huo and Robinson (2006)).
make our advertising measure noisy but a number of studies (e.g. Bound et al, 1984; Chauvin and Hirschey, 1993; Hirschey, Skiba and Wintoki, 2012) test the assumption of setting missing R&D and advertising to zero in large samples, and conclude that it has no little effect on empirical analysis involving R&D and advertising expenditures in general.

4.3 Summary Statistics

Table 1 displays the summary statistics for the customer satisfaction and firm-specific variables that we use in our analysis. In our sample of 1,109 observations, the mean level of customer satisfaction (100 point scale) is 75.3 with a median of 75 and a standard deviation of 6.47. The minimum value on this variable is 49 while the maximum value is 90.

Table 1 also shows that the mean (median) market to book is 1.91 (1.41) and the mean or median firm in our sample has about 3 business segments. The mean (median) level of concentration is 0.06 (0.04). Return on Assets has a mean (median) of 0.14 (0.13) and the mean and median firm size, as measured by the log of assets, are 9.67 and 9.63, respectively. Finally, Table 1 shows that the mean (median) advertising to sales ratio is 3% (1%) and the mean (median) of R&D to sales is 1% (0).

Table 2 displays the correlation matrix between customer satisfaction and other firm-specific variables. We find that customer satisfaction is positively correlated with market-to-book, number of business segments, return on assets, advertising to sales ratio, and R&D to sales ratio. It is negatively correlated with firm size.
5. EMPIRICAL MODEL AND FINDINGS

We organize our findings into two main parts. First, we estimate our proposed models of customer satisfaction expectations. In estimating our models, we employ both OLS estimation as well as Dynamic Panel Generalized Method of Moments Estimation. As we discuss subsequently, the latter method accounts for potential sources of endogeneity. We then examine the market’s reaction to the surprise in customer satisfaction, followed by additional robustness tests.

5.1 Empirical Model and Estimation of Expected Customer Satisfaction

Our base model for examining the determinants of expected customer satisfaction is:

\[ CS_i = \alpha_0 + \alpha_i CS_{i-1} + \beta_1 X_{i-1} + \eta_i + d_t + \epsilon_{it} \]  

(3)

where \( CS_i \) is the customer satisfaction of firm \( i \) in year \( t \), \( X_{i-1} \) is a vector of observable firm characteristics and investments (market-to-book, the number of business segments, concentration, return on assets, firm size, advertising and R&D expenditure) that proxy for the firm’s prior investments in customer satisfaction, \( \eta_i \) is an unobservable firm-fixed effect, \( d_t \) is a year dummy and \( \epsilon_{it} \) is an error term. The firm fixed effect is especially important since it controls for any other unobservable firm characteristics that may be important in determining the expected level of customer satisfaction. The observable firm characteristics are all lagged – they are measured as of the end of the fiscal year prior to the customer satisfaction announcement.
Although we start our empirical analysis with a simple OLS estimation of (3), there are at least three sources of endogeneity that could potentially bias our OLS estimates. Hence, we apply the dynamic panel data estimation methodology to obtain System GMM estimates. Technical Details of the various sources of endogeneity and dynamic panel data estimation are presented in Appendix 1.

Both OLS and System GMM are shown in Table 3. Since we are using panel data for our empirical analysis, it is possible that the residuals for a given firm can be correlated across years (serial correlation), or that the residuals of a given year may be correlated across different firms (cross-sectional dependence); both of these could bias the standard errors downwards and inflate t-statistics (Petersen 2009). Thus, to avoid biased inferences, we include year dummies in all specification and report t-statistics that are clustered by firm and industry in all our regression results.

The first column in Table 3 shows the results from regressing this year’s customer satisfaction on last year’s. The estimate clearly shows that lagged customer satisfaction is persistent; the coefficient on lagged customer satisfaction is 0.91.\(^{11}\) This finding has been documented in the literature before (see, for example, Tuli and Bharadwaj 2006) and is likely due to a combination of two factors: (i) persistence of customer satisfaction arising, as we propose, from the fact that there is some carry-over of the goodwill inherent in customer satisfaction from period-to-period, (ii) the presence of an unobservable fixed effect that is correlated both with customer satisfaction and the firm-specific variables (\(X_{it-1}\)) included in the model in equation (3).

\(^{11}\) This high level of persistence raises the possibility of a unit root in customer satisfaction. However, we are able to reject the null hypothesis of a unit root from Fisher Test for panel unit root using an augmented Dickey-Fuller test.
Next, we report in column (2) the results of estimating, using OLS, a model that includes both firm characteristics and the lagged value of customer satisfaction. Two points are noteworthy. First, the $R^2$ improves from 81% to about 84%, and this increment is statistically significant; the Voung (1989) $Z$-statistic that compares the model reported in column (2) versus the model reported in column (1) is 5.42 ($p < 0.01$). In addition, the $F$-statistic for firm characteristics and marketing investments is a statistically significant 2.12 ($p = 0.04$). These findings suggest that in addition to past customer satisfaction, the firm characteristics and marketing investments that we have chosen to proxy for prior investments in customer satisfaction provide additional explanatory power for the cross-sectional variation in realized customer satisfaction.

While OLS estimates provide some initial support for our theoretical conjecture that expected customer satisfaction will be a function of past customer satisfaction and proxies for the firm’s information environment, these estimates do not effectively address unobservable heterogeneity, simultaneity and reverse causality. For this we turn to the GMM estimates in column (3) of Table 3.

The System GMM results in column (3) of Table 3 provide evidence that past customer satisfaction and our proxies for the firm’s prior investments in customer satisfaction explain the cross-sectional variation in customer satisfaction. Individually, we find that customer satisfaction is positively associated with market-to-book, number of segments, return on assets, and advertising expenditure. Even more importantly, the firm characteristics and marketing investments are jointly significant at the 1% level ($F$-statistic = 3.05).
Table 3 also shows the results of two post-estimation tests of the validity of the dynamic GMM specification as well as the validity of the instrument set. The first test is a test of serial correlation. Table 3 shows the results of an AR(2) test of the null hypothesis of no second order serial correlation. Results of this test confirm that this is the case: the AR(2) test yields a p-value of 0.14. The second test is a Hansen test of over-identification. The Hansen test yields a $J$-statistic which is distributed $\chi^2$ under the null hypothesis of the validity of our instruments. The results in Table 3 reveal a $J$-statistic with a $p$-value of 0.99.

Overall, the results in Table 3 suggest that our proposed empirical model provides a fair approximation of investor expectations of customer satisfaction. Next, we turn to examining the cross-sectional relation between the abnormal stock returns around customer satisfaction announcement and deviations from “expected” customer satisfaction. Of course, these deviations reflect “true” unexpected changes in customer satisfaction and “error” due to model mis-specification (missing variables, incorrect functional forms, exclusion of trends, etc); however, the relatively high goodness of fit measures suggests that the latter is not a serious concern.

5.2 Market Reaction to Surprise in Customer Satisfaction Announcements

In Table 4, we report the Cumulative Abnormal Return by various surprise quintiles, wherein firms are arranged into quintiles based on the difference between actual customer satisfaction and the expected customer satisfaction. Quintile 1 consists of firms having the most negative difference between actual customer satisfaction and the predicted (expected) level of customer satisfaction while Quintile 5 has the most positive
difference. The expected customer satisfaction is obtained via two models: naïve (only utilizes last year’s level of customer satisfaction) and GMM (utilizes both lagged value of customer satisfaction and a vector of lagged firm-characteristics and marketing investments) as reported in column (3) of Table 3. Thus, for the naïve model the “surprise”, $\Delta_{it}$ for firm $i$ at time $t$ is given simply by $\Delta_{it} = CS_{it} - CS_{i,t-1}$, while for the GMM model the surprise is given by $\hat{\epsilon}_{it} = CS_{it} - \alpha_0 \hat{\alpha}_i - \hat{\beta}_i X_{i,t-1} - \hat{\eta}_i - \hat{\epsilon}_i$. In Table 4, we report six-day (0, +5) returns across two risk adjustments: (i) market-adjusted, and (ii) market, size, book-to-market, and momentum adjusted. In each case, the cumulative abnormal return (CAR) is obtained by summing the abnormal return (AR) for each firm over the event window and then averaging across the firms in the quartile. Thus, for each firm $i$,

$$\text{CAR}_i = \sum_{t=0}^{t=+5} \text{AR}_{i,t}$$

(4)

The precise calculation of the abnormal returns for the market adjusted model and for the market, size, book-to-market and momentum adjusted model are detailed in Appendix B. Focusing on the market-adjusted returns in Table 4, we find that the naïve model (model 1) demonstrates a significant abnormal reaction (1.05%, $t=2.99$) only for large positive surprises in customer satisfaction. This is consistent with results reported in Ittner, Larcker, and Taylor (2009). In contrast, the GMM model demonstrates a significant abnormal reaction to both large positive surprises (1.21%, $t=2.24$) and large negative surprises (-0.74%, $t=-2.06$). For both models, the difference between Quintile 5 and Quintile 1 is statistically significant; however, the difference between Quintile 5 and Quintile 1 is bigger for the GMM model (1.95%, $t=3.61$) than for the naïve model.
(1.64%, \( t = 3.32 \)). These results demonstrate that the market does indeed respond in the short-term to the surprise in customer satisfaction with substantially more pronounced effects for the GMM expectations models.\(^\text{12}\) The findings are very similar when the abnormal returns are market, size, book-to-market and momentum adjusted. Finally, quintiles 2, 3, 4 are characterized by less extreme levels of surprise and we find little reaction to those announcements.

To get an idea of the economic significance of the cross-sectional variation of abnormal returns, we note that the average customer satisfaction surprise in Quintile 1 is -3.8, while that in Quintile 5 is 3.4; a difference of 7.2 customer satisfaction points. Again, if we consider the six-day (0, +5) cumulative abnormal reaction (using the GMM expectations model, and market, size, book-to-market and momentum adjustment for the returns in Table 4), the difference in returns between Quintiles 5 and 1 is 2.16%. The average firm in our sample has a market capitalization of $2.96 billion. Thus, 2.16% represents approximately $64 million in market capitalization for the average firm, suggesting that each “unexpected” customer satisfaction point is worth $9 million to the typical firm.

To further put this in context, assume that a firm that is currently in the 25\(^{\text{th}}\) percentile of customer satisfaction (with a score of 71) and is considering improving its score to the 75\(^{\text{th}}\) percentile in customer satisfaction (a score of 80). Our findings reveal that this 9 point improvement in customer satisfaction will increase the market value of the firm by approximately $80 million. These estimates provide some ballpark cost-benefit guidelines for investments in customer satisfaction. In particular, initiatives that

\(^{12}\) All t-statistics in this table are based on standard errors that account for industry and event date clustering.
increase customer satisfaction by 9 points or prevent an anticipated decline in customer satisfaction by 9 points are worthwhile as long as they do not exceed $80 million.

5.3 Robustness Tests

We carry out a number of robustness tests of the analysis in Table 4. In Table 4, we have used an six-day (0, +5) window around the customer satisfaction announcement. However, it is possible that there might be significant leakage of the customer satisfaction announcement prior to the announcement date we have identified and this might be driving our results. In Table 5, we replicate the analysis in Table 4 for a longer window – an eleven-day (-5, +5) window around the announcement. The results in Table 5 show that even with the longer window, there is a positive relation between the announcement return and the magnitude of the surprise. Again, we see that this positive relation is more pronounced for the full GMM model than for the naïve model. The results also show that returns (and the pattern of returns) in the longer window are of a similar magnitude to those in the (0, +5) window.

In Figure 2, we summarize the CARs across the entire eleven-day window from five days before the announcement to five days after (-5, +5). The figure shows the difference between Quintile 5 and Quintile 1 where the abnormal returns are market, size, book-to-market and momentum adjusted. The figure shows that there very little pre-announcement leakage; the difference in abnormal returns between Quintile 5 and Quintile 1 is insignificant in the five days (-5, -1) before the identified announcement date. This is in clear contrast to the significant difference between Quintile 5 and Quintile 1 in the five days (0, +5) following the announcement of customer satisfaction scores.
In untabulated analysis, we examine the robustness of our surprise measure by excluding concentration, log of assets, and R&D expense from our calculation of expected customer satisfaction. These are variables that are not individually significant in the GMM regression in column (3) of Table 3. The abnormal returns we obtain are similar to those we report in Table 4. For example, the (market adjusted) difference in returns between Quintile 5 and Quintile 1 is 2.05% ($t = 3.60$), while for the market, size, book-to-market and momentum adjusted returns, the difference is 1.88% ($t = 3.32$).

Finally, in additional untabulated analysis, we estimate equation (3) using a Box-Cox transformation and calculate our surprise measure using the predicted values. This allows estimation without a priori specification of the functional form. We then examine the Cumulative Abnormal Return by various surprise quintiles. We find results qualitatively and quantitatively similar to that obtained by employing the naïve and GMM models. The abnormal return for the lowest quintile (Quintile 1) is negative but insignificant and the abnormal return for the highest quintile (Quintile 5) is positive and significant. The (market adjusted) difference in returns between Quintile 5 and Quintile 1 is 1.51% ($t = 3.06$), while for the market, size, book-to-market and momentum adjusted returns, the difference is 1.82 ($t = 3.37$). This suggests that our GMM results are not driven by the assumption of a linear model specification.
6. SUMMARY, CONTRIBUTIONS AND LIMITATIONS

6.1 Summary and Contributions

Our research is motivated by the lack of evidence pertaining to short-run investor reaction to customer satisfaction announcements. Clearly, this gap diminishes the received conceptualization of customer satisfaction. Accordingly, we set out to assess short-run investor reaction to customer satisfaction announcements. A key conceptual contribution of our research efforts is to incorporate the well-developed notion of investor expectations into the context of customer satisfaction. In our work, we analyze two distinct “expectations” models: a naïve model where expected customer satisfaction is simply last year’s customer satisfaction, and a model that includes firm characteristics and marketing investments. For both these “expectations” models, we utilize the prediction errors to obtain a measure of the “surprise” in customer satisfaction. We then examine the market’s response to our measure of surprise in customer satisfaction. Doing so, we find that the market does indeed respond in the short-term to the surprise in customer satisfaction with more pronounced effects for our GMM model. This empirical finding is a second contribution of our research efforts.

Our empirical findings differ from those reported in Ittner and Larcker (1998) and Fornell, Mithas, Morgeson, and Krishnan (2006) but complement those documented in Ittner, Larcker, and Taylor (2009). We extend the naïve expectations model analyzed by Ittner, Larcker, and Taylor (2009), motivated by the suggestions in Jacobson and Mizik (2009b). Specifically, we include firm characteristics and marketing investments and utilize GMM to explicitly control for unobserved heterogeneity, simultaneity, and
dynamic endogeneity. Controlling for these various sources of endogeneity allows us estimate the true model with greater confidence. Strikingly, we find that these additional variables merit inclusion from a statistical perspective. As such, they give credence to our enhanced expectations model.

6.2 Limitations

Of course, our work is not without limitations. First and foremost, developments in the theory of investor expectations may suggest other variables that warrant inclusion in a model of customer satisfaction expectations. Thus, we can make no claim that we have developed the “best” model of customer satisfaction expectations; rather, we view our development of a model of customer expectations as an important first-step in understanding this phenomenon. Nevertheless, the statistical significance of the variables in our expectations model along with its ability to demonstrate the anticipated short-term effects reveals the inherent logic and contribution of our expectations model.

Second, we have developed and analyzed a model of customer satisfaction expectations across firms in different industries. It may be possible to build models that are specific to firms in particular sectors, thereby allowing for an expectations model with a somewhat more comprehensive set of predictor variables such as investments in training, service infrastructure improvements, etc. Such an analysis may also yield fairly precise estimates on customer satisfaction expectations, which can then be fruitfully used as a target for determining customer satisfaction incentives. This is indeed the suggestion offered by Jacobson and Mizik (2009b). We hope that better data availability and future research efforts will overcome these limitations.
**Appendix A: Sources of Endogeneity and Dynamic Panel Data Estimation Methodology**

There are three sources of endogeneity:

**Unobservable heterogeneity:** OLS estimation assumes that there are no unobservable firm characteristics which may explain customer satisfaction that are also correlated with any of our explanatory variables, i.e. it assumes that $E(\eta_i \mid X_{i,t-1}) = 0$. However, as we have argued when developing our conceptual model of expected customer satisfaction, this is unlikely to be the case.

**Simultaneity:** OLS estimation assumes that there is no correlation between any of the explanatory or control variables and the error term in (1), i.e. $E(\epsilon_{it} \mid X_{i,t-1}) = 0$. Again, this may not necessarily be the case.

**Dynamic Endogeneity**, or reverse causality: OLS estimation assumes that current levels of the explanatory or control variables are independent of previous shocks to customer satisfaction. This is a particularly strong assumption and one that we have argued is unlikely to hold since it implies that all our explanatory and control variables are random draws through time and do not depend on the firm’s history.

To effectively address these sources of endogeneity, we apply the *dynamic panel data estimation* methodology originally developed by Arellano and Bond (1991) and further developed in a series of papers by Arellano and Bover (1995) and Blundell and Bond (1998). The basic dynamic panel consists of two key steps. First, we take first-differences of (3) in order to eliminate the firm-specific fixed effect.

\[
\Delta CS_{it} = \alpha_0 + \alpha_1 \Delta CS_{i,t-1} + \beta_1 \Delta X_{i,t-1} + \Delta \epsilon_{it} \quad \text{(A1)}
\]
Next, we estimate (A1) via general method of moments (GMM) using values of the explanatory variables lagged two periods (t-2) or earlier, as instruments for the explanatory variables (which as we show in A1 are measured at t-I). The first step removes the omitted variable bias that may arise due to (fixed) unobserved heterogeneity. The last step (coupled with the fact that we also include CS at time t-I in our basic specification) ameliorates any biases due to simultaneity or dynamic endogeneity. The basic idea here is that any effect of historical CS at time t-2 or earlier only affect current CS (CS_t) through its effect on CS_{t-1} and X_{t-1}.

Arellano and Bover (1995) and Blundell and Bond (1998) argue that we can improve the GMM estimator by also including the equation in levels in the estimation procedure. We can then use the first-differenced variables as instruments for the equations in levels in a “stacked” system of equations that includes the equations in both levels and differences. This produces a “system” GMM estimator that involves estimating the following system:

\[
\begin{pmatrix}
CS_t \\
\Delta CS_t
\end{pmatrix} = \alpha_0 + \alpha_1 \begin{pmatrix}
CS_{t-1} \\
\Delta CS_{t-1}
\end{pmatrix} + \beta_1 \begin{pmatrix}
X_{t-1} \\
\Delta X_{t-1}
\end{pmatrix} + \nu_t
\]  

(A2)
Appendix B: Calculation of Abnormal Return for Market Adjusted Model and for Market, Size, Book-to-Market and Momentum Adjusted Model

For the market adjusted model, the abnormal return for each firm is calculated as

\[
AR_{i,t} = R_{i,t} - \hat{\alpha}_i - \hat{\beta}_{i,m} R_{m,t}
\]  

(B1)

where \( R_{i,t} \) is the return for firm \( i \) on day \( t \), \( R_{m,t} \) is the equal-weighted market return, and \((\hat{\alpha}_i, \hat{\beta}_{i,m})\) are parameters computed by regressing the firm’s returns on market returns from 160 days before the announcement date to 10 days before the announcement of customer satisfaction (i.e. a \([-160,-10]\) window relative to the announcement date).

Calculation of abnormal returns for market, size, book-to-market and momentum adjusted model is based on expected returns predicted by a four factor model. The model consists of three factors from Fama and French (1993): the excess return on the market \((R_m - R_f)\); the return difference between a portfolio of “small” and “big” stocks \((SMB)\) and the return difference between a portfolio of “high” and “low” book-to-market stocks \((HML)\), augmented with a momentum factor from Carhart (1997), which is the return difference between a portfolio of stocks with high returns in the past year and a portfolio of stocks with low returns in the past year \((UMD)\). Again, the parameters of the expected returns model are computed from an estimation period stretching from 160 days before the announcement date, to 10 days before the announcement of customer satisfaction (i.e. a \([-160,-10]\) window relative to the announcement date). So for each observation in the sample, the four factor model parameters are estimated from the regression:
\[ R_{i,t} - R_{f,t} = \alpha + \beta_m (R_{m,t} - R_{f,t}) + \beta_{sMB} SMB_t + \beta_{sHML} HML_t + \beta_{sUMD} UMD_t + \varepsilon_{i,t} \]  \hspace{1cm} (B2)

We then apply the four factor model parameters obtained from equation (B2) to calculate the abnormal returns for each of our event windows:

\[ AR_{i,t} = R_{i,t} - [\hat{\alpha}_i + \hat{\beta}_{i,m} (R_{m,t} - R_{f,t}) + \hat{\beta}_{i,sMB} SMB_t + \hat{\beta}_{i,sHML} HML_t + \hat{\beta}_{i,sUMD} UMD_t] \]  \hspace{1cm} (B3)
REFERENCES


Table 1
Summary Statistics of Key Variables

The variables are defined as follows: Customer Satisfaction is the ACSI score. Market-to-book value is the market value of assets divided by the book value of assets, where the market value of assets is computed as book value of assets (COMPUSTAT item: “at”) plus the market value of common stock (the product of COMPUSTAT items: common shares outstanding, “csho” and fiscal year end stock price, “prcc_f”) less the sum of the book value of common stock (COMPUSTAT item: “ceq”) and balance sheet deferred taxes (COMPUSTAT item: “txdb”). Log Segments is the log of the number of business segments which is obtained by counting the number of business segments from the COMPUSTAT Segments database. Concentration, is the Herfindahl index (sum of square-market shares) where market share is computed via sales revenue (COMPUSTAT item: “sale”) reported at the 2-digit SIC code level for all COMPUSTAT companies with the same 2-digit SIC code. Return on assets is computed as operating income before depreciation (COMPUSTAT item: “oibdp”) divided by the book value of assets (COMPUSTAT item: “at”). Log Assets is the log of firm assets, represented by book value of assets. Advertising is the ratio of advertising expenses (COMPUSTAT item: “xad”) to sales (COMPUSTAT item: “sale”). R&D is the ratio of R&D expense (COMPUSTAT item: “xrd”) to sales.

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<th>Variable</th>
<th>Mean</th>
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<th>25% Pctl.</th>
<th>Median</th>
<th>75% Pctl.</th>
<th>Max</th>
<th>Standard Deviation</th>
<th>Skewness</th>
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<td>0.02</td>
<td>4.35</td>
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Table 2
Correlation Matrix for key variables
The variables are defined as follows: Customer Satisfaction is the ACSI score. Market-to-book value is the market value of assets divided by the book value of assets, where the market value of assets is computed as book value of assets plus the market value of common stock less the sum of the book value of common stock and balance sheet deferred taxes. Log Segments is the log of the number of business segments which is obtained by counting the number of business segments from the COMPUSTAT Segments database. Concentration, is the Herfindahl index (sum of square-market shares) where market share is computed via sales revenue reported at the 2-digit SIC code level for all companies with the same 2-digit SIC code. Return on assets is computed as operating income before depreciation divided by the book value of assets. Log Assets is the log of firm assets, represented by book value of assets. Advertising is the ratio of advertising expenses to sales. R&D is the ratio of R&D expense to sales. *p*-values are in parentheses. ***, **, and * represent significance at the 1%, 5% and 10% levels, respectively using two-tailed tests.

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<td>R&amp;D</td>
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Table 3
Regression Results
The dependent variable in all specifications is Customer Satisfaction (ACSI score). Market-to-book value is the market value of assets divided by the book value of assets, where the market value of assets is computed as book value of assets plus the market value of common stock less the sum of the book value of common stock and balance sheet deferred taxes. Log Segments is the log of the number of business segments which is obtained by counting the number of business segments from the COMPUSTAT Segments database. Concentration, is the Herfindahl index (sum of square-market shares) where market share is computed via sales revenue reported at the 2-digit SIC code level for all companies with the same 2-digit SIC code. Return on assets is computed as operating income before depreciation divided by the book value of assets. Log Assets is the log of firm assets, represented by book value of assets. Advertising is the ratio of advertising expenses to sales. R&D is the ratio of R&D expense to sales. t-statistics, based on standard errors clustered by firm and industry are in parentheses. p-values, where appropriate in brackets. *** , ** , and * represent significance at the 1%, 5% and 10% levels, respectively, using two-tailed tests.

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</tr>
<tr>
<td>Lagged CUSTOMER SATISFACTION</td>
<td>0.91***</td>
<td>0.89***</td>
<td>0.62***</td>
</tr>
<tr>
<td></td>
<td>(60.97)</td>
<td>(49.74)</td>
<td>(13.12)</td>
</tr>
<tr>
<td>Constant</td>
<td>6.35***</td>
<td>7.83***</td>
<td>28.06***</td>
</tr>
<tr>
<td></td>
<td>(6.63)</td>
<td>(4.33)</td>
<td>(6.40)</td>
</tr>
<tr>
<td>Time Dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>R^2</td>
<td>0.8125</td>
<td>0.8355</td>
<td></td>
</tr>
<tr>
<td>Young Z-stat of (2) vs. (1) [p-value]</td>
<td>5.42***</td>
<td>&lt;0.01</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>2.12**</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>F-stat of firm characteristics [p-value]</td>
<td>[0.04]</td>
<td>[0.14]</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>3.05***</td>
<td>[0.99]</td>
</tr>
<tr>
<td>AR(2) test [p-value]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hansen test of over-identification [p-value]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of firms (firm-years)</td>
<td>115 (949)</td>
<td>115 (949)</td>
<td>115 (949)</td>
</tr>
</tbody>
</table>
Table 4
Cumulative Abnormal Returns (CAR) and Unexpected Changes in Customer Satisfaction
The table reports the cumulative abnormal reaction (CAR) to the announcement of customer satisfaction scores in a (0, +5) window around the announcement. Day 0 is the date of the announcement of the customer satisfaction scores. Firms are arranged into quintiles based on the difference between actual customer satisfaction and the expected customer satisfaction score, with Quintile 1 having the most negative difference and Quintile 5 having the most positive difference. For Model 1, the expected customer satisfaction is $CS_{t-1}$. For Model 2, the expected customer satisfaction is $\hat{\alpha} - \hat{\beta}_1 CS_{t-1} - \hat{\beta}_2 X_{t-1}$, where $X_{t-1}$ is a vector of variables that includes market-to-book, number of market segments, concentration, industry, return on assets, firm size, advertising, and R&D. t-statistics based on robust standard error are shown in parentheses ***, **, and * represent significance at the 1%, 5% and 10% levels, respectively, using two-tailed tests.

<table>
<thead>
<tr>
<th>Quintile (Q)</th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>All firms</td>
<td>0.38% (1.27)</td>
<td>0.27% (1.20)</td>
</tr>
<tr>
<td>Quintile (Q)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>-0.59% (-1.60)</td>
<td>-0.41% (-1.20)</td>
</tr>
<tr>
<td>2</td>
<td>-0.17% (-0.53)</td>
<td>0.14% (0.42)</td>
</tr>
<tr>
<td>3</td>
<td>0.16% (0.54)</td>
<td>0.57% (1.60)</td>
</tr>
<tr>
<td>4</td>
<td>0.52% (1.59)</td>
<td>0.37% (0.99)</td>
</tr>
<tr>
<td>5</td>
<td><strong>1.05%</strong>* (2.99)</td>
<td><strong>1.35%</strong>* (3.60)</td>
</tr>
<tr>
<td>Q5 minus Q1</td>
<td><strong>1.64%</strong> (3.32)</td>
<td><strong>1.76%</strong>* (3.45)</td>
</tr>
</tbody>
</table>
Table 5
Cumulative Abnormal Returns (CAR) and Unexpected Changes in Customer Satisfaction around a longer event window
The table reports the cumulative abnormal reaction (CAR) to the announcement of customer satisfaction scores in a (-5, +5) window around the announcement. Day 0 is the date of the announcement of the customer satisfaction scores. Firms are arranged into quintiles based on the difference between actual customer satisfaction and the expected customer satisfaction score, with Quintile 1 having the most negative difference and Quintile 5 having the most positive difference. For Model 1, the expected customer satisfaction is \( \hat{CS}_{t-1} \). For Model 2, the expected customer satisfaction is \( \hat{CS}_{t-1} - \hat{\beta}_1 \hat{CS}_{t-1} - \hat{\beta}_2 X_{t-1} \), where \( X_{t-1} \) is a vector of variables that includes market-to-book, number of market segments, concentration, industry, return on assets, firm size, advertising, and R&D. \( t \)-statistics based on robust standard error are shown in parentheses ***, **, and * represent significance at the 1%, 5% and 10% levels, respectively, using two-tailed tests.

<table>
<thead>
<tr>
<th>Quintile (Q)</th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>All firms</td>
<td>0.22% (0.89)</td>
<td>0.35% (1.54)</td>
</tr>
<tr>
<td>Quintile (Q)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>-0.05% (-0.09)</td>
<td>-0.12% (-0.22)</td>
</tr>
<tr>
<td>2</td>
<td>-0.83% (-1.23)</td>
<td>-0.32% (-0.71)</td>
</tr>
<tr>
<td>3</td>
<td>-0.60% (-1.37)</td>
<td>-0.06% (-0.12)</td>
</tr>
<tr>
<td>4</td>
<td>0.39% (0.59)</td>
<td>0.61% (1.37)</td>
</tr>
<tr>
<td>5</td>
<td><strong>1.73%</strong> *** (3.30)</td>
<td><strong>1.98%</strong> *** (3.16)</td>
</tr>
<tr>
<td>Q5 minus Q1</td>
<td><strong>1.79%</strong> ** (2.22)</td>
<td><strong>2.10%</strong> ** (2.50)</td>
</tr>
</tbody>
</table>
Figure 1
Online Search Intensity and Customer Satisfaction Announcements
This figure plots the weekly normalized search intensity for the search term: “american customer satisfaction index” during 2006. Source: Google Insights for Search: http://www.google.com/insights/search/
Figure 2
The figure shows the cumulative abnormal reaction (CAR) around the announcement of customer satisfaction. Day 0 is the date of the announcement of the customer satisfaction scores. Firms are arranged into quintiles based on the difference between actual customer satisfaction and the expected customer satisfaction score, with Quintile 1 having the most negative difference and Quintile 5 having the most positive difference. The figure shows the difference between Q5 and Q1 (Q5 minus Q1). The abnormal returns are market, size, book-to-market and momentum adjusted.