Disentangling the market value of customer satisfaction: Evidence from market reaction to the unanticipated component of ACSI announcements

Vladimir Ivanov a,1, Kissan Joseph b,⁎, M. Babajide Wintoki b,2

a Office of Economic Analysis, U.S. Securities and Exchange Commission, 100 F Street, N.E. Washington DC 20549, United States
b School of Business, University of Kansas, 1300 Sunnyside Avenue, Lawrence, KS 66045-7585, United States

1. Introduction

1.1. Motivation

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 respond only to deviations from these expectations (i.e., "surprises"). 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 the prior allocation of resources devoted to improving customer satisfaction. In our empirical work, we find that the market does indeed respond in the short-run to surprises in customer satisfaction, with more pronounced effects for our second expectations model. Overall, our research offers two distinct contributions. First, it refines the current 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 investments in customer satisfaction.

Published by Elsevier B.V.
However, in their commentary, Fornell, Mithas, and Morgeson (2009) present new analysis that updates the findings of Fornell et al. (2006). They report that the above-market returns reported in Fornell et al. (2006) persist; moreover, they are both economically and statistically significant.3

Clearly, the marketing scholars and practitioners in all of these investigations are fundamentally interested in better understanding the market value of customer satisfaction. Indeed, the chain of effects leading from customer satisfaction to favorable customer behaviors, followed by enhanced firm performance and culminating in a 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 outcomes, 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, & Lehmann, 1994; Bearden & Teel, 1983; Bolton, 1998; Bolton & Drew, 1991; Bolton & Lemon, 1999; Fornell, 1992; Homburg, Koschat, & Hoyer, 2005). Next, the relationship between customer satisfaction and enhanced firm performance, which stems from the aforementioned favorable customer outcomes, has been reported in a growing number of studies (Bolton, 1998; Grua & Rego, 2005; Mittal & Kamakura, 2001; Rust, Zahorik, & 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 & Mansi, 2009, p. 704). In particular, this inconsistent finding is manifested by the lack of a consistent short-run market reaction to customer satisfaction announcements (Fornell et al., 2006; Ittner and Larcker, 1998; Ittner et al., 2009). Given that customer satisfaction has a demonstrated positive impact 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 that they respond only to deviations from these expectations. Such a premise is well-grounded in the 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 the post-launch performance of studio stock price is strongly influenced by expectations of performance built up prior to the 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 reactions to earnings announcements, Ball and Brown (1968) show that the market responds to the unexpected components 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 & Tse, 1992; Kinney, Burgstahler, & 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 reactions for large absolute surprises.4

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 marketing investments allocated to improving 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 that invested in advertising in previous periods will likely exhibit higher levels of customer satisfaction because of the utility-enhancing effects of advertising.

Accordingly, we posit that prior to the release of new customer satisfaction scores, investors have their own private forecasts of the customer satisfaction levels of 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 et al. (2009) take an important first step in this direction when they look at the market reaction to year-over-year changes 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 current 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 customer satisfaction information 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 or 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 customer satisfaction information only after the announcement, when the positive chain of effects resulting from customer satisfaction has, in fact, materialized. Investors may also wait for customer satisfaction information to be filtered through analysts before responding to it. Along these lines, Luo, Homburg, and Wieseke (2010) show that customer satisfaction leads to lower forecast errors from analysts. Because investors generally find it costly to process the information

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3 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 utilized measure of customer satisfaction is the ACSI metric provided by ACSI LLC.

4 Strictly speaking, this body of research does not require individual investors to form expectations; rather, what is required is that investors, in the aggregate, act as though they were responding to deviations from expectations.
searching a customer satisfaction announcement, it is thus worthwhile for them to wait for analyst forecasts before responding.

We respond to the first of these alternative conceptualizations by providing three distinct sets of empirical evidence that demonstrate 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 customer satisfaction metrics. 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—that 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 information may precede the announcement. It is also highly likely that some of the response to customer satisfaction information will follow the announcement. However, we argue that these effects should only hamper our efforts to find any effect at the time of the announcement. Therefore, any effects that we find 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 our findings pertaining to the 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 that were allocated to customer satisfaction. Finally, by examining the market reaction to customer satisfaction announcements, we find that the market does indeed respond to “surprises” in customer satisfaction announcements, with more pronounced effects in our second 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, Progressive Grocer routinely summarizes changes in ACSI scores among food processing companies. In particular, a recent announcement highlights the following improvements: “Sara Lee Corporation showed the biggest improvements in its ACSI score,” “Mars Inc., Nestlé, General Mills Inc. and ConAgra Foods all posted scores of 83,” and “Hershey Foods Corporation edged up a point.”

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 in the computer industry, and Insurance Networking News in the insurance industry. In a similar fashion, ACSI announcements are also highlighted and re-broadcast by several investment websites, for example, Seeking Alpha, a popular investment website recently featured the following headline: “Heinz Ranks Number One in Customer Satisfaction Among All 225 Companies in the American Customer Satisfaction Index.”

Another investment website, www.istockanalyst.com, 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. 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 customer experience for more than 500 million users of Yahoo branded properties around the world.” In addition, Sprint Corporation recently highlighted its strong showing in customer satisfaction via press releases and full-page ads in the Wall Street Journal in which the ACSI logo was prominently displayed in tandem 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, & Gao, 2011; Joseph, Wintoki, & 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 searches 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 during the weeks of ACSI score announcements than in other weeks throughout the period. To further illustrate our point, Fig. 1 displays the level of public interest in ACSI scores by plotting the weekly search intensity for the term “American Customer Satisfaction Index” during the year 2006. The displayed search intensity is normalized by a factor that is unknown 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 during the week of, and the weeks surrounding, the announcement of ACSI scores. We interpret this finding as evidence that ACSI announcements are followed by some investors.

Third, we examine changes in trading volume around ACSI announcements. If trading volume increases around ACSI announcements, we can conclude that there is 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 ranging from fifty (t – 50) to fifteen days before the ACSI announcement (t – 15), and another stretch from fifteen (t + 15) to fifty days after the announcement (t + 50), where t represents the date of the ACSI score announcement. We find that the average volume is 2.8% higher in the ten-day period (−5≤t≤5) around ACSI announcements than during the “non-announcement” window, relative to the market.

Based on these three sets of empirical evidence, we thus conclude that customer satisfaction, as represented 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.

References


7 http://files.shareholder.com/downloads/CMCSA/0x0b313122/1421tchc-96ee-4a79-b5a6-c38a9eed6394/cmc52transcript.pdf.


10 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.

Please cite this article as: Ivanov, V., et al., Disentangling the market value of customer satisfaction: Evidence from market reaction to the unanticipated component of ..., Intern. J. of Research in Marketing (2012), http://dx.doi.org/10.1016/j.ijresmar.2012.09.003
3. Model of customer satisfaction expectations

As previously suggested, we posit that the expectations of the level of customer satisfaction at time \( t \), \( E[C_{S_t}] \), are influenced both by the level of customer satisfaction in period \( t - 1 \), \( C_{S_{t-1}} \), and investments in customer satisfaction during period \( t - 1 \), \( I_{C_{t-1}} \). Formally, we have:

\[
E[C_{S_t}] = \alpha C_{S_{t-1}} + \beta I_{C_{t-1}}.
\] (1)

Eq. (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 improvement, \( I_{C_{t-1}} \).

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

Which variables will investors use to estimate \( I_{C_{t-1}} \)? 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 the logic associated with our use of these seven variables.

With respect to growth opportunities, investors believe that firms with high growth prospects are likely to invest more in customer satisfaction at time \( t - 1 \) because they can potentially recoup these investments as these new opportunities are exploited. High levels of customer satisfaction in current businesses can be gainfully leveraged to enter new businesses via lower acquisition costs (Anderson et al., 1994) or used to benefit from a higher receptivity to cross-selling initiatives (Bolton, 1998). Similarly, firms operating in multiple segments will likely invest more in customer satisfaction because of spillover benefits. Chai and Ding (2009) provide empirical evidence for such customer satisfaction spillovers in the mobile phone industry (between handset manufacturers and network operators). Next, because market concentration is a proxy for barriers to entry (Powell, 1996), it follows that firms operating in concentrated industries will have greater incentives to invest in customer satisfaction because they can appropriate more of the value associated with their investments.

We expect efficiency in converting inputs to outputs and firm size to also straightforwardly impact investments in customer satisfaction. Highly efficient firms will see more benefits from such investments while large firms will choose to invest less on account of the heterogeneous customer base that they are likely to serve (Anderson et al., 1994). Finally, we expect investments in advertising and R&D to positively impact customer satisfaction expectations. As demonstrated by Erdem and Sun (2002), advertising can increase the mean and decrease the variance of customer utility, thereby increasing surplus and customer satisfaction. Similarly, we expect investments in R&D to also allow firms to provide greater product differentiation (Chauvin & Hirsche, 1993; Veliyath & Ferris, 1997). This positive differentiation should also enhance utility and increase customer satisfaction.

Clearly, these seven variables do not exhaust all of the influences of firm investments in customer satisfaction improvements. Rather, we make the more modest claim that, as a group, they capture important aspects of the decision to invest in customer satisfaction and serve as good proxies for the information available to investors. Growth opportunities and the number of segments served reflect the trajectory and depth of market demand for a firm’s product and are therefore intimately related to the future payoffs from customer satisfaction investments. Concentration incorporates the influence of the competitive environment in that it reflects the ability of a firm to appropriate the value that it creates through customer satisfaction investments. Efficiency in 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 in 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. Because 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 value as a proxy for growth opportunities. An increase in growth opportunities at time \( t - 1 \) may cause investors to increase their expectations with regard 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, they will bid up the market value of the firm, thus increasing its market-to-book ratio.

Finally, we acknowledge the dynamic endogeneity, or reverse causality, of customer satisfaction to our firm characteristics. 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 analysis, we are careful to account as much as possible for all these sources of endogeneity in our empirical estimation of expected customer satisfaction.

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

\[
E[C_{S_t}] = \alpha C_{S_{t-1}} + \beta X_{t-1}
\] (2)
where the vector $X$ encapsulates the seven described variables. Then, announcements of customer satisfaction in period $t$, $CS_t$, lead to an 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 et al. (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).

Because our explanatory variables (described below) are from the COMPUSTAT database, we merge the ACSI and COMPUSTAT data. This leaves us with a working sample consisting of 116 firms and 1109 firm-years over the 12-year period from 1995 to 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 to employ the market-to-book ratio as a measure of the growth opportunities associated with the firm in the finance literature (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 the book value of assets (COMPUSTAT item: “at”) plus the market value of common stock (the product of COMPUSTAT items: common shares outstanding, “sho” and fiscal year end stock price, “prc_f”) less the sum of the book value of common stock (COMPUSTAT item: “ceq”) and balance sheet deferred taxes (COMPUSTAT item: “tddb”). 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.12

We use return on assets to measure efficiency, 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 the 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 expenses (COMPUSTAT item: “xrd”) to sales. Per convention, we set the R&D expense to zero if it is missing or not reported because the SEC has long required all publicly traded firms to report any “material” R&D expenditures (Bound, Cummins, Griliches, Hall, & Jaffe, 1984). Similarly, we set the 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 expenditures; the Generally Accepted Accounting Principles (GAAP) require all firms with “material” R&D or advertising expenditures to recognize and disclose these items in 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 expenses indeed represent zero or close to zero expenditures.

Of course, it is possible that some firms may have advertising expenses that they do not recognize; the aforementioned standards do allow for some exceptions and the very definition of “material” may, on the margin, be subject to auditor judgment. This may make our advertising measure noisy, but a number of studies (e.g., Bound et al., 1984; Chauvin & Hirschey, 1993; Hirschey, Skiba, & Babajide Wintoki, 2012) test the assumption of setting the value of missing R&D and advertising expenses to zero in large samples and conclude that it generally has little to no effect on empirical analyses involving R&D and advertising expenditures.

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 1109 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 of this variable is 49 while the maximum value is 90.

Table 1 also shows that the mean (median) market-to-book ratio is 1.91 (1.41) and the mean or median firm in our sample has approximately 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 sizes, 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 the market-to-book ratio, 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 the dynamic panel generalized method of moments estimation. As we will discuss later, the latter method accounts for potential sources of endogeneity. We then examine the market’s reaction to customer satisfaction surprises, followed by additional robustness tests.

5.1. Empirical model and estimation of expected customer satisfaction

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

$$CS_{it} = \alpha_0 + \alpha_1 CS_{it-1} + \beta_1 X_{it-1} + \eta_i + d_t + \epsilon_{it}$$

(3)

where $CS_{it}$ is the customer satisfaction of firm $i$ in year $t$, $X_{it-1}$ is a vector of observable firm characteristics and investments (market-to-book value, the number of business segments, concentration, return on assets, firm size, advertising, and R&D expenditures) 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 because 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 at the end of the fiscal year prior to the customer satisfaction announcement.

Although we start our empirical analysis with a simple OLS estimation of Eq. (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
Table 1

Summary statistics of key variables. The variables are defined as follows: customer satisfaction is the AC$S$ 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 the book value of assets (COMPUSTAT item: “ar”) plus the market value of common stock (the product of COMPUSTAT items: common shares outstanding, “csho” and fiscal year end stock price, “prc_e”), less the sum of the book value of common stock (COMPUSTAT item: “eq”) and balance sheet deferred taxes (COMPUSTAT item: “tdbl”). 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 the 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 the operating income before depreciation (COMPUSTAT item: “oibdp”) divided by the book value of assets (COMPUSTAT item: “ar”). Log assets is the log of firm assets, represented by the book value of assets. Advertising is the ratio of advertising expenses (COMPUSTAT item: “sad”) to sales (COMPUSTAT item: “sale”). R&D is the ratio of R&D expenses (COMPUSTAT item: “rdx”) to sales.

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<th>Variable</th>
<th>Mean</th>
<th>Min</th>
<th>25th percentile</th>
<th>Median</th>
<th>75th percentile</th>
<th>Max</th>
<th>Standard deviation</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 AC$S$ 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 the 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 the 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 the 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.

<table>
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<th>Concentration</th>
<th>ROA</th>
<th>Log assets</th>
<th>Advertising</th>
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<td>Customer satisfaction</td>
<td>1</td>
<td>0.29**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market-to-book</td>
<td></td>
<td>(&lt;0.01)</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log segments</td>
<td>0.12**</td>
<td>(&lt;0.01)</td>
<td>−0.06*</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Concentration</td>
<td>0.02</td>
<td>(0.01)</td>
<td>−0.11**</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ROA</td>
<td>0.38**</td>
<td>(0.01)</td>
<td>0.42*</td>
<td>0.04</td>
<td>0.04</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log assets</td>
<td>−0.21**</td>
<td>(&lt;0.01)</td>
<td>−0.26*</td>
<td>0.05</td>
<td>0.01</td>
<td>−0.35*</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Advertising</td>
<td>0.35**</td>
<td>(&lt;0.01)</td>
<td>0.28*</td>
<td>−0.09*</td>
<td>0.02</td>
<td>0.39</td>
<td>−0.38**</td>
<td>1</td>
</tr>
<tr>
<td>R&amp;D</td>
<td>0.19**</td>
<td>(&lt;0.01)</td>
<td>0.29*</td>
<td>−0.01</td>
<td>−0.11**</td>
<td>0.04</td>
<td>−0.04</td>
<td>0.14*</td>
</tr>
</tbody>
</table>

** Represent significance at the 1% level, using two-tailed tests.
* Represent significance at the 5% level, using two-tailed tests.
Table 3
Regression results. The dependent variable in all specifications is the 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 the 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 the operating income before depreciation divided by the book value of assets. Log assets is the log of aggregated book value of assets. Advertising is the ratio of advertising expenses to sales. R&D is the ratio of R&D expense to sales. R2 0.8125 0.8355

<table>
<thead>
<tr>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>OLS</td>
<td>OLS</td>
<td>System GMM</td>
</tr>
<tr>
<td>Market-to-book</td>
<td>0.11***</td>
<td>0.23**</td>
</tr>
<tr>
<td>Log (segments)</td>
<td>0.08</td>
<td>0.34*</td>
</tr>
<tr>
<td>Concentration</td>
<td>0.25</td>
<td>1.50</td>
</tr>
<tr>
<td>ROA</td>
<td>0.16</td>
<td>8.33***</td>
</tr>
<tr>
<td>Log (assets)</td>
<td>-0.06</td>
<td>0.15</td>
</tr>
<tr>
<td>Advertising</td>
<td>4.51***</td>
<td>6.19*</td>
</tr>
<tr>
<td>R&amp;D</td>
<td>5.30</td>
<td>18.74</td>
</tr>
<tr>
<td>Lagged customer satisfaction</td>
<td>0.91***</td>
<td>0.89***</td>
</tr>
<tr>
<td>Constant</td>
<td>6.35***</td>
<td>7.83***</td>
</tr>
<tr>
<td>Time dummies</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Fixed effects</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>R²</td>
<td>0.8125</td>
<td>0.8355</td>
</tr>
<tr>
<td>Vuong Z-stat of (2) vs. (1) [p-value]</td>
<td>5.42***</td>
<td></td>
</tr>
<tr>
<td>F-stat of firm characteristics [p-value]</td>
<td>2.12***</td>
<td></td>
</tr>
<tr>
<td>AR (2) test [p-value]</td>
<td>[0.04]</td>
<td></td>
</tr>
<tr>
<td>Hansen test of over-identification [p-value]</td>
<td>[0.09]</td>
<td></td>
</tr>
<tr>
<td>Number of firms [firm-years]</td>
<td>115 (949)</td>
<td>115 (949)</td>
</tr>
</tbody>
</table>

*** Represent significance at the 1% level, using two-tailed tests.
** Represent significance at the 5% level, using two-tailed tests.
* Represent significance at the 10% level, using two-tailed tests.

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 value, number of segments, return on assets, and advertising expenditures. 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. The 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 that is distributed J2 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 relationship between the abnormal stock returns around customer satisfaction announcements and deviations from "expected" customer satisfaction. Of course, these deviations reflect "truly" unexpected changes in customer satisfaction and "errors" due to model misspecification (including missing variables, incorrect functional forms, and exclusion of trends); however, the relatively high goodness-of-fit measures suggest that the latter is not a serious concern.

5.2 Market reaction to surprises 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 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 contains those with 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 a 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” ΔSi for firm i at time t is given simply by ΔSi = Ci – Si–1, while for the GMM model, the surprise is given by ΔSi = Ci – α0 – α1Si–1 – β1ΔSi–1 – γ1ΔSi–2 – δ1. 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) of each firm over the event window and then averaging across the firms in the quartile. Thus, for each firm i,

\[ CAR_i = \sum_{t=0}^{5} AR_{it}, \]

The precise calculations 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 et al. (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 in the GMM model (1.95%, t = 3.61) than in the naïve model (1.64%, t = 3.32). These results demonstrate that the market does indeed respond in the short-term to surprises in customer satisfaction, with substantially more pronounced effects in the GMM expectations models.14 The findings are very similar when the abnormal returns are market-, size-, book-to-market- and momentum-adjusted. Finally, Quintiles 2, 3, and 4 are characterized by less extreme levels of surprise and we find little reaction to those announcements.

To obtain 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

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14 All t-statistics in this table are based on standard errors that account for industry and event-date clustering.
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 finding in context, assume that a firm is currently in the 25th percentile of customer satisfaction (with a score of 71) and is considering improving its score to reach the 75th percentile of 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 broad cost–benefit guidelines for investments in customer satisfaction. Specifically, initiatives that increase customer satisfaction by 9 points or prevent an anticipated 9-point decline in customer satisfaction 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 a six-day (0, +5) window around the customer satisfaction announcement. However, it is possible that there might be significant leakage of customer satisfaction information 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 – eleven days (−5, +5) 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 in the full GMM model than in the naïve model. The results also show that the returns (and the pattern of returns) in the longer window are of a similar magnitude to those in the (0, +5) window.

In Fig. 2, we summarize the CARs across the entire eleven-day window, from 5 days before to 5 days after (−5, +5) the announcement. The figure shows the difference between Quintile 5 and Quintile 1 with the abnormal returns being market-, size-, book-to-market- and momentum-adjusted. The figure shows that there is very little pre-announcement leakage; the difference in abnormal returns between Quintile 5 and Quintile 1 is insignificant in the 5 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 5 days (0, +5) following the announcement of customer satisfaction scores.

In an 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 an additional untabulated analysis, we estimate Eq. (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 that are qualitatively and quantitatively similar to those 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 reactions to customer satisfaction announcements. Clearly, this gap diminishes the received conceptualization of customer satisfaction. Accordingly, we set out to assess short-run investor
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 the customer satisfaction and expected customer satisfaction scores, with Quintile 1 representing the most negative difference and Quintile 5 representing the most positive difference. For Model 1, the expected customer satisfaction is \(C_{t-1} \cdot 1 \cdot \frac{1}{1} \), for Model 2, the expected customer satisfaction is \(C_{t-1} \cdot 1 \cdot \frac{1}{1} \), where \(X_{t-1} \) is a vector of variables that includes market-to-book value, number of market segments, concentration, industry, return on assets, firm size, advertising, and R&D. t-Statistics based on robust standard errors are shown in parentheses.

**Table 5**

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Market-adjusted</td>
<td>Market-adjusted</td>
</tr>
<tr>
<td>All firms</td>
<td>0.22% (0.89)</td>
<td>0.22% (0.89)</td>
</tr>
<tr>
<td>1</td>
<td>−0.05% (−0.09)</td>
<td>−1.24%** (−2.20)</td>
</tr>
<tr>
<td></td>
<td>−0.12% (−0.22)</td>
<td>−1.01%* (−1.74)</td>
</tr>
<tr>
<td>2</td>
<td>−0.83% (−1.23)</td>
<td>0.71% (1.30)</td>
</tr>
<tr>
<td></td>
<td>−0.32% (−0.71)</td>
<td>0.05% (1.50)</td>
</tr>
<tr>
<td>3</td>
<td>−0.60% (−1.37)</td>
<td>0.13% (0.22)</td>
</tr>
<tr>
<td></td>
<td>−0.06% (−0.12)</td>
<td>−0.01% (−0.03)</td>
</tr>
<tr>
<td>4</td>
<td>0.39% (0.59)</td>
<td>0.12% (0.20)</td>
</tr>
<tr>
<td></td>
<td>0.61% (1.37)</td>
<td>−0.14% (−0.30)</td>
</tr>
<tr>
<td>5</td>
<td>1.73*** (3.30)</td>
<td>1.41*** (2.70)</td>
</tr>
<tr>
<td></td>
<td>1.98*** (3.16)</td>
<td>1.66** (3.27)</td>
</tr>
<tr>
<td>Q5 minus Q1</td>
<td>1.79*** (2.22)</td>
<td>2.66*** (3.45)</td>
</tr>
<tr>
<td></td>
<td>2.10*** (2.50)</td>
<td>2.67*** (3.32)</td>
</tr>
</tbody>
</table>

*** Represent significance at the 1% level, using two-tailed tests.
** Represent significance at the 5% level, using two-tailed tests.
* Represent significance at the 10% level, using two-tailed tests.

... reactions to customer satisfaction announcements. A key conceptual contribution of our research efforts is the incorporation of the well-developed notion of investor expectations into the customer satisfaction context. 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 of these “expectations” models, we utilize prediction errors to obtain a measure of customer satisfaction “surprise”. We then examine the market’s response to our customer satisfaction surprise measure. In doing so, we find that the market does indeed respond in the short-term to surprises 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 Fornell et al. (2006) and Ittner and Larcker (1998) but complement those documented in Ittner et al. (2009). We extend the naïve expectations model analyzed by Ittner et al. (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 to 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 and service infrastructure improvements. Such an analysis may yield fairly precise estimates of customer satisfaction expectations. 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

The OLS estimation assumes that there are no unobservable firm characteristics that may explain customer satisfaction and that are also correlated with any of our explanatory variables, i.e., it assumes that $E(v_t|X_{it-1}) = 0$. However, as we have argued in developing our conceptual model of expected customer satisfaction, this is unlikely to be the case.

Simultaneity

The OLS estimation assumes that there is no correlation between any of the explanatory or control variables and the error term in Eq. (1), i.e., $E(e_{it}|X_{it-1}) = 0$. Again, this may not necessarily be the case.

Dynamic endogeneity, or reverse causality

The OLS estimation assumes that the 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 because 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 the first-differences of Eq. (3) to eliminate the firm-specific fixed effect:

$$
\Delta C_{it} = \alpha_0 + \alpha_1 \Delta C_{it-1} + \beta_1 \Delta X_{it-1} + \Delta e_{it} \tag{A1}
$$

Next, we estimate Eq. (A1) via the general method of moments (GMM), using values of the explanatory variables that are lagged by two periods ($t - 2$) or more, as instruments for the explanatory variables (which, as we show in Eq. (A1), are measured at $t - 1$). 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 $t - 1$ 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 affects current $CS$ ($C_{it}$) through its effect on $C_{it-1}$ and $X_{it-1}$.

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-differences 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:

$$
\begin{align*}
C_{it} \quad &\Delta C_{it} \\
= &\alpha_0 + \alpha_1 \left( C_{it-1} - \Delta C_{it-1} \right) + \beta_1 \left( X_{it-1} - \Delta X_{it-1} \right) + \epsilon_{it}. \tag{A2}
\end{align*}
$$

Appendix B. Calculation of abnormal returns for the market-adjusted model and for the market-, size-, book-to-market- and momentum-adjusted model

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

$$
AR_{it} = R_{it} - \alpha_0 - \beta_1 R_{m,t} \tag{B1}
$$

where $R_{it}$ is the return of firm $i$ on day $t$, $R_{m,t}$ is the equal-weighted market return, and $(\alpha_0, \beta_1)$ are the parameters computed by regressing the firm’s returns on market returns from 160 to 10 days before the announcement of customer satisfaction (i.e., a $[-160, -10]$ window relative to the announcement date).

The calculation of abnormal returns for the market-, size-, book-to-market- and momentum-adjusted model is based on the 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 for an estimation period stretching from 160 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:

$$
R_{it} - R_f = \alpha + \beta_1 (R_{m,t} - R_f) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \epsilon_{it}. \tag{B2}
$$

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

$$
AR_{it} = R_{it} - \left( \alpha_0 + \beta_1 (R_{m,t} - R_f) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t \right). \tag{B3}
$$

References


Fornell, Claes, & Larcker, David F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18, 39–50.


