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IS CUSTOMER SATISFACTION A RELEVANT METRIC FOR FINANCIAL ANALYSTS?

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Abstract

This study examines the effects of customer satisfaction on analysts' earnings forecast errors. Based on a sample of analysts following companies measured by the American Customer Satisfaction Index (ACSI), we find that customer satisfaction reduces earnings forecast errors. However, analysts respond to changes in customer satisfaction but not to the ACSI metric per se. Furthermore, the effects of customer satisfaction are asymmetric; for example, analysts are more willing to use good news (i.e. an increase in customer satisfaction information) than bad news (i.e. a decrease in satisfaction). Similarly, customer satisfaction reduces negative deviation more than positive deviation of the analysts' forecasts from actual earnings. Furthermore, the effects of customer satisfaction depend upon the base level of satisfaction that the firm has achieved. Finally, the effects of customer satisfaction on analysts' forecast errors differ across firms with volatile satisfaction scores and those with stable satisfaction scores. We discuss the implications of our results for marketers and participants in financial markets.

Keywords: Customer satisfaction; EPS forecast errors; value relevance; ACSI; GMM dynamic models.

> "Many stock analysts aren't convinced that the university [of Michigan]'s customer satisfaction index, in and of itself, is all that important." Hilsenrath (2003) in *The Wall Street Journal* (February 19).

In this paper, we examine the relevance of customer satisfaction, as measured with the American Customer Satisfaction Index (ACSI), for financial analysts[1]. More specifically, we look at how customer satisfaction information influences the financial analysts' earnings forecast accuracy. Part of what has motivated this study is the recent debate on the speed and accuracy with which market participants respond to customer satisfaction information. This debate follows the study by Fornell et al. (2006) and Aksoy et al (2008), who find that the financial market misprices information on customer satisfaction (i.e. there is a delayed reaction by investors to the ACSI). Consequently, the shares of firms that outperform in terms of customer satisfaction generate abnormal returns. Aksoy et al. (2008) find that the stock market initially undervalues positive satisfaction information and then adjusts in the long-term. Jacobson and Mizik (2009a; 2009b; 2009c) and O'Sullivan et al (2009a; 2009b) have questioned these findings. They argue that there is no evidence of widespread mispricing in the financial market with regard to customer satisfaction. The ACSI has incremental value relevance only in the computer and internet sectors (Jacobson and Mizik, 2009a). Different causes have been offered to explain these mixed findings, such as problems associated with data analysis (Fornell et al, 2009a), differences in portfolio construction (Fornell et al., 2009b), the use of time-varying risk factors (O'Sullivan et al. 2009b), and econometric flaws (Jacobson and Mizik, 2009a).

We extend the existing studies by looking at the relevance of customer satisfaction for one type of participant, i.e., the financial analyst. Analysts play an important role as information intermediaries for the investors. They aggregate complex information (e.g., macroeconomic data,

[1] The ACSI results from a survey of customers of a sample of large US companies. Questions concern customers' expectations, their perceptions of product/service quality, value, their satisfaction with various goods and services, loyalty intentions and complaints. It is released every year in February, April, August and November by the University of Michigan Business School.

business plans, and possibly nonfinancial information) and provide (1) earnings forecasts, (2) cash flow forecasts, (3) share price targets, and (4) recommendations. As a result, analysts could be a channel through which customer satisfaction information is incorporated into share prices (Luo et al, 2010). Prior research shows that analysts' earnings forecasts influence stock prices (Lee, 2001). Even the Regulation Fair Disclosure issued by the US Stock Exchange Commission, which prohibits selective disclosure by corporate officials to analysts and institutional investors, has not dramatically affected the informativeness of analysts' outputs (e.g. Mohanram and Sunder, 2006). Despite all recent criticisms for the sell-side analysts, they remain very important for managers and investors. The sell-side analysts have the technical expertise, resources, and time, which many investors do not have. Furthermore, they are able to broadcast their views to a wide range of stakeholders and can cause drastic stock price adjustments when the actual earnings deviate from their expectations (Srinivasan and Hanssens, 2009). Since security analysts play an important role in the valuation of the company, it is interesting to examine the speed with which they impound marketing information reported by companies as well as its relevance when they forecast future earnings. This should advance our knowledge of how marketing contributes to firm value. Nonfinancial information can increase analysts' forecasts accuracies (see Orens and Lybaert, 2007). However, the extent to which analysts use nonfinancial information has received limited attention. One type of nonfinancial information that researchers in accounting (Ittner and Larcker, 1998) and marketing (Anderson et al. 2004) have studied is customer satisfaction. Customer satisfaction influences customer behaviors, which influence the firm's earnings prospects (e.g., Gruca and Lopo, 2005). Consequently, it would be surprising if satisfaction was found to have no impact on earnings forecasts.

This paper addresses several questions about the use of customer satisfaction by the financial analysts namely: (i) Is customer satisfaction a relevant metric for the analysts? If so, is the ACSI a timely metric for the analysts? (ii) Do analysts respond differently to an increase and a decrease in customer satisfaction? (iii) Do analysts' reactions to changes in customer satisfaction depend upon the company's base level of customer satisfaction? For example, will they be more willing to use satisfaction information coming from a company with a high base level of customer satisfaction or not? (iv) Does the effect of a change in customer satisfaction depend upon its magnitude or is it linear irrespective of the magnitude of the change? (v) Do changes in satisfaction from companies with volatile (prior) satisfaction scores have the same information content as similar changes from companies with stable satisfaction scores?

In the next section, we outline the background of our study. We then develop our research hypotheses regarding how customer satisfaction influences forecasts errors. Next, we describe our dataset, specifically, the way we merged data from the ACSI and the Institutional Brokers Estimate System (I/B/E/S). We apply dynamic-panel econometric methods to examine the effects of customer satisfaction on analysts' forecast errors. Further, we present the empirical results. In the last section, we extend our analysis and examine whether the ACSI release leads analysts to revise their earnings forecasts. We also use a match-pair procedure to test the performance of analysts on ACSI versus non-ACSI companies to provide an additional test of the effects of satisfaction on forecast errors. The paper ends with a discussion of the research implications.

Literature Review:

In this section, we summarize prior research on financial analysts that is relevant to our study. Researchers have examined different sources of analysts' earnings forecast errors, but we know little about the role of nonfinancial information.

The Accuracy of the Analyst Forecasts**:** Prior literature suggests that analysts differ in their forecast accuracies and that some specific factors account for these differences. The most studied factors are the firm-specific and forecaster characteristics. Among the firm characteristics, company size has been the most studied. It appears that analyst forecasts are more accurate for larger firms (e.g., Lang and Lundholm, 1996), and, in a meta-analysis, Garcıa-Meca and Sanchez-Ballesta (2006) report an average effect of -0.145 between company size and forecast error. Large firms have more stable growth and earnings (e.g., Hodgkinson, 2001), are more transparent (e.g., Lang and Lundholm, 1996), provide private information (e.g., Jaggi and Jain, 1998), and have a larger analyst coverage (e.g., Atiase, 1985).

Some studies have examined the impact of investments in intangible assets. Aboody and Lev (1998) find that the absolute size of an analyst's forecast error, in the computer programming and prepackaged software, has a positive association with the capitalized amount of software development costs. Barron et al. (2002) find that an analyst's forecasts are negatively associated with a firm's R&D spending. Gu and Wang (2005) also find that an analyst's forecast errors are larger for firms with innovative technologies. In addition, Dehning, Pfeiffer, and Richardson (2006) find that investments in IT increase dispersion and error in analyst forecasts.

The largest majority of studies have concerned the characteristics of the analysts themselves. While some authors have reported positive effects of the firm-specific experience (e.g., Clement, 1999), others have reported no effect of general experience (e.g., Jacob et al, 1999). Firm-specific experience provides the ability to identify more precisely the factors that drive a company's earnings. Experienced analysts can also use their previous forecast errors to improve their future forecasts. Garcıa-Meca and Sanchez-Ballesta (2006), however, find that, on average, only firm-specific experience has a negative effect on forecast error. Clement (1999) and Jacob et al. (1999) find that the number of companies followed reduces accuracy, as larger portfolios reduce the amount of time devoted to each company.

The size of the brokerage house reflects the resource availability. Analysts in large brokerage houses have access to increased resources, private communications with managers, and tend to be top talent and to have more sophisticated forecasting models than do other analysts. The meta-analysis conducted by Garcıa-Meca and Sanchez-Ballesta (2006) shows that larger brokerage firms are more accurate than their peers (-0.0256, $p<0.001$).

Another driver of the forecast error is the brokerage house affiliation. Garcıa-Meca and Sanchez-Ballesta (2006) find a negative average (bivariate) correlation (-0.03, $p<0.01$) between affiliation and forecast error. Analysts employed by investment banks are more accurate than those employed by independent firms. They have greater resources and access to information, and their affiliated houses can attract analysts with better forecasting ability.

Almost all previous studies suggest that recent forecasts are more accurate than those issued earlier (e.g., Jaggi and Jain, 1998). Garcıa-Meca and Sanchez-Ballesta (2006) report an average positive correlation of 0.2516 ($p<0.01$) between the forecasting horizon and forecast error. Analysts providing forecasts later in the period are more accurate, as they can observe the predictions of other analysts (e.g., Sinha, Brown, and Das, 1997).

Analysts forecast errors also appear to exhibit positive serial correlation (e.g., Abarbanell and Bernard, 1992). The serial correlation represents evidence that financial analysts either do not incorporate new information into their earnings forecasts immediately or underreact to new information when forecasting future earnings (e.g., Abarbanell and Bernard, 1992). More recently, Kwag and Stephens (2007) show that analysts do underreact to more recent earnings information but that this underreaction fades away over time.

Overall, the majority of the studies on analysts forecast errors have focused on individual factors. Their explanatory power has been low, suggesting that additional factors explain the analyst’s forecast errors. In this paper, we focus on nonfinancial information.

The Use of Nonfinancial Information by Analysts: Do analysts use nonfinancial information, and does it matter? A number of papers report that nonfinancial indicators of investments in intangible assets are important predictors of revenues (e.g., Trueman, Wong and Zhang, 2001), operating income (Behn and Riley, 1999) and firm value (Amir and Lev, 1996). However, researchers have produced mixed results on the use of nonfinancial information.

One group of studies suggests that analysts pay little attention to the disclosure of nonfinancial information. Nielsen (2008) finds that analysts infrequently discuss intellectual capital in their reports. Garcia-Meca and Martinez (2007) find that although analysts report information regarding a company's strategy, customers, and processes, they less often provide information about research, development, and innovation. Furthermore, analysts use this information in the case of highly profitable companies. Easton and Jarrell (1988) find that analysts do not account for the benefits of Total Quality Management programs and consequently underestimate resulting earnings. Benson et al (2006) find that analysts underestimate earnings of firms with high-involvement HRM practices. On the other side, Dempsey et al (1997) find that analysts use a broad range of leading indicators to assess long-term organizational success. Brown (1997) also reports that analysts consider the "Discussion & Analysis" part of the 10-K reports to be important for their forecasts.

As for the effects of nonfinancial information, researchers tend to agree on its value for financial analysts. McEwen and Hunton (1999) find that the use of financial statement information alone is associated with forecasting error. In a 1999 survey entitled "Metrics that Matter", Ernst and Young reported that analysts' use of nonfinancial information improved their forecast accuracy. Vanstraelen et al. (2003) find a positive relationship between nonfinancial information disclosure and forecast accuracy. Finally, Oriens and Lybaert (2007) report that the use of forward-looking information has a positive association with analyst’ forecast accuracy.

Customer Satisfaction and financial analysts: Williams and Viser (2002) argue that investors do not see customer satisfaction as an important intangible asset when they have to evaluate a business. They no longer believe that satisfying customers yields a competitive advantage. In his paper, Hilsenrath (2003) cites Tom Goetzinger, a Morningstar Inc. analyst who follows Home Depot and is familiar with the ACSI data, as saying he that he does not pay too much importance to the ACSI except when there are significant score movements. This analyst is cited as saying: "In general, I've always been leery of telephone surveys." In addition, the influence of customer satisfaction may be marginal when public information obtained by analysts substitutes for privately acquired information. Indeed, research shows that stocks with high analyst coverage are more informative than stocks with lower analyst coverage (Hong et al, 2000). It is thus possible for large analyst coverage to substitute for the lack of customer satisfaction information.

Academicians find that analysts use nonfinancial information (e.g., Vanstraelen et al. 2003; Oriens and Lybaert, 2007) and that customer satisfaction, a proxy for nonfinancial information, could play a significant role in analysts' earnings forecast process (e.g., Tuli and Bharadwaj, 2009). More specifically, in their robustness analyses, Tuli and Bharadwaj (2009) report that customer satisfaction has a negative association with the dispersion of the analyst earnings forecast. Unfortunately, researchers have not investigated the relevance of customer satisfaction for the individual analyst as a separate issue. In sum, the extent to which the analysts use satisfaction information and its relevance for their earnings forecasts remain open questions.

Research Hypotheses

Is customer satisfaction relevant for financial analysts?

We examine the effects of customer satisfaction, as measured with the ACSI, on the analyst's forecast errors. We draw on prior studies in accounting and finance (e.g., Clement, 1999; Jacob et al. 1999) and extend these studies by including customer satisfaction information. We examine both positive and negative satisfaction information, given their asymmetric effects for the market participants (e.g., Eastwood et al. 1999). We consider that customer satisfaction provides forward-looking information (Anderson et al. 2004) that is relevant for determining future cash flows (Gruca and Lopo, 2005). This notion of relevant information stems from the information hypothesis (Fama and Laffer, 1971), which suggests that providing reliable and relevant information to the financial market: (1) improves decision making thanks to reduced information asymmetry, (2) reduces investor risk due to lower uncertainty, and (3) enhances trading profits due to lowered transaction costs. Customer satisfaction influences repeat purchase behavior (e.g., Bolton, 1998), word of mouth (e.g., Anderson, 1998), cross-selling rates (e.g., Verhoef et al, 2001), the purchase of premium options (e.g., Ngobo, 2005), and price premiums (e.g., Homburg et al, 2005). By influencing these behaviors, customer satisfaction enables firms to maintain and increase their revenues (e.g., Rust et al, 2002). Customer satisfaction can reduce a firm's cost of future transactions, including costs of attracting new customers (e.g., promotional, personal selling expenditures), when it establishes a stable customer base. Highly satisfied customers are likely to recommend the firm’s products to other consumers (Anderson, 1998) and generate additional business at a lower cost for the firm (Villanueva et al, 2008). In addition, customer satisfaction reduces the company’s operating costs associated with defects and complaints (Fornell and Wernerfelt, 1988). Other studies report a direct link between satisfaction and profitability (e.g., Anderson et al, 1997). Additionally, Srivastava et al (1998) argue that market-based assets such as customer satisfaction can accelerate and enhance cash flows (see Gruca and Lopo, 2005). If customer satisfaction is value relevant, because it is a leading indicator of future cash flows, the information hypothesis (Fama and Laffer, 1971) suggests that it should reduce uncertainty. This will lead to lower forecast errors.

Is the ACSI a timely metric for the Analysts?

At the beginning of every forecasting period, analysts have initial public information (e.g. previous period financial statements) and may obtain independent private signals about the future earnings (Guttman, 2010). The American Customer Satisfaction Index (ACSI) is a metric that is published in the middle of the quarter (see Figure 1). The data-collection process in the ACSI also precedes its public release by some time. Furthermore, the ACSI asks consumers to refer to their previous experiences and not to the experiences that take place at the time the scores are released. Therefore, the ACSI may be a good metric for the changes that have taken place in companies in terms of customer satisfaction and dissatisfaction. Yet, because it does not come out earlier, this metric becomes less relevant for analysts. Analysts can obtain information related to the causes of customer satisfaction/dissatisfaction from different sources (e.g., press releases, annual reports) not from the ACSI alone or per se. Information available to the analysts include the quality reviews from the *Wall Street Journal* (Tellis and Johnson, 2007), the product competitiveness data from *Fortune* (e.g. Luo, 2010), new product introductions (e.g. Chaney et al. 1991), negative publicity resulting from product recalls (e.g. Chen et al. 2009) or marketing alliance announcements (e.g. Swaminathan and Moorman, 2009). Thus, financial analysts can infer the change in customer satisfaction well before the ACSI is published. In other words, there may be a “leakage” of satisfaction information to the market participants in advance of the ACSI release[2]. Thus, the ACSI is a lagging indicator, i.e., it accounts for what happened in the market but not what is happening at the time the analysts make their forecasts. If the analysts adjust their forecasts to reflect the information related to customer satisfaction before the ACSI release, there

[2] For example, in 2005, Safeway Inc. announced an investment of $100 million for developing its image of a retailer with "quality perishables, strong proprietary brands, redesigned stores, and world-class service". Safeway’s Chairman was expecting that: “The changes the company was doing in its stores will entice households that have defected to rivals, as well as inspire the grocer's still-loyal customers to spend more money than they have been” (Progressive Grocer, April 6, 2005). The analysts following Safeway Inc may have picked up this information and revised their earnings forecasts before the ACSI, which would capture and report such changes in the store base only in the next ACSI release (i.e. in April of the next year).

should be a smaller impact of the ACSI after its publication. We test the hypothesis that ACSI is not a timely metric by looking at the response coefficient, which measures the sensitivity of the analyst's forecast errors to the customer satisfaction information. If analysts had impounded customer satisfaction information into their earnings forecasts before the ACSI publication, the response coefficient should have a larger impact before than after the ACSI publication, assuming that the ACSI does capture the changes in satisfaction that customers experienced[3]. We hypothesize that:

H1: The association between a change in ACSI (*i.e.* a proxy for customer satisfaction) and forecast error is stronger for the forecasts made before the ACSI release and weaker for the forecasts made after the ACSI publication.

Do analysts respond more rapidly to increases or to decreases in customer satisfaction?

H1 assumes that analysts respond symmetrically to an increase and a decrease in customer satisfaction. Yet, authors, in the market-based accounting literature, have extensively documented that the market speed of response to earnings surprise / news is asymmetric by nature. Empirically, they observe that good news is reflected into share price faster than bad news (e.g., Bernard and Thomas, 1989). This asymmetry is primarily due to the unbalanced reaction of analyst earnings forecasts to good and bad news (Kothari, 2001). Analysts underreact to bad news and overreact to good news (Easterwood and Nutt, 1999). The rationale is that bad news make the future earnings figures more difficult to be determined, as analysts have to reconsider most of their company valuation process including the key valuation variables (e.g. business plans, growth rate) while good news can be incorporated more easily into an analyst's forecast plan (e.g. DeBondt and Thaler, 1990; Abarbanell and Bernard, 1992). Thus, if customer

[3] If analysts react slowly to customer satisfaction, it may be possible to observe significant effects of customer satisfaction even after the ACSI publication. In this case, satisfaction information obtained through other sources may confound with satisfaction information revealed by the ACSI. Nevertheless, while the existence of significant effects of the ACSI during the period following its publication are not necessarily evidence of its use by analysts, the pre-release effects of the ACSI are an indication that analysts had access to satisfaction information. It also implies that the ACSI is just capturing these changes but with a lag.

satisfaction is relevant for the future cash flows (Gruca and Lopo, 2005), positive information such as an increase in satisfaction should be incorporated into the earnings forecasts more rapidly than negative satisfaction information[4]. Therefore, assuming that the ACSI is a proxy for the changes in customer satisfaction, we hypothesize that:

> H2: An increase in customer satisfaction is reflected into earnings forecast errors faster than a decrease in customer satisfaction.

Are analysts forecast errors larger (or smaller) after a decrease or an increase in satisfaction?

Coëna, Desfleursb and L'Her (2009) show that the type of earnings (i.e., profits vs. losses) and the variations in earnings (i.e., increases vs. decreases in earnings) are the main factors to consider when studying the accuracy of financial analysts' forecasts. Negative information generates more information asymmetry than positive information (e.g., Brown et al, 2009). Miller (2002; Barron et al, 2008) also shows that when a company's news turns out bad, its level of information disclosure decreases, causing analysts to have little public information at their disposal. Consequently, analysts have to acquire more information on their own. This increases the possibility that the analysts' forecasts deviate from actual earnings. The sources of this asymmetry are not fully understood (Kothari, 2001) [5]. Nevertheless, some researchers have proposed a cognitive-bias explanation based on prospect theory (Tversky and Kahneman, 1984). Ding, Charoenwong, Seetoh (2004) argue that analysts are either *unable* or *unwilling* to forecast a decline in earnings and that this increases the chances that their forecasts deviate from actual earnings. They find that analysts make larger forecast errors during times of negative earnings growth than during positive ones. One of their explanations is that analysts' incentives are tied

[4] We use the terms positive and negative satisfaction information in line with the accounting literature that assimilates a "loss" to negative information and a "gain' to positive information. Thus, positive satisfaction information refers to an increase in satisfaction while negative satisfaction refers to a decrease in satisfaction.

[5] The incentive-based explanation suggests that as earnings become less predictable (e.g., following a loss or a decrease in earnings), analysts issue optimistic forecasts to please managers and consequently gain (or limit the loss of) access to managers' private information (Das et al. 1998). This is questionable because optimistic earnings forecasts result in negative earnings surprises and negative market reactions (e.g., Kasznik and McNichols 2002) but also because of the enactment of the Regulation Fair Disclosure (RFD), that now prohibits selective disclosure by corporate officials to analysts.

with the market sentiment (e.g. the investor trading activity). Consequently, because of the investors' loss aversion, analysts tend to avoid making pessimistic forecasts. By being overly optimistic, analysts increase the likelihood of making forecast errors. Daniel et al. (1998) argue that analysts revise their forecasts imperfectly after bad news because they tend to be overconfident in their private information.

Drawing upon these studies, we argue that a decrease in customer satisfaction will reduce an analyst's forecasting ability in the negative direction more than in the positive direction. In other words, analysts are more likely to make forecasts that exceed the actual earnings following a decrease in customer satisfaction than following an increase in customer satisfaction. Positive customer satisfaction information is associated with greater cash flows (Gruca and Lopo, 2005) and smaller uncertainty about future financial performance (Tulip and Bharadwaj, 2009). Therefore, analysts should be more willing to use it. A decrease in customer satisfaction is likely to decrease customer retention rates, cross-selling rates, induce negative word-of-mouth activity, increase complaints costs, and ultimately affect the firm's cash flows. Because a decrease in customer satisfaction makes it difficult for the analysts to determine future profitability, they should be unable to use negative customer satisfaction in predicting future earnings (Ding et al. 2004). In addition, because analysts are unwilling to make pessimistic forecasts, their forecast errors should be larger following a decrease in customer satisfaction. Consequently, the size of the deviation from actual earnings is likely to be larger following a decrease and smaller following an increase in satisfaction. We hypothesize that:

H3a: A decrease in ACSI leads the analysts to make forecasts that deviate from actual earnings in the negative direction more than in the positive direction.

H3b: An increase in satisfaction leads the analysts to make forecasts that deviate from actual earnings in the positive direction more than in the negative direction.

Are the effects of changes in customer satisfaction nonlinear[6]*?*

Analysts should react to customer satisfaction news that surprises them. Therefore, prior customer satisfaction efforts should influence how the changes in customer satisfaction will affect the analysts' earnings forecasts errors. Gomez et al (2004) found that the effect of an increase in customer satisfaction on the retailer's sales was decreasing with the level of customer satisfaction. Like these authors, we consider that there will be a diminishing sensitivity of the analysts' forecast errors to changes in satisfaction depending on the previous level of customer satisfaction achieved by the firm. A company with low current levels of customer satisfaction will require only small investments in satisfaction drivers to improve its revenues and earnings. When an increase in customer satisfaction by a firm with a low level of satisfaction reaches the market, the analysts are likely to be positively surprised, causing them to make higher forecasts. They are likely to pay much attention to (or be willing to use) that new information because of the significant score movements (Hilsenrath, 2003). A firm with high current levels of satisfaction is likely to need a much larger effort to produce impacts of a similar magnitude (Gomez et al. 2004). Furthermore, it is less likely to cause significant behavioral consequences, as customers' expectations about the firm are already high. Therefore, that change is less likely to modify the future cash flows and it should provide little additional information to the analysts.

Tellis and Johnson (2007) found that large firms were penalized more by poor reviews of quality than they were rewarded for good reviews. Their research suggests that when the market participants receive negative satisfaction information from a highly performing firm, they are likely to be negatively surprised. For the analysts, this implies that this should lead them to make downwards earnings forecasts. Here, we consider that the previous satisfaction reputation of the

[6] We thank one reviewer for suggesting this hypothesis.

highly performing firms should attenuate the negative effects that a decrease in customer satisfaction can have on their earnings (Anderson et al. 2004). Therefore, we hypothesize that:

> H4a. The negative effect of an increase in customer satisfaction on earnings forecast errors decreases with the base level of customer satisfaction.

> H4b: The positive effect of a decrease in customer satisfaction on earnings forecast errors decreases with the base level of customer satisfaction.

The impact of customer satisfaction on the forecast error may also depend upon the magnitude of the change in customer satisfaction (Mittal et al. 1998). Each additional instance of negative performance in customer satisfaction may yield diminishing (positive) effects on the forecast errors. Indeed, once the analysts have accounted for the negative cash flow prospects caused by the decrease in satisfaction, any marginal piece of negative customer satisfaction information becomes less relevant for the analysts. Similarly, an increase in customer satisfaction may have diminishing (negative) effects on the earnings forecast errors, as the initial instances provide more information than later ones. Therefore, we hypothesize that:

> H5: Earnings forecast errors will display diminishing sensitivity to additional instances of decreases or increases in customer satisfaction.

In the same lines, we hypothesize that the nonlinear effects of changes in satisfaction may depend upon the timing of the ACSI. When there are small changes in satisfaction, analysts may be unable to pick them up before the ACSI release because they are not obvious. However, when there are large changes, analysts incorporate them more quickly into their forecasts, whether they are negative or positive changes, as they are easy to notice. Therefore, higher levels of changes in satisfaction should have larger effects on forecast errors before the ACSI publication than after.

> H6: Large changes in satisfaction have larger effects on forecast errors before the ACSI publication than after its publication.

Finally, the nonlinear effects of customer satisfaction can be related to the volatility of the firm's satisfaction scores. More specifically, changes in the level of satisfaction from a highly volatile company, i.e. with unstable satisfaction scores, may have different information content for the financial analysts than similar changes from firms with less volatile satisfaction scores. The reason is that the changes in satisfaction coming from companies with volatile satisfaction scores are less persistent than similar changes from relatively stable companies. In other words, they will mean revert rapidly. Consequently, we expect an increase in customer satisfaction from a volatile firm to reduce the earnings predictability more than an increase in satisfaction from a less volatile firm (e.g. Prakash et al. 1985). Positive satisfaction news from volatile companies does not correctly reflect the future firm performance while such news from a stable firm does (Grewal et al. 2010). Therefore, analysts should be unwilling to incorporate an increase in satisfaction from volatile firms, i.e. it has a less negative effect on the forecast errors. Alternatively, a decrease in customer satisfaction will have less positive effects on the forecast errors when that change is from a highly volatile company than when it is from a stable company. The rationale is that analysts know that that decrease in customer satisfaction does not last for a long time and will rapidly revert to the mean level of satisfaction. Therefore, we hypothesize that:

H7a. The negative effect of an increase in customer satisfaction on earnings forecast errors decreases with the level of volatility of the company's satisfaction score.

H7b: The positive effect of a decrease in customer satisfaction on earnings forecast errors decreases with the level of volatility of the company's satisfaction score.

Data:

We began by selecting firms from the American Customer Satisfaction Index (ACSI) project at the University of Michigan Business School. We selected all of the ACSI firms in the Institutional Brokers Estimate System (I/B/E/S) files. The use of individual analyst data (instead of consensus data) allows us to test hypotheses on a large sample of forecasts and account for the analysts' characteristics. Consistent with prior studies (e.g., Clement, 1999), we use the latest forecast by each analyst each quarter for each firm. Because the ACSI is a quarterly database, we use quarterly forecasts (see Appendix & Figure 1).

[Insert Figure 1 about here]

We used data for 111 companies, followed by 1,671 analysts over the entire period of the study. Table 1 presents the different variables used in our models (Clement, 1999; Duru and Reeb, 2002). We must point out that these variables are standard controls in models of analysts earnings forecasts in accounting and finance (see Ramnath et al. 2008). We collected firm-level customer satisfaction scores from the American Customer Satisfaction (ACSI) at the University of Michigan (see Fornell et al. 1996). The ACSI is a national economic indicator of customer evaluations of the quality of products and services available to household consumers in the United States. It is updated quarterly with new measures for different sectors of the economy replacing data from the prior year. The first scores came out in October 1994. We composed a 10-year datasheet of quarterly data on customer satisfaction (1995-2004). The ACSI defines customer satisfaction as the overall evaluation of the purchase and consumption experience to date. Satisfaction is measured with three items and a 10-point scale: (i) overall feeling of satisfaction, (ii) the evaluation of quality regarding expectations, and (iii) the quality regarding ideal. A company's score is based on all its surveyed customers. Each company has its score of satisfaction reported only once a year and in the same quarter over time.

[Insert Table 1 about here]

Table 2 shows a strong correlation between firm experience and general experience. We have thus created another variable labeled "Analyst Experience" as an average score. We have over 12,000 observations but end up with fewer observations because of the use of lagged values.

[Insert Table 2 about here]

Model Specifications:

Prior research suggests that past forecast errors are determinants of current forecast errors (Ali et al. 1992). The econometric model should thus include a lagged dependent variable to account for the persistence in forecast errors over time. Furthermore, as we use a panel dataset, ignoring the unobserved firm- and analyst-specific heterogeneity would lead to biased and inconsistent estimates (Wooldridge, 2002). Regarding observable heterogeneity, a large majority of the studies (see Ramnath et al. 2008 for a review) suggests that analyst forecast errors can be influenced by several factors, notably (1) individual characteristics (e.g., experience), (2) firm-specific effects (e.g., company size), (3) industry-specific effects (e.g., utilities versus competitive industries), and (4) the national business climate (e.g., Consumer Confidence Index). Finally, in an efficient market, participants do not react to events that they expect to happen, as their expectations already reflect what is expected (Jacobson and Mizik, 2009c). This implies that analysts may expect the new ACSI scores and that the release of these scores will not induce a change in the analysts' forecasts (Ittner et al, 2009). We thus examine analysts' reactions to *new ACSI information* and not to its level. We measure new satisfaction information in terms of changes in ACSI (e.g., Tuli and Bharadwaj, 2009). This is consistent with studies in accounting and finance where new information, such as earnings surprise, is measured in terms of changes or deviations (e.g., Conrad et al, 2002). Jacobson and Mizik (2009c) report that the association between stock return and satisfaction is stronger when one aligns the data by the occurrence of satisfaction changes rather than by the ACSI release date. Given the above, we test our first hypothesis (H1) with the following equation:

$$
\begin{aligned}
ln\,FE_{hit} = {} & \sum_{j=2}^{J} \gamma_j^{Industry} \times INDUSTRY_j + \sum_{t=2}^{T} \gamma_t \times YEAR_t + \sum_{q=2}^{Q} \gamma_q \times Quarter_q \\
& + \gamma^{SAT-POST} \times \Delta ln\,ACSI_{it} \times \phi + \gamma^{SAT-ANTE} \times \Delta ln\,ACSI_{it} \times (1-\phi) + \gamma^{FE} \times ln\,FE_{hit-1} \\
& + \gamma^{FEXP} \times ln\,EXP_{ht} + \gamma^{Age} \times ln(AGE)_{hit} + \gamma^{NIND} \times ln\,NIND_{ht} + \gamma^{NFIRM} \times ln\,NFIRM_{ht} + \gamma^{RESS} \times ln\,RESS_{ht} \\
& + \gamma^{Size} \times ln(Mvalue)_{it} + \gamma^{Div} \times ln(DIV)_i + \gamma^{Loss} \times LOSS_{it} + \gamma^{COV} \times ln\,COV_{it} + \gamma^{VOL} \times ln\,VOL_{it} + \varepsilon_{hit}
\end{aligned} \tag{1}
$$

where FE_{hit} = forecast errors for analyst *h* regarding firm *i* for quarter *t* (or ending in *t*),

$INDUSTRY_j$ = the industry-specific dummies

$YEAR_t$ = the time-specific dummies

$QUARTER_q$ = the quarter-specific dummies

FE_{hit-1} = lagged forecast error by analyst *h* for firm *i* in quarter ending in *t-1*

EXP_{ht} = the experience of analyst *h* in quarter *t*,

$NIND_{ht}$ = the number of industries followed by analyst *h* in quarter *t*,

$NFIRM_{ht}$ = the number of firms followed by analyst *h* in quarter *t*.

$RESS_{ht}$ = the number of analysts of the brokerage firm of analyst *h* in quarter *t*.

AGE_{hit} = age of the forecast made by analyst *h* for firm *i* in quarter *t*

$\ln Mvalue_{it}$ = the size of firm *i* in quarter *t*,

DIV_i = the diversification score for firm *i*,

$LOSS_{it}$ = 1 if the earnings reported in quarter *t* are negative and zero otherwise,

COV_{it} = the analyst coverage of firm *i* in quarter *t*,

VOL_{it} = the earnings volatility for firm *i* up to quarter *t*.

$\Delta ACSI_{it}$ = the change in ACSI for firm *i* in period *t* or new ACSI information,

ϕ = 1 if the forecast has been made after the ACSI release and 0 otherwise,

γ = the regression coefficient,

$\varepsilon_{hit} = \alpha_h + \delta_i + \eta_{hit}$ = the error term.

The error term has three components: α_h & δ_i are the analyst- and firm-specific unobserved effects, and η_{hit} represents all unobserved factors that vary across analysts, firms, and over time. The residual term (η_{hit}) is estimated net of the unobserved fixed analyst and firm effects; it is assumed to be uncorrelated with the analyst (α_h) and firm (δ_i) effects for any *t*. Equation (1) allows us to compare the effects of satisfaction before and after the release of the ACSI scores (see Figure 1). For example, if ϕ =1, we have the equation for forecasts made after the ACSI announcement. Equation (1) includes a lagged dependent variable as well as endogenous independent variables (e.g., ACSI). Therefore, the econometric problem at hand is that of estimating an unobserved fixed-effect dynamic panel-data model with endogenous explanatory variables. The most adopted approach for dealing with a dynamic panel model is the first-differenced GMM estimator. Indeed, when there is a lagged dependent, both the OLS and GLS produce inconsistent estimates. Because it relies on moment conditions rather than full density, the GMM estimator provides heteroskedasticity-consistent and asymptotically correct standard errors for statistical inferences. However, there are some econometric weaknesses with the first-differenced GMM method. First, the variables in levels may be poor instruments for first-differenced variables (Arellano and Bover, 1995). Blundell and Bond (1998) have shown that when the explanatory variables are persistent over time, the lagged levels of these variables are weak instruments for the regression equation expressed in first-differences. Second, we cannot estimate the coefficients on time invariant explanatory variables (e.g. industry dummies) because the first-differencing transformation eliminates these variables from the model. Therefore, we employ the GMM-System estimator (Blundell and Bond, 1998), which allows for time-invariant regressors that would disappear in a GMM in differences. The GMM-System approach combines in a system the first-differenced equation with the same equation expressed in levels, and it controls for unobserved effects with orthogonal deviations. Our unit of analysis is the analyst-firm combination (Taylor, 2006). It then uses the lagged levels as instruments for the first-differenced equations and the lagged first-differences as instruments for the levels equations.

Validity of instruments requires the absence of second-order serial correlation in the residuals. We check the validity of instruments with Hansen's test of overidentifying restrictions, where non-rejection of the null hypothesis implies that the instruments as a group are exogenous, meaning that a higher p-value of the Hansen statistic is better. We test for serial correlation on the differenced residuals. The test for the AR (1) process in first differences usually rejects the null hypothesis of no correlation. We thus look at the test for AR (2). H1 will be supported if the coefficient for a change in satisfaction is larger before than after the ACSI release.

Next, we expand equation (1) with dummy variables in order to analyze the speed of reaction to changes in customer satisfaction (H2). The resulting model is as follows:

$$\begin{aligned}
(2)\quad & \ln FE_{hit} = \sum_{j=2}^{J} \gamma_j^{Industry} \times INDUSTRY_j + \sum_{t=2}^{T} \gamma_t \times YEAR_t + \sum_{q=2}^{Q} \gamma_q \times Quarter_q \\
& + \gamma^{SAT-POST\times POSITIVE} \times \Delta \ln ACSI_{it} \times \phi \times (\varphi) + \gamma^{SAT-POST\times NEGATIVE} \times \Delta \ln ACSI_{it} \times \phi \times (1-\varphi) \\
& + \gamma^{SAT-ANTE\times POSITIVE} \times \Delta \ln ACSI_{it} \times (1-\phi) \times (\varphi) + \gamma^{SAT-ANTE\times POSITIVE} \times \Delta \ln ACSI_{it} \times (1-\phi) \times (1-\varphi) \\
& + \gamma^{FE} \times \ln FE_{hit-1} + \gamma^{FEXP} \times \ln EXP_{ht} + \gamma^{Age} \times \ln(AGE)_{hit} + \gamma^{NIND} \times \ln NIND_{ht} + \gamma^{NFIRM} \times \ln NFIRM_{ht} \\
& + \gamma^{RESS} \times \ln RESS_{ht} + \gamma^{Size} \times \ln(Mvalue)_{it} + \gamma^{Div} \times \ln(DIV)_i + \gamma^{Loss} \times LOSS_{it} + \gamma^{COV} \times \ln COV_{it} \\
& + \gamma^{VOL} \times \ln VOL_{it} + \varepsilon_{hit}
\end{aligned}$$

where ϕ =1 if the forecast has been made after the ACSI release and 0 otherwise, and φ= 1 if there is a positive change in ACSI and 0 otherwise[7]. We define the other variables as above. Equation (2) allows us to compare the effects of satisfaction before and after the release of the ACSI scores (see Figure 2). Therefore, if ϕ =1, we have the equation for forecasts made after the ACSI publication. If ϕ =1 & φ=1, then we obtain the effect of a positive change in satisfaction <u>after</u> the ACSI announcement (i.e., $\gamma^{SAT-POST\times POSITIVE}$).

We test the hypothesis about the asymmetric effects of customer satisfaction (H3) by extending equation (2) with dummy variables reflecting the asymmetric effects of satisfaction on negative deviation (i.e., forecasts exceed actual earnings) and on positive deviation (i.e., actual earnings exceed forecasts). Equation (3) is the appropriate specification for that purpose:

$$\begin{aligned}
(3)\quad & \ln FE_{hit} = \sum_{j=2}^{J} \gamma_j^{Industry} \times INDUSTRY_j + \sum_{q=2}^{Q} \gamma_q^{Quarter} \times Quarter_q + \sum_{t=2}^{T} \gamma_t^{TIME} \times YEAR_t \\
& + \gamma_{Error<0}^{SAT-POST\times POSITIVE} \times \Delta \ln ACSI_{it} \times \phi \times (\varphi) \times (1-\kappa) + \gamma_{Error\geq 0}^{SAT-POST\times POSITIVE} \times \Delta \ln ACSI_{it} \times \phi \times (\varphi) \times (\kappa) \\
& + \gamma_{Error<0}^{SAT-POST\times NEGATIVE} \times \Delta \ln ACSI_{it} \times \phi \times (1-\varphi) \times (1-\kappa) + \gamma_{Error\geq 0}^{SAT-POST\times NEGATIVE} \times \Delta \ln ACSI_{it} \times \phi \times (1-\varphi) \times (\kappa) \\
& + \gamma_{Error<0}^{SAT-ANTE\times POSITIVE} \times \Delta \ln ACSI_{it} \times (1-\phi) \times (\varphi) \times (1-\kappa) + \gamma_{Error\geq 0}^{SAT-ANTE\times POSITIVE} \times \Delta \ln ACSI_{it} \times (1-\phi) \times (\varphi) \times (\kappa) \\
& + \gamma_{Error<0}^{SAT-ANTE\times NEGATIVE} \times \Delta \ln ACSI_{it} \times (1-\phi) \times (1-\varphi) \times (1-\kappa) + \gamma_{Error\geq 0}^{SAT-ANTE\times NEGATIVE} \times \Delta \ln ACSI_{it} \times (1-\phi) \times (1-\varphi) \times (\kappa) \\
& + \gamma^{FE} \times \ln FE_{hit-1} + \gamma^{FEXP} \times \ln EXP_{ht} + \gamma^{Age} \times \ln(AGE)_{hit} + \gamma^{NIND} \times \ln NIND_{ht} \\
& + \gamma^{NFIRM} \times \ln NFIRM_{ht} + \gamma^{RESS} \times \ln RESS_{ht} + \gamma^{Size} \times \ln(Mvalue)_{it} + \gamma^{Div} \times \ln(DIV)_i \\
& + \gamma^{Loss} \times LOSS_{it} + \gamma^{COV} \times \ln COV_{it} + \gamma^{VOL} \times \ln VOL_{it} + \varepsilon_{hit}
\end{aligned}$$

We define the variables as above except that here κ = 1 when there is a positive deviation (or $AE_{hi(t+1)} - EF_{hit}$ >= 0) and 0 when there is a negative deviation (i.e., $AE_{hi(t+1)} - EF_{hit}$ <0). Equation (3) imbeds different relationships. For example, the impact of an increase in customer

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[7] We use the ACSI publication as a cutoff period to examine whether an increase in customer satisfaction is reflected into the earnings forecasts faster than a decrease in customer satisfaction.

satisfaction (φ =1) on positive deviation (κ = 1) when the analysts release their EPS forecast early in the reporting period (ϕ =1) is $\gamma_{Error\geq 0}^{SAT-ANTE\times POSITIVE}$.

H4a and H4b state that the base level of customer satisfaction moderates the association between changes in satisfaction and forecast error. We use the Equation (4), which expands equation (2) with interactions, to test these hypotheses:

(4)

$$\begin{aligned}
\ln FE_{hit} = {} & \sum_{j=2}^{J} \gamma_j^{Industry} \times INDUSTRY_j + \sum_{t=2}^{T} \gamma_t \times YEAR_t + \sum_{q=2}^{Q} \gamma_q \times Quarter_q + \gamma^{\ln SATLAG} \times \ln ACSI_{it-1} \\
& + \gamma^{SAT-POST\times POSITIVE} \times \Delta \ln ACSI_{it} \times \phi \times (\varphi) + \gamma^{SAT-POST\times NEGATIVE} \times \Delta \ln ACSI_{it} \times \phi \times (1-\varphi) \\
& + \gamma^{SAT-ANTE\times POSITIVE} \times \Delta \ln ACSI_{it} \times (1-\phi) \times (\varphi) + \gamma^{SAT-ANTE\times POSITIVE} \times \Delta \ln ACSI_{it} \times (1-\phi) \times (1-\varphi) \\
& + \gamma^{SAT-POST\times POSITIVE\times \ln SATLAG} \times \Delta \ln ACSI_{it} \times \phi \times (\varphi) \times \ln ACSI_{it-1} + \gamma^{SAT-POST\times NEGATIVE\times \ln SATLAG} \times \Delta \ln ACSI_{it} \times \phi \times (1-\varphi) \times \ln ACSI_{it-1} \\
& + \gamma^{SAT-ANTE\times POSITIVE\times \ln SATLAG} \times \Delta \ln ACSI_{it} \times (1-\phi) \times (\varphi) \times \ln ACSI_{it-1} + \gamma^{SAT-ANTE\times POSITIVE\times \ln SATLAG} \times \Delta \ln ACSI_{it} \times (1-\phi) \times (1-\varphi) \times \ln ACSI_{it-1} \\
& + \gamma^{FE} \times \ln FE_{hit-1} + \gamma^{FEXP} \times \ln EXP_{ht} + \gamma^{Age} \times \ln(AGE)_{hit} + \gamma^{NIND} \times \ln NIND_{ht} + \gamma^{NFIRM} \times \ln NFIRM_{ht} + \gamma^{RESS} \times \ln RESS_{ht} + \gamma^{Size} \times \ln(Mvalue)_{it} \\
& + \gamma^{Div} \times \ln(DIV)_i + \gamma^{Loss} \times LOSS_{it} + \gamma^{COV} \times \ln COV_{it} + \gamma^{VOL} \times \ln VOL_{it} + \varepsilon_{hit}
\end{aligned}$$

Where $\ln ACSI_{it-1}$ is the lagged value of customer satisfaction, i.e. the ACSI score observed in the previous year. The rest of variables and parameters are defined as above.

H5 states that the earnings forecast errors will display diminishing sensitivity to additional instances of decreases or increases in customer satisfaction. H6 states that large changes in satisfaction have larger effects on forecast errors before the ACSI publication than after its publication. We test both hypotheses with the following model:

$$\begin{aligned}
\ln FE_{hit} = {} & \sum_{j=2}^{J} \gamma_j^{Industry} \times INDUSTRY_j + \sum_{t=2}^{T} \gamma_t \times YEAR_t + \sum_{q=2}^{Q} \gamma_q \times Quarter_q + \\
& + \gamma^{SAT-POST\times POSITIVE} \times \Delta \ln ACSI_{it} \times \phi \times (\varphi) + \gamma^{SAT-POST\times NEGATIVE} \times \Delta \ln ACSI_{it} \times \phi \times (1-\varphi) \\
& + \gamma^{SAT-ANTE\times POSITIVE} \times \Delta \ln ACSI_{it} \times (1-\phi) \times (\varphi) + \gamma^{SAT-ANTE\times POSITIVE} \times \Delta \ln ACSI_{it} \times (1-\phi) \times (1-\varphi) \\
(5) \quad & + \gamma^{SAT-POST\times POSITIVEQ} \times (\Delta \ln ACSI)_{it}^2 \times \phi \times (\varphi) + \gamma^{SAT-POST\times NEGATIVEQ} \times (\Delta \ln ACSI)_{it}^2 \times \phi \times (1-\varphi) \\
& + \gamma^{SAT-ANTE\times POSITIVEQ} \times (\Delta \ln ACSI)_{it}^2 \times (1-\phi) \times (\varphi) + \gamma^{SAT-ANTE\times POSITIVEQ} \times (\Delta \ln ACSI)_{it}^2 \times (1-\phi) \times (1-\varphi) \\
& + \gamma^{FE} \times \ln FE_{hit-1} + \gamma^{FEXP} \times \ln EXP_{ht} + \gamma^{Age} \times \ln(AGE)_{hit} + \gamma^{NIND} \times \ln NIND_{ht} + \gamma^{NFIRM} \times \ln NFIRM_{ht} \\
& + \gamma^{RESS} \times \ln RESS_{ht} + \gamma^{Size} \times \ln(Mvalue)_{it} + \gamma^{Div} \times \ln(DIV)_i + \gamma^{Loss} \times LOSS_{it} + \gamma^{COV} \times \ln COV_{it} \\
& + \gamma^{VOL} \times \ln VOL_{it} + \varepsilon_{hit}
\end{aligned}$$

We define all the variables as above, except that we now include the quadratic variables for a decrease and an increase in satisfaction. If the quadratic coefficients are significant and as expected, then this is an indication that H5 is supported. If those coefficients are larger before the ACSI announcement than after, then this would be a support for H6. Finally, it is possible to examine the asymmetric, nonlinear, and moderated effects of customer satisfaction by combining equations (4) and (5). We did not adopt such a model because of high multicollinearity.

Results & Analysis

The relevance of ACSI for the analysts

Table 3 outlines the results of the models linking changes in satisfaction with earnings forecast errors[8]. Model 1estimates the effects of a (symmetric) change in satisfaction on earnings forecast error. It shows that an increase in satisfaction decreases the forecast error. Next, we consider the effects of a change in satisfaction before and after the ACSI publication. To compare Models (2) & (1), we apply the MMSC-BIC criterion proposed by Andrews and Lu (2001). It is similar to the BIC (Bayesian information criterion) and it is based on the Hansen statistic. Model 2 has no better fit than Model 1.

---- Insert Table 3 about here ----

We started with Model 3 (see Table 3), which simply distinguishes between a decrease and an increase in satisfaction. This model has a better fit than Model 2 and Model 1. It implies that we have to distinguish between negative and positive satisfaction information. Next, we estimated Model 4, which corresponds to equation (2). The results show that this model has a better fit than all the other specifications. It shows that an increase in satisfaction reduces the forecast error before (-11.313, p=0.000) more than after (-6.866, p=0.000) the ACSI publication.

[8] We checked the sensitivity of the results by estimating the effects of customer satisfaction with a first-difference GMM specification. The estimated model tried to answer the following question *"Does a change in ACSI lead to a change in forecast errors between two consecutive quarters?"* We use two consecutive quarters because for each company, the ACSI data is announced once a year. When we estimate the effects of a change in ACSI on a change in forecast error between current quarter and previous year's corresponding quarter, we end up with a very small sample size of 1,432 observations. Instead, when we estimate the effect of a change in ACSI (say quarter 1, 2000 versus quarter 1, 1999) on the difference in forecast error between two consecutive quarters (say between quarter 2 of 2000 and quarter 1 of 2000), we find that a change in satisfaction is still associated with a decrease in forecast errors (number of observations = 3,610). Nevertheless, we prefer our model in equation (1), as it measures analysts' immediate response to new information.

However, a decrease in satisfaction increases the forecast error after (6.123, p=0.000) more than before the ACSI release. Thus, consistent with H2, an increase in satisfaction gets reflected into the earnings forecasts faster than a decrease in customer satisfaction. Concerning H1, the results indicate that it is not a change in customer satisfaction per se that is relevant. Rather, an increase in satisfaction is more relevant than a decrease in satisfaction[9]. Furthermore, we find that volatility is associated with higher forecast errors (0.056, p=0.000). Consistent with prior research (e.g., Clement, 1999), forecast errors are smaller for larger companies (-0.688, p=0.000). Corporate diversification is associated with higher forecast errors (1.053, p=0.000), reflecting the difficulty of understanding all the business segments of the company. The number of forecast revisions is associated with biased forecasts (0.654, p=0.000). This may occur when analysts herd with each other to protect their reputations and when they reflect the consensus more than their own beliefs about the firm. Analysts following many firms have a larger forecast error (0.234, p=0.000). Earlier forecasts increase the forecast error (0.236, p=0.000). As expected, analysts are more biased about companies with negative prior earnings (1.573, p=0.000).

The asymmetric effects of customer satisfaction on negative and positive deviation:

Table 4 presents the estimates of equation (3). Model 1 reports the results based on an equation in which we do not yet account for the timing of the ACSI. It shows that the effects of changes in satisfaction on positive/negative deviations are asymmetric. An increase in satisfaction reduces both negative (-12.324) and positive (-7.331) deviations of the forecasts from actual earnings. The impact is larger on negative deviation than on positive deviation, meaning that an increase in satisfaction reduces analysts' pessimism more than it reduces their overconfidence in future cash flows. A decrease in satisfaction has no effect.

[9] When we used a change in the residuals of an AR (1) model of ACSI as new information, our results did not change. Similarly, when we use the percentage changes (Ittner et al. 2009), we still find that ACSI has a negative effect on forecast errors.

---- Insert Table 4 about here ----

In Model 2, we analyze the asymmetric effects before and after the ACSI release. The χ^2 comparing Model 1 and Model 2 suggests that the latter has a better fit than the former (χ^2 (8) =17.15, p<0.001). Model 2 shows that before (-12.779) or after (-10.594) the ACSI publication, an increase in satisfaction reduces negative deviation. It also reduces positive deviation whether that positive deviation is computed in reference to the forecasts made before (-8.197) or after (-7.209) the ACSI announcement. However, the coefficients remain larger before the ACSI release than after. Turning to the decrease in satisfaction, we can see that it increases both positive (8.274) and negative (3.247) deviations. Nevertheless, its effects appear only after the ACSI publication. Thus, a decrease in satisfaction increases forecast errors in the positive direction but an increase in satisfaction reduces negative deviation more than it reduces positive deviation.

The moderating effects of prior customer satisfaction level

Table 5 reports the estimate results for equation (4). We started with a model in which we do not account for the timing of the ACSI (Model 1). It shows that the effects of a change in satisfaction are asymmetric and nonlinear. The moderating coefficients for both a decrease (-1.869, p=0.038) and an increase (1.665, p=0.002) in satisfaction are significant and as expected. This is in line with H4a and H4b. Next, we estimated equation (5) to account for the timing of the ACSI (i.e. Model 2). It turns out that Model 2 fits the data better than Model 1. The main effects in Model 2 are as observed previously, i.e. analysts are more willing to use positive satisfaction information than negative information. Consequently, the impact of an increase in satisfaction is larger before (-9.494, p=0.000) than after (-6.734, p=0.002) the ACSI announcement. Negative information is used with some delay (8.887, p=0.000), reflecting the view that analysts are less willing to use negative information or unable to forecast future earnings following bad news.

Turning to the moderating effect of prior level of satisfaction, Table 5 shows that the base level of satisfaction significantly reduces the effect of an increase (2.202, p=0.030) or a decrease (-6.621, p=0.000) in satisfaction on the analyst's forecast error. Nevertheless, this happens only after the ACSI is published. In other words, analysts are more willing to use positive satisfaction information than negative one irrespective of the base level of satisfaction the firm has already achieved. As time passes by (or after the ACSI publication), analysts readjust their opinions. One way for them to do so is to incorporate the firm's prior performance in terms of customer satisfaction. Furthermore, when bad customer satisfaction news from a highly performing firm reaches the analysts, they readjust their opinions more than when they receive good news.

The diminishing sensitivity of earnings forecast errors to changes in customer satisfaction:

Table 5 presents the results regarding the diminishing sensitivity of forecast error to customer satisfaction. Before estimating equation (5), we consider some alternative models. We start with the asymmetric and nonlinear model (i.e. Model 1). The results indicate that earnings forecast errors exhibit diminishing sensitivity to both an increase and a decrease in satisfaction. However, given the range of the ACSI values in the data, it would be difficult for any change in satisfaction to reverse the downward (upwards) trend in forecast error. Then, we estimated equation (5). Again, although the model fit is better, the magnitudes of the quadratic coefficients are not large enough to reverse the curves.

-------- Insert Table 5 about here --------

The moderating role of customer satisfaction volatility

Table 6 reports the estimate results for models in which we consider the moderating influence of satisfaction volatility. In Model 1, we test H7a and H7b. Model 1 is like equation (1) augmented with Ln (Satisfaction Volatility) and its interactions with an increase and a decrease in satisfaction. The results show that satisfaction volatility per se does not significantly influence the forecast errors (0.053, p=0.935). On average, while an increase in satisfaction reduces the analysts' forecast errors (-18.269, p=0.000), its decrease is associated with a higher forecast error (9.224, p=0.002). Nevertheless, consistent with H7a, we find that an increase in satisfaction has a less negative effect on forecast error as the satisfaction volatility increases (0.179, p=0.000). Similarly, in line with H7b, we can see that as the satisfaction volatility increases, the positive influence of a decrease in satisfaction decreases (-0.181, p=0.005). Next, we estimated Model 2 that accounts for the timing of effects. The BIC suggests that Model 2 fits the data better than Model 1. Model 2 shows that on average an increase in satisfaction reduces forecast errors (-22.708, p=0.000) while a decrease in satisfaction increases the forecast error (13.471, p=0.000). The effects of changes in satisfaction appear mostly before the ACSI announcement with the magnitude being larger for an increase in satisfaction compared to a decrease in satisfaction. Again, we can see that the benefits of an increase in satisfaction decrease as the volatility of satisfaction scores increases (11.833, p=0.000). In other words, while analysts incorporate positive information more rapidly, their reaction is slower when this information is from a company with volatile prior satisfaction performance than when it is from a less volatile firm. The decrease in satisfaction has a less positive effect on forecast error as the satisfaction volatility increases (-10.936, p=0.000). In other words, it seems that analysts do not trust any decrease in satisfaction as they expect that change to mean-revert.

-----------Insert Table 6 about here ---------------

Extended Analysis:

In search for more evidence for the relevance of customer satisfaction for the financial analysts, we conducted some additional analyses.

Does ACSI provide incremental information to earnings surprises?

Jacobson and Mizik (2009c) report that ACSI has no incremental value for stock returns in a model that accounts for changes in Returns on Assets (ROA). Here, we examine whether accounting for the changes in earnings affects the impact that satisfaction has on forecast errors (see Table 6). We created a variable, which corresponds to the change in EPS observed in the previous quarter (e.g. a change observed in the April-June quarter over the previous quarter influences the forecast error of the next quarter). Model 1 shows that analysts overreact to positive earnings surprises, i.e. they are optimistic about firms that increased their quarter earnings in the past quarter. This optimism (i.e., analysts project these trends to continue) leads to a larger forecast error (0.662, p=0.000). However, an increase in satisfaction still decreases forecast errors mostly before the release of the ACSI scores (-9.269, p=0.000). Therefore, new ACSI information has value relevance for analysts over and above earnings surprises. Model 2, which estimates the moderating influence of prior satisfaction as well as the asymmetric effects of customer satisfaction, shows that the results remain the same even if we control for the influence of changes in earnings. These results indicate that customer satisfaction provides additional information above and over that provided by prior earnings.

---------Insert Table 7 about here-----------

Do changes in ACSI influence the number of forecast revisions by analysts?

Analysts revise their forecasts when they learn new relevant information about the firm. If the information in the ACSI is relevant for analysts, it should influence the level of forecast revisions by analysts. We estimated a model, like equation 2, in which the dependent variable is the logarithmic value of the number of revisions made by the analyst (see Table 8).

-------Insert Table 8 about here-----

In Model 1, we find that an increase in customer satisfaction results in higher number of earnings forecast revisions before the ACSI publication (0.652, p=0.002). After the ACSI publication, the number of revisions decreases (-1.173, p=0.002). The effect of a decrease in satisfaction on the number of forecasts is not statistically significant. In Model 2, we examined the effects of changes in ACSI on the ***average value of the consecutive revisions*** made by the analyst during a quarter. A positive value on this dependent variable means that on average, the analyst revised upwards during the quarter, while a negative value means a downward revision. Our results show that, on average, an increase in satisfaction results in upwards revisions (1.340, p=0.000) but over time (e.g. after the ACSI publication), the analysts make revisions that are smaller in value (-0.628, p = 0.000). Again, the effects are more positive before than after the ACSI announcement, confirming that analysts respond earlier than after the ACSI release. Following a decrease in customer satisfaction, we can see that analysts make downward revisions of their earnings forecasts (-0.769, p = 0.000). Nevertheless, as time passes by, they tend to upgrade their forecasts (1.265, p = 0.000). This may reflect the accumulation of additional information about the firm.

Are analysts more accurate with firms in the ACSI surveys than with non-ACSI firms?

To examine the robustness of our results to an alternative methodology, we examined the effects of customer satisfaction using a matched-pair procedure that compares the analyst’s absolute forecast error on firms where ACSI data is available versus firms where ACSI data is not available (see Sinha et al. 1997; Jacob et al. 1999). If the ACSI is value relevant, we should find that the forecast errors are smaller for firms in the ACSI survey than for similar non-ACSI firms. Because we are comparing the performance of the analysts, we started by selecting all the analysts who track ACSI firms. Then, for each of these analysts, we selected all the companies that s/he has been following over the period of our study and for which data appeared in the I/B/E/S. Next, we retained only companies with the same two-digit SIC code. The ACSI already tracks the largest firms in their primary industries; it was not always possible to match with other companies of the same size and analyst coverage. For example, analyst n°4672 tracks the following companies: ACSI companies (AMR CP, CONTL AIRLINES, DELTA AIR LINES, SOUTHWEST AIRLS, USAIR GROUP INC) and Non-ACSI companies (AIR EXPRESS INTL, AIRBORNE INC, ALASKA AIR GROUP, ALLEGIS CORP). In this case, we exclude ALLEGIS CORP because it operates in another sector (i.e., Wholesale Industrial Equipment and Supplies). In addition, all the firms in the "Consumer Staples" sector for which we had data in IBES were all part of the ACSI project. Therefore, we excluded this sector from our comparisons. In the end, we have 414 analysts who follow both types of firms within the same 2-digit SIC industries (97 non-ACSI firms and 56 ACSI firms). It appears that the analyst coverage is greater for the ACSI (16.49) compared to the non-ACSI (13.22) firms ($F=2226.13$, $p=0.000$). ACSI companies are also followed by larger brokerage companies than the non-ACSI firms (12.78 versus 11.95, $F=67.37$, $p=0.000$). Analysts make more revisions for the ACSI firms (1.47) compared to the non-ACSI firms (1.44) ($F = 17.63$, $p=0.000$). There is greater volatility among the non-ACSI firms (0.32) compared to the ACSI firms (0.20) ($F=26.76$, $p=0.000$).

To examine the differences between the two types of firms in terms of forecast error, we proceeded with a GMM-SYSTEM model. Table 9 reports the results with and without control variables. Model 1 shows that there is a difference between ACSI and non-ACSI companies. However, the difference disappears when we control for some of the variables identified in prior research (see Model 2). Therefore, we cannot accept the idea that there is a difference between

ACSI and non-ACSI companies followed by the same analyst. The difference we observe in Model 1 is due to the traditional drivers of forecast errors.

----Insert Table 9 about here----

Conclusion

The main objective of our research was to address several questions about the use of customer satisfaction by the financial analysts, namely:

(i) Is customer satisfaction a relevant metric for the analysts? If so, is the ACSI a timely metric for the analysts?
(ii) Do analysts respond differently to an increase and a decrease in customer satisfaction?
(iii) Do analysts' reactions to changes in customer satisfaction depend upon the company's base level of customer satisfaction?
(iv) Does the effect of a change in customer satisfaction depend upon its magnitude or is it linear irrespective of the magnitude of the change?
(v) Do changes in satisfaction from companies with volatile (prior) satisfaction scores have the same information content as similar changes from companies with stable satisfaction scores?

Five key results emerge from our research. *First,* we find that analysts are not influenced by the <u>ACSI metric per se.</u> They account for customer satisfaction information, specifically the increase in customer satisfaction, well before the release of the ACSI scores. Analysts seem to capture customer satisfaction information from alternative information sources (e.g., press releases). This is probably true for both ACSI and non-ACSI firms, as, on average, for every analyst, there is no significant difference in terms of research quality between the ACSI and non-ACSI firms. Indeed, it is difficult based on the different analyses to accept that the ACSI score reflects information not previously available to analysts at the time it is announced.

Second, by viewing ACSI as a proxy for customer satisfaction efforts, our research provides evidence that analysts respond more rapidly to positive satisfaction information than to negative satisfaction information (Easterwood and Nutt, 1999). Our results are consistent with the cognitive-bias explanation of analysts' forecast errors, which suggests that analysts are unwilling or unable to forecast earnings following bad news such as a decrease in customer satisfaction (Ding et al. 2004). Indeed, we find that a decrease in satisfaction is associated with larger forecast errors (namely, negative deviations from actual earnings). Following an increase in customer satisfaction (or good news), analysts tend to make higher forecasts. Consequently, their earnings forecasts errors tend to be smaller, specifically negative deviations from actual earnings. We also find that a decrease in customer satisfaction can lead to higher positive errors in the sense that analysts tend to make higher forecasts after a decrease in customer satisfaction. This occurs over time and not immediately after a decrease in customer satisfaction.

Third, we find that the effects of changes in satisfaction depend upon the base level of satisfaction. An increase in satisfaction has a lower impact on analyst earning forecast accuracy when that increase is from a firm with a high base level of satisfaction. In other words, it brings little additional information to the analysts than a similar increase from a low-satisfaction firm. However, when a high-satisfaction firm experiences a decrease in satisfaction, analysts respond less negatively to that bad news. This means that high customer satisfaction insulates firms from negative shocks, i.e. analysts believe that a decrease in satisfaction will have a smaller impact on the variability of the future cash flows of a firm with a base level of satisfaction[10].

Fourth, we expected the earnings forecast errors to exhibit diminishing sensitivity to both an increase and a decrease in satisfaction. The results did reveal a reduction in the effect of

[10] In other analyses not reported here, we examined the analysts' responses to changes in customer satisfaction across sectors. Our findings regarding the utilities were interesting as well. We found that analysts following utilities are not responsive to (not affected by) a negative change in customer satisfaction. In these industries, customer dissatisfaction does not automatically affect revenues, due to switching costs (Fornell, 1992). We found that the analysts of companies in information technology and telecommunications sectors respond to a decrease in customer satisfaction with a lag as well. This may explain why Jacobson and Mizik (2009c) report a mispricing effect in the computer and Internet sectors. If analysts initially undervalue customer satisfaction information and readjust in the long term, then it becomes possible to beat the market.

customer satisfaction after a certain level. Nevertheless, given the range of the ACSI values in our data, it would be difficult for any change in satisfaction to reverse the downward (upwards) trend in forecast error.

Fifth, we find that the effects of changes in customer satisfaction depend upon the volatility of the firm's satisfaction scores. The increase in satisfaction decreases the analyst forecast errors. However, as the volatility of the satisfaction scores increases, the negative effect of an increase in satisfaction decreases. Similarly, while the decrease in satisfaction increases the forecast error (i.e. it has a positive coefficient), this effect becomes less positive as the volatility of the firm's satisfaction scores increases. In sum, when the analysts know that a change in satisfaction will not persist, they are less willing to incorporate that information into their earnings forecasts.

Research Contributions:

We shed new light on the ongoing debate about the mispricing of customer satisfaction information as measured by the ACSI. Our results suggest that there is probably a mispricing of the ACSI metric and not one of customer satisfaction information. The reason is that the timing of the ACSI release and the occurrence of customer satisfaction among the company's customers are different. If we expect the ACSI score or the change in it to drive share price or analysts' forecasts and recommendations, we may be disappointed because analysts will not respond to the ACSI at its release. However, given that analysts do account for customer satisfaction well before the ACSI announcement, it still is possible for any test of the association between ACSI and financial performance to find a significant association between the two variables. Overall, these results suggest that when the purpose of the study is to examine the speed and accuracy with which information is impounded in financial metrics, the ACSI metric may not be relevant.

However, if the purpose is to investigate the firm-level effects of customer satisfaction, the ACSI is a good proxy of the company's customer satisfaction efforts.

The empirical findings indicate that there may be a mispricing of the positive satisfaction information when that news is from a firm with a high base level of satisfaction. Similarly, there may be a mispricing of negative satisfaction information when that negative news comes from a high-satisfaction firm. Thus, we speculate that because high customer satisfaction insulates firms from negative shocks, the probability of mispricing satisfaction information should be higher for high-satisfaction firms compared to the low-satisfaction firms. The results also suggest that the mispricing of the satisfaction information will be greater for companies with volatile satisfaction scores compared to firms with stable satisfaction scores. Interestingly, our results resonate with recent research by Grewal et al (2010) that shows that satisfaction heterogeneity (variance) reduces the effects of satisfaction level on shareholder value.

Our results also have some implications for the asymmetric analysis of the effects of customer satisfaction (e.g. Anderson and Mittal, 2000). Prospect theory (Kahneman and Tversky 1979), which has been shown to be descriptive in a variety of settings (e.g. Thaler 1985; Deleersnyder et al, 2004), shows that individuals have a greater aversion for losses than a positive valence for gains of equivalent magnitude, predicting a stronger reaction to losses than to gains. Research in accounting and finance has consistently shown that analysts' response is asymmetrically strong to positive vis-à-vis negative earnings surprises. We also find that positive satisfaction information receives greater weight than negative satisfaction information. This is a surprising finding because it appears inconsistent with the notion of loss aversion. Why then would financial analysts react more strongly to positive than to negative satisfaction information? We believe that our results are indirectly in line with the propositions of Tversky and

Kahneman's (1979) prospect theory. Prospect theory suggests that investors have a loss aversion. Research in accounting and finance shows that analysts' incentives are tied to the market sentiment or the investors' trading activity. The incentive-based theories of analysts' forecast errors also suggest that analysts issue optimistic forecasts following bad news to please managers and gain access to private information as well as investors (see e.g. Ding et al. 2004). Our findings do show that analysts make larger forecast errors following a decrease in satisfaction and that this error is essentially due to over-forecasting. Therefore, in line with prospect theory, our results suggest that it is because they account for the investors' loss aversion that analysts are unwilling to forecast an earnings decline. They are overly optimistic and over-estimate EPS.

Implications for Marketing Managers

Our study contributes to the development of a foundation for a better understanding of the relationship between marketing investments and financial performance (Webster, Malter, Ganesan, 2003; Varadarajan, 1992). It shows that one way in which marketing can regain its place on the table is through helping financial analysts. Prior research suggests that analysts can influence share price movements through their forecasts. As a result, by enabling analysts to make accurate forecasts, customer satisfaction is likely to interest analysts and to contribute to a better image of marketing investments among analysts, CFOs, and CEOs. This means that marketers could improve the legitimacy of marketing by getting analysts to seek customer metrics to explain the growth of the companies that they follow. For the corporate managers, this study examines the extent to which one specific type of nonfinancial information, i.e., customer satisfaction, often reported by firms, influences analysts' forecasts accuracies and how this can influence their disclosure strategy. Our results imply that since analysts respond to changes (mostly to positive ones) in customer satisfaction, managers should know that it is possible to influence the analysts' opinions regarding their companies by providing them with all types of information indicative of improvements in customer satisfaction (e.g. customer service investments). For example, managers can report this data during conference calls. Conference calls are a disclosure medium where management can reiterate the important drivers of profitability. By disclosing plans for increasing customer satisfaction, managers can improve the analysts' expectations of the next period's earnings.

Limitations and future research:

This study also has some limitations, which provide a foundation for additional research. We limited our sample to firms for which we had data available in the I/B/E/S database. Furthermore, we have examined only the short-run effects of customer satisfaction. Additional research going beyond the immediate (same-quarter) effects to long-run effects may provide additional insights into the role of nonfinancial information (such as customer satisfaction) for analyst forecasts and firm valuation. This study also examined the effects of customer satisfaction on forecast errors. The next step would be to examine the relationship between customer satisfaction and analysts' recommendations. In doing so, future research should also consider the nonlinear effects of customer satisfaction on forecast errors (e.g. moderating role of prior satisfaction level, the volatility of the satisfaction scores), and, consequently, examine the effects of the magnitude of "good news" versus "bad news" beyond the asymmetric effects of customer satisfaction. In sum, our findings suggest that if financial analysts neglect customer satisfaction information, they might deprive themselves of an important proxy for nonfinancial information.

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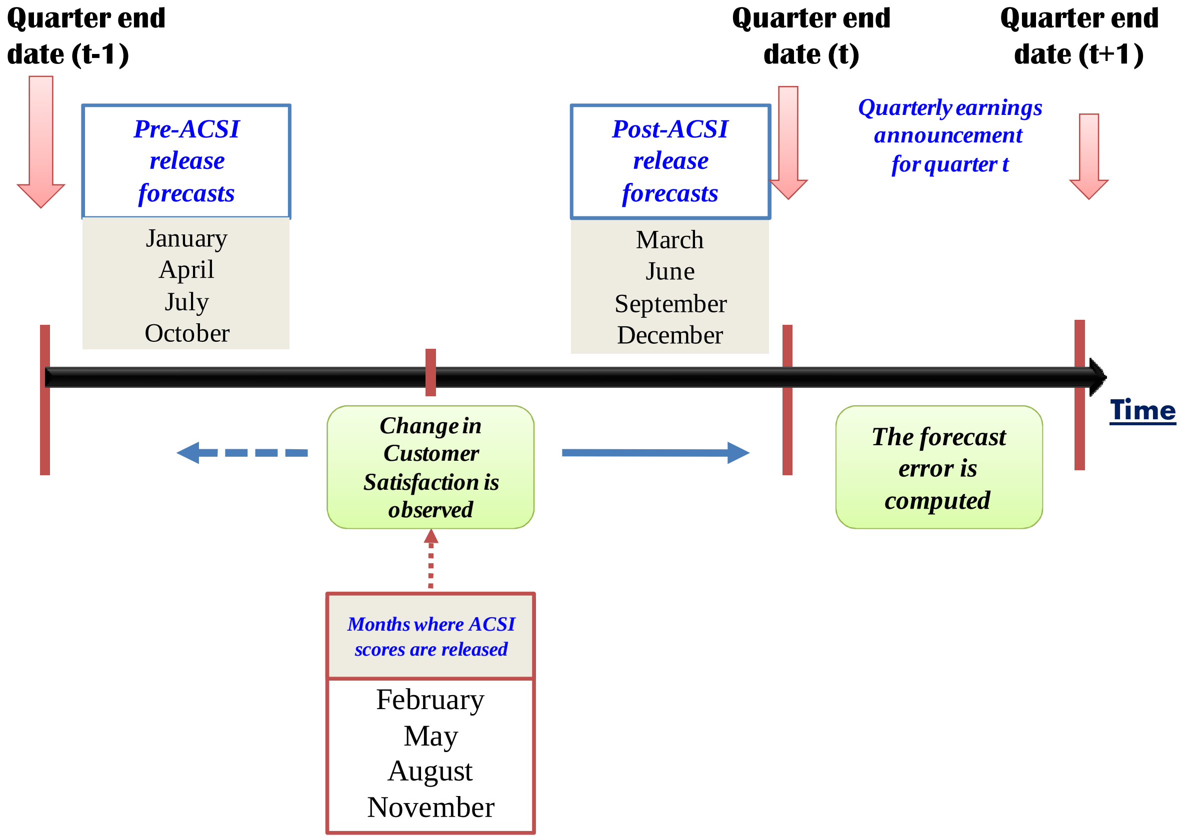
FIGURE 1: TIMELINE OF VARIABLES



Note:

- The dotted line means that we link changes in satisfaction with forecasts errors that we compute in reference to the forecasts that the analysts made prior to the ACSI announcement. We assume that the market may have already reacted to information about customer satisfaction that is reflected in measures other than the ACSI metric.
- The solid line means that we link changes in customer satisfaction to forecasts made after the ACSI announcement. Here we assume that the market reacts to new information about customer satisfaction. Or, that analysts who make forecasts later in the reporting period respond with a lag to changes in customer satisfaction that occurred earlier
- Given that it is difficult to pinpoint the event date where ACSI scores are available, we consider the entire month of publication. Excluding the two first weeks of each publication month did not affect the results.

TABLE 1: VARIABLE OPERATIONALIZATION

Variables	Description
Forecast error ($FE_{hi(t+1)}$)	$FE_{hi(t+1)} = \lvert (AE_{hi(t+1)}) - EF_{hit}) \rvert / \lvert EF_{hit} \rvert$, $AE_{hi(t+1)}$ refers to the actual earnings of firm *i* reported in quarter *t+1* followed by analyst *h*, and EF_{hit} refers to the earnings forecasted by that analyst. Thus, our dependent is the ratio of the absolute values of the deviation between actual earnings and earnings forecasts, divided by the absolute values of the earnings forecasts. The use of absolute values allows us to estimate effects of customer satisfaction on the magnitude of the error.
Firm-specific experience($FEXP_{hit}$)	The number of prior quarters for which the analyst *h* following firm *i* in quarter *t* provided at least one forecast for that firm.
General experience ($GEXP_{ht}$)	The number of quarters (irrespective of the firm) during which analyst *h* following firm *i* in industry *j* supplied at least one forecast during the previous quarters through quarter *t*.
The number of companies ($NFIRM_{ht}$)	The number of firms that analyst *h* follows in quarter *t*.
Number of industries ($NIND_{ht}$)	The number of 2-digit SIC industries followed by analyst *h* in quarter *t*.
Size of the brokerage firm ($RESS_{ht}$)	The number of analysts employed by the brokerage firm that employs analyst *h* who follows firm *i* in quarter *t*.
Forecast Efficiency (FE_{hit})	The lagged forecast error made by analyst *h* in quarter *t*.
Age of the forecast (Age_{hit})	The number of days between the time when the analyst issues the forecast and the last day of the quarter. The larger the value the earlier the forecast was made.
Company size ($\ln Mvalue_{it}$)	The logarithm of the firm's market value one quarter before the release of analysts' earnings forecasts.
Diversification (DIV_i)	The number of business segments of firm i in time t
Analyst Coverage (COV_{it})	The number of analysts who follow the company
Business uncertainty or volatility (VOL_{it})	The standard deviation of earnings per share (EPS) computed over the four preceding quarters. This yields a time-varying measure of volatility.
Prior performance ($LOSS_{it}$)	A dummy variable (*LOSS*) that equals one (1) if the net income of firm *i* is reported to be negative and zero otherwise.

TABLE 2:
CORRELATIONS AND DESCRIPTIVE STATISTICS

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	18	17	Mean	Std. Dev.
1. ln (forecast error)	1.00																	-2.756	4.426
2. ln (lagged forecast error)	0.17	1.00																-2.698	4.341
3. ln (# of revisions)	0.15	0.12	1.00															1.120	0.722
4. ln (ACSI)	-0.09	-0.09	-0.17	1.00														4.315	0.086
5. ln (EPS forecast)	-0.03	0.01	-0.09	0.01	1.00													-1.099	0.909
6. ln(Market Value)	-0.12	-0.11	0.02	0.23	0.00	1.00												9.395	1.500
7. ln (Earnings volatility)	0.13	0.12	0.06	-0.09	0.26	-0.21	1.00											-3.609	2.670
8. ln (Analyst coverage)	-0.02	-0.01	0.21	-0.19	-0.10	0.32	-0.14	1.00										2.692	0.501
9. ln (Brokerage firm size)	0.00	-0.01	0.02	0.00	0.06	-0.02	0.05	-0.12	1.00									2.560	0.893
10. ln(Diversification)	0.01	0.00	-0.03	0.10	-0.03	0.27	-0.10	0.04	-0.03	1.00								1.502	0.856
11. ln (Firm experience)	0.08	0.08	-0.04	0.04	0.07	-0.11	0.11	-0.26	0.15	-0.19	1.00							1.762	0.978
12. ln (General experience)	0.02	0.03	0.10	-0.08	0.09	0.04	0.08	0.07	0.19	-0.07	0.20	1.00						2.150	0.967
13. ln (number of firms)	0.08	0.08	-0.04	0.04	0.07	-0.11	0.11	-0.26	0.15	-0.19	1.00	0.20	1.00					1.112	0.750
14. ln (number of industries)	0.00	0.01	0.08	-0.01	-0.13	0.01	-0.04	0.22	-0.08	-0.14	0.23	0.07	0.23	1.00				0.150	0.297
15. ln (age of the forecast)	0.04	0.00	0.02	-0.01	0.06	-0.03	-0.03	-0.03	0.00	-0.05	0.04	0.03	0.04	0.03	1.00			2.412	0.785
16. LOSS	0.09	0.07	0.11	-0.20	-0.03	-0.19	0.00	-0.06	0.03	-0.11	-0.01	-0.02	-0.01	-0.07	0.02	1.00		0.069	0.254
17. Ln(Satisfaction Volatility)	0.07	0.08	0.05	-0.29	0.11	-0.03	0.02	0.08	-0.02	-0.10	0.03	-0.02	0.03	-0.06	0.04	0.31	1.00	0.701	0.471

TABLE 3: THE INFLUENCE OF CHANGES IN ACSI ON EARNINGS FORECASTS ERRORS

	Model 1		**Model** 2		**Model** 3		**Model** 4	
	Coef.	P>z	Coef.	P>z	Coef.	P>z	Coef.	P>z
Intercept	-9.119	0.000	-8.867	0.000	-9.338	0.000	-9.033	0.000
Effects of Customer Satisfaction Variables								
• ΔACSI	-3.237	0.000						
• ΔACSI after publication ($\gamma^{SAT-POST}$)			-0.686	0.103				
• ΔACSI before publication ($\gamma^{SAT-ANTE}$)			-4.165	0.000				
• ΔACSI (+) ($\gamma^{SAT-POSITIVE}$)					-9.919	0.000		
• ΔACSI (-) ($\gamma^{SAT-NEGATIVE}$)					2.609	0.006		
• Δln(ACSI) $^{(-)}$ after publication ($\gamma^{SAT-POST\times NEGATIVE}$)							6.123	0.000
• Δln(ACSI) $^{(+)}$ after publication ($\gamma^{SAT-POST\times POSITIVE}$)							-6.866	0.000
• Δln(ACSI) $^{(-)}$ before publication ($\gamma^{SAT-ANTE\times NEGATIVE}$)							1.624	0.150
• Δln(ACSI) $^{(+)}$ before publication ($\gamma^{SAT-ANTE\times POSITIVE}$)							-11.313	0.000
Control Variables								
Ln (Lagged forecast error)	-0.004	0.024	-0.003	0.066	-0.004	0.126	-0.003	0.086
Ln (volatility)	0.064	0.000	0.059	0.000	0.061	0.000	0.056	0.000
Ln (Market Value)	-0.695	0.000	-0.691	0.000	-0.653	0.000	-0.688	0.000
Ln (revisions)	0.670	0.000	0.660	0.000	0.650	0.000	0.654	0.000
Ln (diversification)	1.072	0.018	0.992	0.035	0.967	0.056	1.053	0.032
Ln (coverage)	0.275	0.004	0.195	0.001	0.203	0.025	0.174	0.107
Ln (brokerage firm size)	-0.061	0.132	-0.053	0.252	-0.038	0.353	-0.061	0.332
Ln (experience)	-0.052	0.841	0.024	0.930	-0.010	0.970	-0.041	0.879
Ln (number of firms)	0.212	0.000	0.211	0.005	0.173	0.063	0.234	0.000
Ln (number of industries)	0.249	0.510	0.242	0.527	0.337	0.375	0.261	0.483
Ln (age of the forecast)	0.238	0.000	0.242	0.000	0.242	0.000	0.236	0.000
Loss	1.463	0.000	1.440	0.000	1.552	0.000	1.573	0.000
Y_3 (1996)	0.473	0.170	0.459	0.185	0.454	0.189	0.511	0.141
Y_4 (1997)	0.163	0.664	0.114	0.762	0.166	0.663	0.171	0.654
Y_5 (1998)	0.455	0.284	0.369	0.393	0.382	0.372	0.457	0.291
Y_6 (1999)	0.490	0.296	0.395	0.401	0.394	0.405	0.463	0.335
Y_7 (2000)	0.490	0.323	0.401	0.432	0.475	0.352	0.604	0.244
Y_8 (2001)	0.539	0.304	0.447	0.404	0.599	0.263	0.688	0.210
Y_9 (2002)	0.160	0.767	0.070	0.901	0.205	0.714	0.296	0.605
Y_10 (2003)	0.775	0.173	0.685	0.242	0.761	0.195	0.851	0.154
Y_11 (2004)	0.171	0.774	0.079	0.897	0.143	0.815	0.245	0.694
Q_1 (first quarter)	10.185	0.000	9.807	0.000	10.127	0.000	10.022	0.000

Q_2 (second quarter)	15.720	0.000	15.567	0.000	16.158	0.000	15.955	0.000
Q_3 (third quarter)	12.685	0.000	12.491	0.000	12.881	0.000	12.795	0.000
Consumer Discretionary products	1.530	0.006	1.660	0.002	1.611	0.005	1.795	0.002
Consumer Staples	1.527	0.133	1.670	0.109	1.884	0.087	2.117	0.042
Energy	2.140	0.533	2.646	0.443	3.671	0.285	4.169	0.234
Financials	16.891	0.164	18.109	0.134	18.501	0.130	18.805	0.119
Health Care	-7.909	0.000	-7.930	0.000	-8.129	0.000	-7.922	0.000
Industrials	-4.058	0.000	-3.893	0.000	-4.067	0.000	-3.905	0.000
Information Technology	-7.444	0.000	-7.298	0.000	-7.479	0.000	-7.116	0.000
Telecommunication Services	-2.255	0.206	-2.187	0.223	-2.359	0.201	-2.607	0.153
# of Observations								
Sargan test of overidentifying restrictions	196.200	0.990	196.800	0.990	194.760	0.990	198.019	0.990
Arellano-Bond test for AR(1) in first differences	-11.539	0.000	-11.553	0.000	-11.507	0.000	-11.530	0.000
Arellano-Bond test for AR(2) in first differences	0.525	0.590	0.539	0.589	0.506	0.610	0.525	0.590
Test of equality of ACSI parameters	-		151.560	0.000	362.800	0.000	377.550	0.000
MMSC BIC	181177.060		181177.970		181169.430		181143.360	

TABLE 4: ESTIMATE RESULTS FOR THE ASYMMETRIC EFFECTS OF CUSTOMER SATISFACTION ON NEGATIVE AND POSITIVE DEVIATION FROM ACTUAL EARNINGS

	Model 1		Model 2	
	Coef.	P>z	Coef.	P>z
Positive Δln(ACSI) if Error <0	-12.324	0.000		
Positive Δln(ACSI) if Error >=0	-7.331	0.000		
Negative Δln(ACSI) if Error <0	1.900	0.136		
Negative Δln(ACSI) if Error >=0	1.145	0.235		
Negative Δln(ACSI) after ACSI announcement if Error >=0			8.274	0.001
Negative Δln(ACSI) after ACSI announcement if Error <0			3.247	0.043
Positive Δln(ACSI) after ACSI announcement if Error >=0			-7.209	0.000
Positive Δln(ACSI) after ACSI announcement if Error <0			-10.594	0.000
Negative Δln(ACSI) before ACSI announcement if Error >=0			-1.672	0.220
Negative Δln(ACSI) before ACSI announcement if Error <0			1.591	0.321
Positive Δln(ACSI) before ACSI announcement if Error >=0			-8.197	0.000
Positive Δln(ACSI) before ACSI announcement if Error <0			-12.779	0.000
Control Variables				
Ln (Lagged forecast error)	-0.005	0.031	-0.008	0.011
Ln (volatility)	0.067	0.000	0.062	0.000
Ln (Market Value)	-0.647	0.000	-0.737	0.000
Ln (revisions)	0.636	0.000	0.590	0.000
Ln (diversification)	1.078	0.026	1.311	0.009
Ln (coverage)	0.205	0.118	0.271	0.048
Ln (brokerage firm size)	-0.046	0.304	-0.082	0.228
Ln (experience)	-0.114	0.680	-0.122	0.665
Ln (number of firms)	0.171	0.072	0.124	0.278
Ln (number of industries)	0.335	0.369	0.303	0.424
Ln (age of the forecast)	0.239	0.000	0.236	0.000
Loss	1.692	0.000	1.681	0.000
Y_3 (1996)	0.439	0.207	0.496	0.154
Y_4 (1997)	0.178	0.641	0.156	0.685
Y_5 (1998)	0.430	0.323	0.520	0.238
Y_6 (1999)	0.457	0.342	0.574	0.236
Y_7 (2000)	0.640	0.221	0.689	0.196
Y_8 (2001)	0.749	0.172	0.820	0.143
Y_9 (2002)	0.330	0.563	0.424	0.470
Y_10 (2003)	0.927	0.123	1.025	0.093
Y_11 (2004)	0.328	0.601	0.394	0.534
Q_1 (first quarter)	10.432	0.000	10.581	0.000
Q_2 (second quarter)	15.799	0.000	15.431	0.000
Q_3 (third quarter)	12.737	0.000	12.356	0.000
Consumer Discretionary products	1.408	0.012	1.629	0.005
Consumer Staples	1.960	0.062	2.023	0.074
Energy	2.462	0.487	2.817	0.441
Financials	16.555	0.172	16.444	0.171
Health Care	-7.853	0.000	-7.112	0.000
Industrials	-4.151	0.000	-3.847	0.000
Information Technology	-7.695	0.000	-7.318	0.000
Telecommunication Services	-2.301	0.199	-2.610	0.167
Intercept	-9.215	0.000	-8.805	0.000
# of Observations				
Sargan test of overidentifying restrictions	192.600	0.990	191.090	0.990
Arellano-Bond test for AR(1) in first differences	-11.541	0.000	-11.467	0.000
Arellano-Bond test for AR(2) in first differences	0.496	0.620	0.432	
Test of equality of ACSI parameters	546.780	0.000	386.630	0.000
MMSC-BIC	181081.58		181064.430	

TABLE 5: ESTIMATE RESULTS FOR THE ASYMMETRIC, NONLINEAR, AND MODERATED EFFECTS CUSTOMER SATISFACTION

	Model 1		Model 2		Model 3		Model 4	
	Coef.	P>z	Coef.	P>z	Coef.	P>z	Coef.	P>z
Intercept	-10.279	0.006	-7.586	0.167	-7.152	0.010	-8.10	0.013
Asymmetric effects of satisfaction								
ΔACSI (+) ($\gamma^{SAT-POSITIVE}$)	-8.863	0.000			-14.514	0.000		
ΔACSI (-) ($\gamma^{SAT-NEGATIVE}$)	3.798	0.001			10.341	0.000		
Asymmetric effects of satisfaction with ACSI timing								
Δln(ACSI) $^{(-)}$ *after* publication ($\gamma^{SAT-POST\times NEGATIVE}$)			8.887	0.000			7.747	0.000
Δln(ACSI) $^{(+)}$ *after* publication ($\gamma^{SAT-POST\times POSITIVE}$)			-6.734	0.002			-2.243	0.064
Δln(ACSI) $^{(-)}$ *before* publication ($\gamma^{SAT-ANTE\times NEGATIVE}$)			0.841	0.605			10.377	0.000
Δln(ACSI) $^{(+)}$ *before* publication ($\gamma^{SAT-ANTE\times POSITIVE}$)			-9.494	0.000			-18.948	0.000
Moderating effect of prior level of satisfaction								
ΔACSI (+) *lnACSI$_{it-1}$($\gamma^{SAT-POSITIVE\times \ln SATLAG}$)	1.665	0.002						
ΔACSI (-) *lnACSI$_{it-1}$($\gamma^{SAT-NEGATIVE\times \ln SATLAG}$)	-1.869	0.038						
o ***With the ACSI timing***								
Δln(ACSI) $^{(-)}$ *after* publication*lnACSI$_{it-1}$ ($\gamma^{SAT-POST\times NEGATIVE\times \ln SATLAG}$)			-6.621	0.000				
Δln(ACSI) $^{(+)}$ *after* publication*lnACSI$_{it-1}$ ($\gamma^{SAT-POST\times POSITIVE\times \ln SATLAG}$)			2.202	0.030				
Δln(ACSI) $^{(-)}$ *before* publication *lnACSI$_{it-1}$($\gamma^{SAT-ANTE\times NEGATIVE\times \ln SATLAG}$)			-1.311	0.114				
Δln(ACSI) $^{(+)}$ *before* publication*lnACSI$_{it-1}$ ($\gamma^{SAT-ANTE\times POSITIVE\times \ln SATLAG}$)			1.369	0.060				
Asymmetric & nonlinear effects								
ΔACSI $(+)^2$ ($\gamma^{SAT-POSITIVEQ}$)					0.028	0.000		
ΔACSI $(-)^2$ ($\gamma^{SAT-NEGATIVEQ}$)					0.057	0.000		
Asymmetric & Nonlinear effects with ACSI timing								
** <u>after the ACSI announcement</u>								
Δln(ACSI) $^{(-)}$ ^{2}*after* publication ($\gamma^{SAT-POST\times NEGATIVEQ}$)							0.000	0.956
Δln(ACSI) $^{(+)}$ ^{2}*after* publication ($\gamma^{SAT-POST\times POSITIVEQ}$)							-0.009	0.007
** <u>before the ACSI announcement</u>								
Δln(ACSI) $^{(-)2}$*before* publication ($\gamma^{SAT-ANTE\times NEGATIVEQ}$)							0.053	0.000
Δln(ACSI) $^{(+)2}$*before* publication ($\gamma^{SAT-ANTE\times POSITIVEQ}$)							0.047	0.000
Control Variables								
ln(Lagged forecast error)	-0.003	0.258	0.258	0.199	0.008	0.000	0.007	0.000
Ln (ACSI) $_{it-1}$	-	-	.266	0.192			1.038	0.159
Ln (volatility)	0.063	0.000	0.060	0.000	0.068	0.000	0.070	0.000
ln(Market Value)	-0.646	0.000	-0.704	0.000	-0.605	0.000	-0.632	0.000
Ln (revisions)	0.657	0.000	0.644	0.000	0.683	0.000	0.682	0.000

Ln (diversification)	1.071	0.037	1.207	0.017	0.946	0.000	0.870	0.002
Ln (coverage)	0.209	0.003	0.149	0.192	0.273	0.000	0.308	0.000
Ln (brokerage firm size)	-0.095	0.072	-0.088	0.212	-0.171	0.000	-0.219	0.000
Ln (experience)	-0.113	0.679	-0.105	0.709	0.212	0.324	0.225	0.309
Ln (number of firms)	0.109	0.320	0.076	0.509	0.174	0.002	0.255	0.000
Ln (number of industries)	0.321	0.400	0.358	0.350	0.443	0.100	0.404	0.153
Ln (age of the forecast)	0.244	0.000	0.234	0.000	0.236	0.000	0.223	0.000
Loss	1.735	0.000	1.727	0.000	1.415	0.000	1.401	0.000
Y_3 (1996)	0.489	0.155	0.498	0.151	0.265	0.419	-0.043	0.923
Y_4 (1997)	0.202	0.594	0.148	0.702	0.066	0.847	0.335	0.288
Y_5 (1998)	0.484	0.256	0.512	0.242	0.243	0.516	0.057	0.802
Y_6 (1999)	0.534	0.257	0.560	0.246	-0.048	0.905	0.259	0.070
Y_7 (2000)	0.644	0.218	0.629	0.242	0.045	0.918	0.035	0.730
Y_8 (2001)	0.798	0.143	0.773	0.170	-0.028	0.951	-0.035	0.485
Y_9 (2002)	0.412	0.473	0.417	0.485	-0.386	0.414	-0.373	0.000
Y_10 (2003)	0.961	0.111	0.999	0.110	0.090	0.855	0.095	0.294
Y_11 (2004)	0.368	0.555	0.399	0.540	-0.605	0.235	-0.610	0.000
Q_1 (first quarter)	10.390	0.000	10.866	0.000	5.297	0.000	5.396	0.000
Q_2 (second quarter)	15.987	0.000	15.956	0.000	7.637	0.000	7.622	0.000
Q_3 (third quarter)	12.578	0.000	12.806	0.000	4.228	0.000	4.562	0.000
Consumer Discretionary products	1.449	0.013	1.849	0.004	-0.221	0.537	-0.244	0.554
Consumer Staples	2.205	0.048	2.228	0.048	1.532	0.018	1.399	0.022
Energy	3.130	0.375	2.249	0.535	1.638	0.371	1.272	0.507
Financials	16.982	0.160	16.135	0.174	10.749	0.176	8.678	0.270
Health Care	-7.804	0.000	-7.323	0.000	-4.756	0.000	-4.812	0.000
Industrials	-3.962	0.000	-3.697	0.000	-1.247	0.003	-1.287	0.002
Information Technology	-7.636	0.000	-7.224	0.000	-3.228	0.004	-3.169	0.005
Telecommunication Services	-2.781	0.155	-2.207	0.271	-3.961	0.000	-4.147	0.000
# of Observations	7585		7585		7585		7585	
Sargan test of overidentifying restrictions	191.334	0.990	190.600	0.990	238.49	0.990	239.880	0.990
Arellano-Bond test for AR(1) in first differences	-11.540	0.000	-11.580	0.000	-11.554	0.000	-11.550	0.000
Arellano-Bond test for AR(2) in first differences	0.521	0.600	0.508	0.611	.749	0.610	0.739	0.460
Test of equality of ACSI parameters	10.010	0.006	17.550	0.000	773.99	0.000	999.530	0.000
MMSC-BIC	181067.2		181012.7		181043.8		180940.8	

TABLE 6: THE MODERATING INFLUENCE OF SATISFACTION VOLATILITY

	Model 1		Model 2	
Estimated Effects	Coef.	P>z	Coef.	P>z
Intercept	-9.258	0.000	-9.146	0.000
Ln(Satisfaction Volatility)	.053	0.935	-.484	0.476
Δln(ACSI) $^{(+)}$	-18.269	0.000		
Δln(ACSI) $^{(-)}$	9.224	0.002		
Δln(ACSI) $^{(+)}$ x Ln(Satisfaction Volatility)	.179	0.000		
Δln(ACSI) $^{(-)}$ x Ln(Satisfaction Volatility)	-.181	0.005		
Δln(ACSI) $^{(-)}$ *after* publication			-11.481	0.078
Δln(ACSI) $^{(+)}$ *after* publication			-4.805	0.112
Δln(ACSI) $^{(-)}$ *before* publication			13.471	0.000
Δln(ACSI) $^{(+)}$ *before* publication			-22.708	0.000
Δln(ACSI) $^{(-)}$ *after* publication x Ln(Satisfaction Volatility)			16.747	0.006
Δln(ACSI) $^{(+)}$ *after* publication x Ln(Satisfaction Volatility)			-1.168	0.665
Δln(ACSI) $^{(-)}$ *before* publication x Ln(Satisfaction Volatility)			-10.936	0.000
Δln(ACSI) $^{(+)}$ *before* publication x Ln(Satisfaction Volatility)			11.833	0.000
Ln(Lagged dependent)	-.006	0.040	-.005	0.093
Ln (Volatility)	.064	0.000	.064	0.000
Ln (Market Value)	-.681	0.000	-.701	0.000
Ln (Revisions)	.668	0.000	.638	0.000
Ln (Diversification)	1.079	0.041	1.202	0.019
Ln (Coverage)	.227	0.022	.211	0.101
Ln (Brokerage firm size)	-.079	0.089	-.063	0.284
Ln (Experience)	-.035	0.895	-.165	0.540
Ln (Number of firms)	.192	0.031	.195	0.057
Ln (Number of industries)	.274	0.474	.249	0.509
Ln (Age of the forecast)	.242	0.000	.216	0.000
LOSS	1.526	0.000	1.589	0.000
Y_3 (1996)	.457	0.188	.549	0.116
Y_4 (1997)	.159	0.676	.235	0.541
Y_5 (1998)	.393	0.370	.588	0.183
Y_6 (1999)	.421	0.380	.633	0.192
Y_7 (2000)	.571	0.276	.819	0.122
Y_8 (2001)	.639	0.240	.853	0.120
Y_9 (2002)	.254	0.653	.498	0.387
Y_10 (2003)	.828	0.160	1.128	0.061
Y_11 (2004)	.232	0.705	.562	0.369
Q_1 (first quarter)	10.214	0.000	10.624	0.000
Q_2 (second quarter)	16.634	0.000	16.463	0.000
Q_3 (third quarter)	13.128	0.000	13.194	0.000
Consumer Discretionary products	1.950	0.012	2.097	0.007
Consumer Staples	1.851	0.123	1.520	0.176
Energy	4.561	0.220	2.919	0.439
Financials	19.204	0.121	17.667	0.151
Health Care	-8.376	0.000	-7.617	0.000
Industrials	-4.181	0.000	-3.686	0.000
Information Technology	-7.648	0.000	-7.182	0.000
Telecommunication Services	-3.183	0.114	-2.381	0.262
# of Observations				
Sargan test of overidentifying restrictions	194.033	0.99	192.64	0.99
Arellano-Bond test for AR(1) in first differences	-11.508	0.000	-11.52	0.000
Arellano-Bond test for AR(2) in first differences	0.509	0.61	0.51	0.60
Test of equality of ACSI parameters			641.62	0.000
MMSC-BIC	179024.204		178850.492	

TABLE 7: RESULTS ACCOUNTING FOR CHANGES IN PRIOR EARNINGS

Estimated effects	Coef.	P>z	Coef.	P>z
Intercept	-9.032	0.000	-10.389	0.104
$Ln(EPS_{it-1} - EPS_{it-2})$	**0.662**	**0.000**	**0.673**	**0.000**
Asymmetric effects of satisfaction with ACSI timing				
Δln(ACSI) (-) *after* publication ($\gamma^{SAT-POST \times NEGATIVE}$)	5.723	0.000	8.404	0.000
Δln(ACSI) (+) *after* publication ($\gamma^{SAT-POST \times POSITIVE}$)	-6.729	0.000	-5.236	0.020
Δln(ACSI) (-) *before* publication ($\gamma^{SAT-ANTE \times NEGATIVE}$)	-0.357	0.791	1.231	0.458
Δln(ACSI) (+) *before* publication ($\gamma^{SAT-ANTE \times POSITIVE}$)	-9.269	0.000	-8.620	0.000
Moderating influence of prior satisfaction				
Δln(ACSI) (-) *after* publication*lnACSI$_{it-1}$ ($\gamma^{SAT-POST \times NEGATIVE \times \ln SATLAG}$)			-6.186	0.015
Δln(ACSI) (+) *after* publication*lnACSI$_{it-1}$ ($\gamma^{SAT-POST \times POSITIVE \times \ln SATLAG}$)			2.757	0.014
Δln(ACSI) (-) *before* publication *lnACSI$_{it-1}$($\gamma^{SAT-ANTE \times NEGATIVE \times \ln SATLAG}$)			-0.835	0.388
Δln(ACSI) (+) *before* publication*lnACSI$_{it-1}$ ($\gamma^{SAT-ANTE \times POSITIVE \times \ln SATLAG}$)			1.086	0.197
Ln (ACSI) $_{it-1}$			0.485	0.724
Ln (Lagged dependent)	-0.005	0.003	-0.005	0.073
Ln (Volatility)	0.061	0.000	0.065	0.000
Ln (Market Value)	-0.732	0.000	-0.776	0.000
Ln (Revisions)	0.658	0.000	0.634	0.000
Ln (Diversification)	1.235	0.014	1.453	0.006
Ln (Coverage)	0.182	0.071	0.183	0.180
Ln (Brokerage firm size)	-0.033	0.578	-0.078	0.243
Ln (Experience)	-0.078	0.777	-0.126	0.652
Ln (Number of firms)	0.194	0.002	0.129	0.242
Ln (Number of industries)	0.255	0.492	0.260	0.493
Ln (Age of the forecast)	0.216	0.000	0.228	0.000
LOSS	1.601	0.000	1.639	0.000
Y_3 (1996)	-0.711	0.178	-0.747	0.163
Y_4 (1997)	-0.200	0.607	-0.238	0.550
Y_5 (1998)	-0.546	0.078	-0.574	0.068
Y_6 (1999)	-0.177	0.431	-0.129	0.583
Y_7 (2000)	-0.191	0.215	-0.072	0.651
Y_8 (2001)	0.151	0.039	0.189	0.019
Y_9 (2002)	-0.291	0.002	-0.194	0.075
Y_10 (2003)	0.332	0.005	0.390	0.003
Y_11 (2004)	-0.244	0.094	-0.174	0.285
Q_1 (first quarter)	10.882	0.000	11.033	0.000
Q_2 (second quarter)	16.712	0.000	16.228	0.000
Q_3 (third quarter)	13.337	0.000	12.669	0.000
Consumer Discretionary products	2.020	0.001	1.885	0.003
Consumer Staples	2.294	0.032	2.563	0.023
Energy	2.888	0.419	2.689	0.445
Financials	18.926	0.119	13.928	0.240
Health Care	-7.751	0.000	-7.160	0.000
Industrials	-3.573	0.000	-3.312	0.000
Information Technology	-7.025	0.000	-7.175	0.000
Telecommunication Services	-2.118	0.243	-3.094	0.095
# of Observations	4066		4066	
Sargan test of overidentifying restrictions	195.5222	0.997	191.324	0.99
Arellano-Bond test for AR(1) in first differences	-11.489	0.000	-11.509	0.000
Arellano-Bond test for AR(2) in first differences	.479	0.631	.483	0.628
Test of equality of ACSI parameters	754.31	0.000	309.05	0.000

TABLE 8: THE EFFECTS OF CUSTOMER SATISFACTION ON FORECAST REVISIONS

	Model 1 (revisions)		Model 2 (value)	
	Coef.	P>z	Coef.	P>z
Intercept	1.138	0.278	-2.185	0.000
Δln(ACSI) (-) *after* publication ($\gamma^{SAT-POST\times NEGATIVE}$)	.603	0.287	1.265	0.000
Δln(ACSI) (+) *after* publication ($\gamma^{SAT-POST\times POSITIVE}$)	-1.173	0.002	-0.628	0.000
Δln(ACSI) (-) *before* publication ($\gamma^{SAT-ANTE\times NEGATIVE}$)	.211	0.452	-0.769	0.000
Δln(ACSI) (+) *before* publication ($\gamma^{SAT-ANTE\times POSITIVE}$)	.652	0.002	1.340	0.000
Ln (Lagged dependent)	.226	0.000	0.432	0.000
Ln (Volatility)	.014	0.000	0.036	0.000
Ln (Market Value)	-.028	0.088	0.149	0.000
Ln (Diversification)	-.223	0.133	-0.342	0.000
Ln (Coverage)	.368	0.000	0.160	0.000
Ln (Brokerage firm size)	.052	0.023	-0.005	0.661
Ln (Experience)	-.190	0.000	-0.073	0.085
Ln (Number of firms)	.256	0.000	0.072	0.003
Ln (Number of industries)	-.075	0.324	-0.034	0.760
Ln (Age of the forecast)	.009	0.007	-0.011	0.000
Loss	.001	0.963	0.207	0.000
Y_3 (1996)	.091	0.107	0.055	0.589
Y_4 (1997)	-.008	0.905	0.059	0.601
Y_5 (1998)	.116	0.155	0.019	0.875
Y_6 (1999)	.004	0.965	0.143	0.262
Y_7 (2000)	-.002	0.979	0.121	0.361
Y_8 (2001)	.215	0.049	0.092	0.497
Y_9 (2002)	.098	0.389	0.089	0.519
Y_10 (2003)	-.016	0.890	0.086	0.542
Y_11 (2004)	.038	0.758	0.014	0.925
Q_1 (first quarter)	.173	0.844	0.011	0.968
Q_2 (second quarter)	-.465	0.719	-0.739	0.033
Q_3 (third quarter)	-.644	0.440	-0.896	0.002
Consumer Discretionary products	-1.367	0.004	-1.087	0.000
Consumer Staples	-.512	0.214	-1.047	0.066
Energy	-4.407	0.005	-0.341	0.245
Financials	-3.754	0.367	1.384	0.408
Health Care	.121	0.865	1.045	0.000
Industrials	.211	0.402	-0.051	0.731
Information Technology	.596	0.446	0.155	0.526
Telecommunication Services	.593	0.411	0.882	0.004
# of Observations	7686		4552	
Sargan test of overidentifying restrictions	159.02	0.92	107.19	0.99
Arellano-Bond test for AR(1) in first differences	-13.61	0.000	-8.795	0.000
Arellano-Bond test for AR(2) in first differences	-.110	0.91	.434	0.663
Test of equality of ACSI parameters	46.28	0.000	15.61	0.003

TABLE 9: DIFFERENCES BETWEEN ACSI AND NON-ACSI COMPANIES REGARDING ANALYSTS' FORECAST ERRORS

	Model 1			Model 2		
	Coef.	**z**	**P>z**	**Coef.**	**z**	**P>z**
Intercept	1.229	14.280	0.000	1.154	1.940	0.052
The lagged dependent variable	0.017	4.980	0.000	.031	6.66	0.000
Dummy variable ACSIFIRM = 1 and 0 otherwise	-1.243	-7.050	0.000	-.096	-0.32	0.749
Control Variables						
Earnings volatility				.006	3.43	0.001
Number of firms followed				-.045	-4.11	0.000
Analyst coverage				.133	7.73	0.000
Number of revisions				.012	1.88	0.060
Consumer Confidence Index				-.004	-0.12	0.905
Experience				-.032	-2.33	0.020
Brokerage firm size				.017	1.36	0.173
Loss				-.008	-1.70	0.088
Age of the forecast				.004	0.14	0.889
Q_1 (first quarter)				-.021	-3.22	0.001
Q_2 (second quarter)				-.028	-6.12	0.000
Q_3 (third quarter)				1.279	3.79	0.000
Telecommunication services				-.603	-2.45	0.014
Industrials				-.583	-1.64	0.101
Financials				4.493	1.01	0.311
Health Care				-.342	-0.75	0.456
Utilities				.566	1.85	0.065
# of Observations	18247			18247		
Sargan test of overidentifying restrictions	226.621		0.049	142.310		0.6163
Arellano-Bond test for AR(1) in first differences	-3.400		0.0007	-2.470		0.0134
Arellano-Bond test for AR(2) in first differences	0.574		0.565	0.568		0.569

APPENDIX 1: MATCHING DATASETS

The American Customer Satisfaction Index reports quarterly customer satisfaction data for each company on its website once a year. For example, data for *Prudential Financial, Inc*. is published in February only every year (which the ACSI project calls the fourth quarter). I/B/E/S, however, reports data for Prudential Financial, Inc. for every quarter of the year. Therefore, we need to reorganize the data. We proceed as follows. First, using the ACSI data, we refer to customer satisfaction scores reported in February as first-quarter data, in May as second-quarter data, in August as third-quarter data, and in November as fourth-quarter data. Second, we relate the customer satisfaction data made available in February to earnings forecasts for the quarter closing in March. Consequently, for companies whose satisfaction scores appear in February, we use only their forecasts for the quarter ending in March. For companies whose satisfaction scores appear in May, we use only their forecasts for the quarter ending in June, and so on.

We need to combine the ACSI date with the earnings forecast date. However, we do not know the exact date where ACSI scores are available to analysts or whether they are even available to analysts on the forecast date recorded by I/B/E/S. We examined the ACSI publication and commentary dates on the www.theacsi.org. For example, in 2000, commentaries appeared on August 19, May 20, February 22, and November 22. However, Fornell et al. (2006) suggest (footnote 3) possibilities of the prior leakage of customer satisfaction information because the "ACSI results were routinely provided under embargo to the public relations and market research units of corporate subscribers and to *The Wall Street Journal* about two weeks before the release" (p.7-8). Therefore, we distinguished between two periods. In period 1, we retain only the forecasts made by the analyst from the month of ACSI release. This is also justified by the fact that these latest forecasts should capture all the information at the disposal of the analyst. For Coca Cola Company, for example, we have 12 analysts who made at least one forecast in the fourth quarter (October through December). However, some of the analysts made their forecasts before November, the ACSI publication month for Coca Cola Company. Therefore, in this period, we exclude all the forecasts made prior to November and retain only the analysts with forecasts in December. In period 2, we include only the forecasts made before the month of the ACSI release. Here, we assume that the market may have already reacted to information about customer satisfaction that is reflected in measures other than the ACSI metric. That is, information about customer satisfaction is available to market participants on an earlier and timelier basis. We join the two periods in our estimation equations.

Time span: Fornell et al. (2006) states that: "although ACSI has measured customer satisfaction since 1994, before the second quarter of 1999, the results were published once a year in *Fortune magazine*, making it difficult to pinpoint the event date because readers received the magazine on different dates." Indeed, the ACSI data were the object of significant press coverage in 1995 (Stewart, 1995) and later, in 1998 (Lieber, 1998; Martin, 1998; Grant, 1998), in a series of articles published in *Fortune* Magazine. The first publication of the ACSI data in *Fortune* was on December 11, 1995. However, subscribers may have obtained the issue two weeks earlier (Ittner and Larcker, 1998). Therefore, we added the forecasts made from November 27, 1995 to December 1, 1995 and combined them with the forecasts made in 1996 through 2004. We distinguished between the two periods (i.e., 1995-1999: 1 versus 1999:2 through 2004) with a dummy variable but found no significant differences in the effects of ACSI.