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Prepared for "Wall Street Meets Marketing Strategy" by the The Marketing Science Institute (MSI) and the Emory Brand Institute (EmoryBI)
Version of 16/09/2008

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Acknowledgements: A Marketing Science Institute Grant supported this research. The authors thank Chiraz BenAli and Sebastien Lorenzini for valuable research support and K. L. Womack, Edith Ginglinger, for their insightful comments on this work. This paper has considerably benefited from comments of JM reviewers.

ABSTRACT

Abstract

This paper examines the usefulness of customer satisfaction to analysts when preparing their earnings forecasts. We draw on theory in marketing to predict how customer satisfaction should be associated with earnings forecasts and forecast errors. We assembled a dataset of companies studied in the American Customer Satisfaction Index (University of Michigan), which also appear on the Institutional Brokers Estimate System (I/B/E/S) files. By combining these sources, we were able to analyze the forecast errors of 1,875 analysts following 90 companies yielding 8,034 year-firm-analyst observations. We control for factors known to influence the earnings forecasts, such as firm profitability and risk, as well as potential unobservable factors using a Mixed-effects regression. We find that customer satisfaction has a negative association with the analysts' forecast errors because it allows analysts forecasts to be closer to the business reality. The influence of customer satisfaction varies across sectors. Specifically, we found that in the Information technology sector (i.e. Computer, the Internet Software & Services - e.g. EBay), customer satisfaction has the largest negative impact on earnings forecast errors. In sum, our findings suggest that analysts that neglect customer satisfaction information may deprive themselves of an important proxy of non-financial information, specifically in the information technology sector.

Key Words: Customer satisfaction; forecast accuracy/error; multilevel modeling

"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)

Many studies have documented the economic benefits of increasing customer satisfaction for the firms. Researchers have found that customer satisfaction has significant effects on various indicators: return on investment (e.g. Anderson, Fornell and Lehmann, 1994; Anderson, Fornell and Rust, 1997), market value of equity (e.g. Ittner and Larcker, 1998; Fornell, Mithas, Morgeson, and Krishnan, 2006), cash flows growth and variability (e.g. Gruca and Rego, 2005), Tobin's q (e.g. Mittal, Anderson, Sayrak, and Tadikamalla 2005; Anderson, Fornell, Mazvancheryl, 2004), credit ratings and debt costs (Anderson and Mansi, 2008).

While marketers generally agree on the positive impact of customer satisfaction, it is unclear whether and how market participants use information on customer satisfaction when they have to predict firm performance. If customer satisfaction is really a lead indicator of future performance, investors should recognize and reward it in an efficient market (Jacobson and Mizik, 2007). Yet, Williams and Viser's (2002) argue that customer satisfaction is relatively unimportant for investors. Fornell, Mithas, Morgeson, and Krishnan (2006), recently, have found that ACSI ratings relate significantly to market valuation, e.g. a 1% change in ACSI is associated with a 4.6% change in market value. A portfolio of stocks in the top 20% of ACSI ratings (relative to their competition) and above the ACSI national average generates a cumulative return of 40% compared to 13% for the S&P 500 index. Nevertheless, Fornell et al (2006) found that the news about the ACSI ratings does not reliably move stock prices over the short term. Aksoy, Cooil, Groening, Keiningham, and Yalçın (2008) also find that that purchasing a portfolio of stocks consisting of firms with high levels and positive changes in customer satisfaction will outperform the other portfolios combinations (e.g. low levels and negative changes) along with the S&P 500. These authors suggest that there is a lag in the investors' response to customer satisfaction. They found that initially the stock market undervalues positive satisfaction information, but it adjusts in the long-term. Jacobson and Mizik (2007) found that except for the

Computer and Internet sectors, customer satisfaction does not provide incremental information to accounting performance measures in explaining stock prices. However, one question remains: how does customer satisfaction come into share prices?

Much of the evidence on the effects of customer satisfaction comes from direct analyses of its influence on financial performance. Previous studies have bypassed the analysis of whether and how customer satisfaction information is accounted for or how it translates into stock pricing and valuation. An important route through which customer satisfaction efforts *could* translate into the stock pricing is the financial analysts' forecasts and recommendations (see Figure 1). Analysts play an important role as information intermediaries for the investors. Financial analysts aggregate complex information for other market participants (e.g. macroeconomic data, business plans, and possibly non-financial information) and provide (1) earnings forecasts, (2) share price targets, and (3) buy-sell-hold recommendations. Recent papers have called for a study of analysts' role. For example, Srinivasan and Hanssens (2008) ask, "How do analysts' interpretations of marketing activities such as product-price changes impact stock returns?" (p.23).

Despite some frustration over traditional financial statements and the fact that non-financial information can increase analysts' forecasts accuracies (see Orens and Lybaert, 2007; Vanstraelen, Zarzesky, and Robb, 2003), the extent to which analysts use non-financial information has received limited attention. The primary sources of information for the analysts remain prior earnings, SEC filings, industry information, macro-economic information (e.g. inflation), and management communication (Rammath, Rock, and Shane, 2008). One type of non-financial information that researchers in accounting (Ittner and Larcker, 1998) and marketing (Anderson et al. 1994; 1997) have studied is customer satisfaction, an indicator of the quality of the firm-customer relationships.

Rationally, the efficient market theory suggests, analysts would accurately use all available information. However, because they are far from being rational, analysts tend to ignore other available information. Thus, we examine whether customer satisfaction information, namely the ACSI index, known at the time of the forecast is related to the forecast error. A significant effect of customer satisfaction implies that analysts are not properly using available information. Customer satisfaction should not be a factor that explains the differences in the forecast errors if the analysts account for customer satisfaction. If customer satisfaction has a significant association with the forecast errors, this means that some analysts appropriately use customer satisfaction data while others do not. Non-financial measures contain incremental information over accounting numbers (Srivastava, Shervani, and Fahey, 1998) and hence, are likely to be important in earnings forecasts beyond accounting measures. Prior studies have shown that customer satisfaction positively influences customer behaviors, which influence various components of a company's revenues (e.g. Bolton, 1998; Anderson et al., 1994) and profitability (e.g. Banker et al., 2000). Therefore, it should be surprising if one does not find a significant relationship between customer satisfaction and earnings forecasts.

We address the role of customer satisfaction information by looking at how analysts' earnings forecasts relates to customer satisfaction, rather than its effects on stock prices or firm value. More specifically, the questions we address are the following: (1) would analysts' forecasts be more accurate if they account for customer satisfaction information? Do analysts have access to customer satisfaction through its proxies or some of its correlates (e.g. previous market value of the firm)? Do the variables generally used to explain analysts' errors (e.g. analyst coverage and the firm-specific experience) better reflect customer satisfaction information so that it should show no incremental value beyond that reflected in those variables? Does the relevance of customer satisfaction vary across industries?

Identifying accurate forecasts is important because earnings forecasts are an input to analysts' stock recommendations and many financial measures (e.g. cost of capital). For analysts, being able to produce accurate forecasts has implications for their own careers and their employers. For example, the annual rankings of financial analysts published by the *Wall Street Journal* rely on forecast accuracy and analysts that are more accurate are likely to keep their jobs. Furthermore, this study has the potential to raise the credibility of marketing to the CFOs and CEOs. By demonstrating the value of customer satisfaction data, we could get analysts to seek out even more systematically customer metrics from marketers to explain their followed companies' growth. For marketers, studying the role of analysts, as an information channel, may help better understand how marketing metrics in general and customer satisfaction data, in particular, come into share prices. Finally, for the corporate managers, this study examines the extent to which one specific type of non-financial information, i.e. customer satisfaction, often reported by firms, influences analysts' forecasts accuracies, and how this can influence their disclosure strategy.

The paper proceeds as follows. The next section outlines the background of our study. Then, we develop our research model and hypotheses regarding how customer satisfaction influences forecasts errors. Further, we give an overview of the data. Next, we present the details of the models. We provide the findings, and discuss the research implications.

RELATED LITERATURE

In this section, we summarize prior research on financial analysts that is relevant to our study. Our review will argue the following main point. Prior research has examined different sources of analysts' earnings forecast errors but we know little about the role of non-financial information. Specifically, there is a dearth of research on the role of customer satisfaction despite its reported importance (e.g. Anderson et al. 1994; 2004; Banker et al. 2000).

Analyst Forecast Accuracy: 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 the forecaster characteristics. Among the firm characteristics, company size has been the most studied. It appears that analyst forecasts are more accurate for larger firms (Brown, 1997; Brown et al., 1987; Hope, 2003; Lang and Lundholm, 1996; Lys and Soo, 1995). In a meta-analysis, Garcıa-Meca and Sanchez-Ballesta (2006) report an average effect of -0.145. The arguments include the fact that large firms have more stable growth and earnings (Chung and Kim, 1994; Hodgkinson, 2001), are more transparent (Lang and Lundholm, 1996), provide private information (Jaggi and Jain, 1998), and have larger analyst coverage (Atiase, 1985). Parkash, Dhaliwal, and Salataka (1995) also found that errors are larger for riskier firms.

Some of the studies have examined the impact of investments in intangible assets. Aboody and lev (1998) examined the impact of intangible accounting in terms of capitalization versus expensing. They found that the absolute size of analysts' forecasts errors has a positive association with the capitalized amount of software development costs. They argue that analysts would prefer full expensing because all they require for the forecasting of earnings are the changes in the level of expense. Barron, Byard, Kile, and Riedl (2002) found that analysts' forecasts are negatively associated with a firm's level of R&D spending. Gu and Wang (2005) also find that analysts' forecast errors are larger for firms with diverse and innovative technologies. Dehning, Pfeiffer and Richardson (2006) found that investments in IT have a positive association with the amount of dispersion and error in financial analyst forecasts as well. Thus, it appears that firms with higher intangible assets have higher information asymmetry, which makes it difficult for the analysts to forecast their earnings.

The largest majority of the studies have concerned the characteristics of the analysts themselves. These include the analyst experience, the complexity of the task, the brokerage firm size, forecasting horizon, age of the forecast, and the affiliation of the house. While some authors have reported positive effects of firm-specific experience (Clement, 1999; Jacob, Lys, and Neale, 1999; Mikhail, Walther, and Williams, 1997), others have reported no effect of general experience (Jacob, Lys, and Neale, 1999). Firm specific experience provides the ability to identify more precisely the factors that drive a company's earnings. In addition, experienced analysts are able to 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. Through their long experience, analysts are able to develop a better understanding of the company's business. The researchers have measured portfolio complexity with the number of firms and industries followed by analysts. Clement (1999) and Jacob et al. (1999) found that the number of companies followed reduces the analyst's accuracy, as larger portfolios reduce the amount of time devoted to each company. Garcıa-Meca and Sanchez-Ballesta (2006) found that, on average, forecast error has a positive association with the number of industries.

The size of the brokerage house reflects the resource availability. Analysts in large brokerage houses have access to increased resources, private communications with managers, tend to be top talents, and to have more sophisticated forecasting models than other analysts do. Garcıa-Meca and Sanchez-Ballesta (2006) found that larger brokerage firms are more accurate than their peers are (-0.0256, $p<0.001$). Another driver of the forecast error is whether the brokerage house is affiliated. The meta-analysis of Garcıa-Meca and Sanchez-Ballesta (2006) found a negative average association (-0.03, $p<0.01$) between affiliation and forecast error. Analysts employed by investment banks are more accurate than those employed by independent firms are. Affiliated analysts have greater resources, access to information, reputation, and that affiliated houses can attract analysts with better forecasting ability. Almost all previous studies suggest that the recent forecasts are more accurate than those issued earlier are (O'Brien 1988; Brown et al. 1987; Das and Saudaragan, 1998; Jacob et al. 1999; Jaggi and Jain, 1998; Lys and Soo, 1995). Garcıa-Meca and Sanchez-Ballesta (2006) report an average positive relationship of 0.2516 ($p<0.01$) between forecasting horizon and forecast error. Analysts providing forecasts later in the period are more accurate, as they have the advantage of observing the predictions of other analysts (Sinha, Brown, and Das, 1997). Even though, the majority of the studies have focused on these factors, it remains that their explanatory power is low. This indicates that other factors probably explain differences in analysts' accuracies.

The Use of Non-financial Information by Analysts: Do analysts use non-financial information and does it matter? A growing number of papers report that non-financial indicators of investments in intangible assets are important predictors of revenues (Ittner and Larcker, 1998; Behn and Riley, 1999; Trueman, Wong and Zhang, 2001; Nagar and Rajan, 2001), operating income and expenses (Behn and

Riley, 1999). Studies of the stock price response also suggest that nonfinancial information drives firm value (Amir and Lev, 1996; Trueman et al., 2001; Mizik and Jacobson, 2008). However, researchers have produced mixed results regarding the use of non-financial information by financial analysts. One group of studies suggests that analysts pay little attention to the disclosure of non-financial information. Nielsen (2008) found that analysts, infrequently, discuss intellectual capital in their reports. Garcia-Meca and Martinez (2007) found that, though analysts, in the Spanish context, report information regarding a company's strategy, customers, and processes, they less often provide information about research, development, and innovation. Furthermore, these analysts use this information in the case of highly profitable companies. Easton and Jarrell (1988) found that analysts were not able to account for the benefits of Total Quality Management (TQM) programs and consequently underestimated the resulting earnings. Similarly, Benson, Young, and Lawler (2006) report that analysts consistently underestimated earnings of firms with high-involvement human resources management practices. On the other side, Dempsey, Gatti, Grinnell and Cats-Baril (1997) surveyed 420 senior investment officers, directors of research and financial analysts regarding the frequency of use, predictive value, and ease of acquisition of a variety of financial and non-financial performance measures. They found that analysts go well beyond the traditional financial measures and use a broad range of leading indicators to assess long-term organizational success. Brown (1997) reported that analysts considered the "Discussion & Analysis" part of the 10-K reports (which discusses non-nonfinancial information) as important for their forecasts.

As for the effects of non-financial information, researchers tend to agree on the value of this type of information to financial analysts. McEwen and Hunton (1999) found that the use of financial statement information alone is associated with forecasting error. In a survey entitled "Metrics that Matter", Ernst and Young, in 1999, reported that analysts' use of non-financial information improved their forecast accuracy. Vanstraelen et al (2003) found a positive relationship between non-financial information disclosure and analysts’ forecast accuracies in Belgium, the Netherlands, and Germany.

Oriens and Lybaert (2007) report that the use of forward-looking information has a positive association with analyst' forecast accuracy.

Thus, prior research has examined the sources of analysts' earnings forecasts and the type of information used. The primary sources of error have included the forecaster characteristics and firm-specific factors. However, the extent to which the analysts use customer satisfaction and its relevance to their earnings forecasts remain an open question. Indeed, customer and employee information tends to be the least used of all. The most important type of non-financial information for the analysts tend to be the management's strategies and plans for the future and forward looking information such as new products to be developed in the next 10-years and sales forecasts. Yet, non-financial information has the potential to decrease earnings forecast errors.

RESEARCH HYPOTHESES

While existing research indicates that customer satisfaction is associated with firm performance, it does not directly address how customer satisfaction information may influence the financial analysts. Yet, it may not automatically follow that customer satisfaction will lead to lower earnings forecasts errors. First, analysts may not have access to customer satisfaction data, which tends to be private information. Second, they may not believe in its causal effects. Williams and Viser (2002) argue that investors do not see customer satisfaction as an important intangible asset when they have to evaluate a business. One reason is that they no longer believe that satisfying customers yields a competitive advantage. Furthermore, Williams and Viser (2002) argue that the CEOs are indifferent to customer satisfaction as well because they consider that many other factors "have a much more direct and fast effect on share price than customer satisfaction figures."(p.195). In his paper, Hilsenrath (2003) cites Tom Goetzinger, a Morningstar Inc. analyst who follows Home Depot, familiar with the ACSI data, as saying he doesn't 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". Third, the influence of customer satisfaction may be marginal, when public information obtained by analysts substitute for the privately acquired information. Empirical evidence indicates that stocks with high analyst coverage are more informative (Hong, Lim and Stein, 2000) and that analysts' forecasts and recommendations affect stock prices (Givoly and Lakonishok, 1979; Francis and Soffer, 1997). Thus, it is possible for large analyst coverage to substitute for the lack of private information. In this case, customer satisfaction should have no incremental value. In the specific case of the American Customer Satisfaction Index (ACSI), it is possible that the market notices changes in customer satisfaction well before the ACSI publishes them. If analysts accounts for customer satisfaction changes well in advance, the ACSI becomes irrelevant. Therefore, the business press suggests that there should not be a significant association between customer satisfaction and earnings forecast errors.

We hold a different view. We believe that customer satisfaction should play some role in the analysts' forecasts. In Figure 1, we provide the conceptual model that underlies our propositions. First, we consider the influence of customer satisfaction, a proxy for nonfinancial information, on the actual earnings per share. We need to ensure that customer satisfaction does have an influence on the company's earnings per share. If it is confirmed, then we can examine how accounting for customer satisfaction in the earnings forecasts may reduce the analyst's forecast errors. Second, we consider that if customer satisfaction influences forecast errors, it should influence the forecasts made by the analysts. Below we develop these ideas.

*********** Insert Figure 1 about here *************

***Customer satisfaction and Earnings per Share*:** Customer satisfaction influences customer behaviors that can stabilize and enhance the earnings components such as sales and costs. Prior studies found that customer satisfaction influences repeat purchase behavior (e.g. Bolton, 1998), word of mouth or referral activity (e.g. Anderson, 1998), cross-selling rates (e.g. Verhoef, Franses, and Hoekstra, 2001), frequency of purchase (e.g. Bolton et al, 2000), the purchase of premium options (e.g. Ngobo, 2005), price premiums or reduced price elasticity (e.g. Homburg, Koschate, and Hoyer, 2005). By affecting these aspects, customer satisfaction allows firms to maintain and increase their revenues (e.g. Rust, Moorman, and Dickson, 2002). Customer satisfaction also reduces the firm's cost of future transactions (e.g. customer acquisition) through securing a stable customer base and costs related to customer complaints and product returns (Fornell, 1992). Other studies report a direct link between customer satisfaction and profitability (e.g. Anderson et al. 1997) and cash flows growth and variability (e.g. Gruca and Lopo, 2005). Srivastava, Shervani and Fahey (1998) suggest that market-based assets such as customer satisfaction have the potential to accelerate and enhance the level of cash flows and to lower their volatility. Consequently, we hypothesize that:

H 1: The association between customer satisfaction and earnings per share is positive.

Customer satisfaction and analysts' earnings forecasts: Because customer satisfaction influences customer behaviors that can enhance the company's cash flows (Gruca and Lopo, 2005), we believe that it should make the analysts' earnings forecasts to be closer to the actual earnings. In other words, accounting for the customer satisfaction information in an earnings model will increase its explanatory power because customer satisfaction is an important predictor of future performance (Anderson et al. 1994; Banker et al. 2000). Therefore, we hypothesize that:

H 2: Customer satisfaction has a positive association with the analysts' earnings forecasts.

Customer satisfaction and earnings forecast errors: Mechanically, by allowing analysts to make realistic forecasts, customer satisfaction will reduce the earnings forecasts errors. Thus, we consider that customer satisfaction will reduce the forecast errors because it will help analysts to make forecasts that are close to the actual firm performance. This leads to the following hypothesis:

H3: Customer satisfaction has a negative association with the analysts' earnings forecast errors.

DATA

Before formally modeling the relationship between customer satisfaction and analysts' earnings forecast errors, we present a descriptive analysis of the data. To study the effects of customer satisfaction on analysts' outputs, we need a sample of firms that have data on customer satisfaction. Therefore, we began by selecting firms from the American Customer Satisfaction Index (ACSI) project at the University of Michigan Business School. Then, we selected all the ACSI firms in the Institutional Brokers Estimate System (I/B/E/S) files. We used the Masked Detail tape that provides earnings forecasts and forecast dates for individual analysts as well their revision dates. By combining these sources, we were able to come up with an initial number of forecasts for companies. However, we had to make some choices based on the standard practices in accounting and finance publications. For example, we eliminated analysts who had not made at least four (4) forecasts in the dataset. We also eliminated some industries because many firms are not public companies but only subsidiaries or SBUs of large companies. Because the ACSI is a quarterly database, we use predictions made one quarter ahead. We match the forecast earnings to the realized earnings for every relevant period.

It is important to understand the timing of ACSI scores to understand how we linked the data with the IBES forecast values (see Figure 2). The American Customer Satisfaction Index reports customer satisfaction data quarterly for each company once a year. For example, data for *Prudential Financial, Inc*. is published in February only every year (which the ACSI project calls fourth quarter). The 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, and in November as fourth quarter data.

**********Insert Figure 2 about here***********

We relate the customer satisfaction data made available in February to earnings forecasts for quarter closing in March. Consequently, for companies whose satisfaction scores appear in February, we use only their forecast errors for the quarter ending in March. For companies whose satisfaction scores appear in May, we use only their forecast errors for 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 if they are even available to analysts on the forecast date recorded by the I/B/E/S. Thus, we try to synchronize the forecast dates as closely as possible to the dates at which the ACSI scores are available. We examined the ACSI publication and commentary dates on the www.theacsi.org. For example, in 2000 commentaries appeared on 19 August, 20 May, 22 February, and 22 November. However, Fornell et al (2006) indicate (footnote 3) possibilities of 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). Consequently, we defined a window that goes back two weeks before the publication date, i.e. in February we included forecasts made from February 1. Furthermore, 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. To distinguish between the two periods (i.e. 1995-1999: 1 versus 1999:2 through 2004), we created a dummy variable to separate the effects of ACSI. The results showed no significant differences.

**********Insert Table 1 about here *************

Variables

Dependent Variable: We used the absolute value of the analyst's earnings forecast error because it is the most widely adopted and easier to interpret than the signed measure. We determined this measure as follows: $FE_{t+1hij} = \left|(AE_{t+1hij} - EF_{thij})\right| / EF_{thij}$ where AE_{t+1hij} refers to the actual earnings of firm *i* in industry *j* and quarter *t+1* that was followed by analyst *h* and EF_{thij} refers to the earnings forecasted by that analyst. When the analyst made at least two forecasts, we retained the latest one to be sure that it includes the most recent information prior to the release of the company's quarterly earnings. We use the earnings provided in the I/B/E/S because they exclude the special, extraordinary items, discontinued operations, and effects of accounting changes. This is important, as customer satisfaction should typically influence operating earnings.

Independent variables (analyst level): Consistent with the research purpose and prior studies, we include the following measures: (1) experience, (2) portfolio or task complexity, and (3) analyst's resources. *Experience:* We use two measures to capture the analyst's abilities and skills regarding earnings forecasting. They are the firm-specific experience and the general experience. Firm-specific experience refers to number of prior quarters for which the analyst *h* following firm *i* in industry *j* in quarter *t* provided at least one forecast for that firm. General experience corresponds to the number of quarters (irrespective of the firm) analyst *h* following firm *i* in industry *j* supplied at least one forecast during the previous quarters through quarter *t*. *Task complexity:* Task complexity refers to the number of firms and industries followed by the analyst. The number of companies followed by the analyst measures the number of firms that analyst *h* follows in quarter *t*. The number of industries is a measure of the number of 4-digit SIC industries followed by analyst *h* in quarter *t*. *Analyst Resources:* Resources reflect the size of the brokerage firm. Brokerage Size measures the number of analysts employed by the brokerage firm employing analyst *h* who follows firm *i* in industry *j* in quarter *t*.

Independent Variables (Firm-level): We control for company size, number of analysts (or coverage), business uncertainty or volatility, and prior performance. In line with our research model, we add customer satisfaction data to assess its incremental value for analysts. *Company size* is measured with the logarithm of the firm's market value one quarter before the release of analysts' earnings forecasts. We expect a negative relation between firm size and forecast error. *Analyst Coverage* measures the number of analysts who follow the company, and consistent with prior research, we expect a negative relation between the number of analysts and forecast error. *Business uncertainty or volatility* is supposed to increase the forecasting difficulty for the analyst. We use the standard deviation of earnings per share (EPS) computed over the preceding quarters to measure the firm's volatility. *Prior performance* accounts for prior profitability. Hwang et al. (1996) find that analysts' forecasts errors are larger for loss firms than for the profitable firms. We include a dummy variable (*LOSS*) that equals one (1) for firms that report negative earnings in the quarter preceding the forecasting period and 0 otherwise.

Customer Satisfaction Scores: We collect firm-level customer satisfaction scores from the American Customer Satisfaction project at the University of Michigan. We composed an 11-year datasheet of quarterly data on customer satisfaction. We use the satisfaction data made available on the ACSI website, which provides data for many firms since 1994 (see Fornell et al. 1996). The ACSI is a quarterly survey of customers. The first scores came out in October 1994. Since then, there has been a quarterly updating. Therefore, we analyze the ACSI quarterly. The ACSI project defines customer satisfaction as an overall evaluation of the purchase and consumption experience to-date. Satisfaction (3 10-point items) reflects the customer's overall feeling of satisfaction, evaluation of quality regarding expectations, and quality regarding ideal. A company's satisfaction score is the satisfaction of all its interviewed customers. It ranges from 0 to 100.

MODEL FORMULATION

We develop a model that summarizes the current research on predicting earnings forecast errors, i.e. which accounts for analysts, firm, and possibly industry factors. Indeed, we need to test whether ACSI provides incremental information over standard measures that generally influence analysts' forecast errors. In particular, we must control for well-known covariates, such as firm size, profitability, risk, and analyst coverage. Furthermore, the problem, as shown in the data, is that the number of firms is too small in some industries. This makes it difficult to estimate the within-industry as well as the between-industry variation reliably. Indeed, when estimating multilevel models, it is desirable to have as many units as possible at the top level of the multilevel hierarchy (Snijders, 2005). Therefore, we decided to estimate only three levels: (1) the within-analyst variation, (2) the within-firm (or between analyst) variation, and (3) the between-firm variation, and aggregate industries into sectors the influence of which is captured with dummy variables (Jacobson and Mizik, 2007). We specify the dependent variable (i.e. earnings forecast or the forecast error) for analyst *h* (*h*=1,…*H*) following firm *i* (i=1,…,I) operating in industry *j* (j=1,…,J) in quarter *t+1* (t=1,…,T) as follows:

$$\text{(1)}\quad \begin{aligned} y_{hij(t+1)} = {} & \alpha_{0hi} + \sum_{p=2}^{P} \alpha_p \times SEC_{j,p} + \sum_{p=2}^{P} \alpha_p \times QTR_p + \alpha^{CCI} \times CCI_t \\ & + \pi_{00i}^{LEPS} \times y_{ijt} + \sum_{p=1}^{P} \pi_{00i,p}^{X} \times X_{ijt,p} + \pi_{00i}^{SAT} \times ACSI_{ijt} + \varepsilon_{(t+1)hij} \end{aligned}$$

Here $y_{(t+1)hij}$ refers to the dependent variable (e.g. forecast, forecast error) for analyst *h* regarding firm *i* in sector *j* and quarter *t+1*. To capture the analysts' response to earnings announcement or any "post-earnings announcement drift", we control for prior earnings (y_{ijt} **).** Indeed, one of the most widely discussed forecasting anomalies is "post-earnings announcement drift," which is said to stem partly from an under-reaction to past earnings announcements (Zhang, 2008). QTR_p refers to a vector of quarter effects (e.g. February, May, August, and November) which examines quarter-specific effects associated with customer satisfaction (ACSI) publication. SEC_j is a vector of sector dummy variables. CCI_j refers to the consumer confidence index in time t. It captures the consumers' optimism on the state of the economy and it may affect the company's future earnings as it influences consumers' activities of spending. X_{hijt} is a vector of firm-level control variables (i.e. other firm-specific variables such as analyst coverage, risk), $ACSI_{ijt}$ refers to the customer satisfaction score of firm *i* in sector *j* in quarter *t*, π reflects the impact of firm-level control variables and customer satisfaction. α_{0hij} is the intercept and $\varepsilon_{(t+1)hij}$ is an error term. We control for unobserved heterogeneity using the following relationship:

$$(2)\ \alpha_{0hi} = \kappa_{000} + \sum_{p=1}^{P} \pi_{000,p}^{Z} \times Z_{hijt,p} + \tau_{00i} + \mu_{0hi}$$

Where the average forecast error (or grand mean) is κ_{000}, τ_{00i} is the firm-specific error term, μ_{0hi} is the analyst-specific error term, which allow us to capture the between-firm and the within-firm variation respectively. We control for the observed analyst heterogeneity with Z_{hijt}, which is a vector of the characteristics of analyst *h* following firm *i* sector *j* and time *t*. We control for response heterogeneity with the following relationship:

$$(3)\ \pi_{00i}^{LEPS} = \pi_{000}^{LEPS} + \tau_{00i}^{LEPS}$$

$$(4)\ \pi_{00i}^{X} = \pi_{000}^{X} + \tau_{00i}^{X}$$

$$(5)\ \pi_{00i}^{SAT} = \pi_{000}^{SAT} + \tau_{00i}^{SAT}$$

Where the mean effect of each predictor is π_{000} and τ_{00i} is the variation around that mean. By combining equations (2) through (5) with equation (1), we obtain the following general relationship:

$$
\begin{aligned}
y_{hij(t+1)} = \kappa_{000} &+ \sum_{p=1}^{P} \pi_{000,p}^{Z} \times Z_{hijt,p} + \sum_{p=2}^{P} \alpha_p \times SEC_{j,p} + \sum_{p=2}^{P} \alpha_p \times QTR_p + \alpha^{CCI} \times CCI_t \\
&+ \pi_{000}^{LEPS} \times y_{ijt} + \tau_{00i}^{LEPS} \times y_{ijt} + \sum_{p=1}^{P} \pi_{000,p}^{X} \times X_{ijt} + \sum_{p=1}^{P} \tau_{00i,p}^{X} \times X_{ijt,p} \\
&+ \pi_{000}^{SAT} \times ACSI_{ijt} + \tau_{00i}^{SAT} \times ACSI_{ijt} \\
&+ \tau_{00i} + \mu_{0hi} + \varepsilon_{(t+1)hij}
\end{aligned} \tag{6}
$$

Equation (6) subsumes many standard models used in accounting and finance when $ACSI_{ijt}$ is excluded. Nevertheless, our standard model (i.e. Equation 6 with $ACSI_{ijt} = 0$) differs from previous studies, as we assume that the intercept as well as some parameters will differ across industries. Furthermore, our model deals with cross-sectional dependence between analysts following the same company. The forecasts' of analysts are related for a given firm. If a firm has a particularly good period due to some unforeseen event, it is likely that all the analysts will make inaccurate forecasts. This phenomenon induces cross-sectional dependency in the error term.

Equation (6) will serve to test hypotheses 2 and 3. A significant coefficient of the ACSI variable allows us to reject our null hypothesis of no effect on either earnings forecasts or forecast errors. We expect the ACSI coefficient to be positive for the earnings forecasts (H2) and negative for the forecast errors (H3). To test H1, we consider a different equation that excludes analysts.

$$
\begin{aligned}
EPS_{ij(t+1)} = \beta_{00} &+ \sum_{p=2}^{P} \beta_p \times SEC_{j,p} + \sum_{p=2}^{P} \beta_p \times QTR_p + \beta^{CCI} \times CCI_t \\
&+ \beta_{00}^{LEPS} \times y_{ijt} + \zeta_{0i}^{LEPS} \times y_{ijt} + \sum_{p=1}^{P} \beta_{00,p}^{X} \times X_{ijt} + \sum_{p=1}^{P} \zeta_{0i,p}^{X} \times X_{ijt,p} \\
&+ \beta_{00}^{SAT} \times ACSI_{ijt} + \zeta_{0i}^{SAT} \times ACSI_{ijt} \\
&+ \omega_{0i} + \varepsilon_{(t+1)ij}
\end{aligned} \tag{7}
$$

Here *EPS* refers to the earnings per share of firm i in sector j and quarter t+1. The other variables are defined as above. β, ζ, ω, and $\mu_{(t+1)ij}$ are the model parameters. We expect the ACSI coefficient (β_{00}^{SAT}) to be positive for the actual earnings (H1). If there are sector differences in the way customer satisfaction influences actual, forecasted earnings, and forecast errors, we can test these differences by enhancing our equations with interactions between sector dummies and ACSI variable.

FINDINGS

Descriptive statistics: In Table 2, we report the descriptive statistics for the key variables.

********Insert Table 2 about here**********

The average number of firms covered by an analyst in our sample is approximately four (4.10). It is worth noting that the number of analysts per firm and firms per analyst are not comparable to those reported in other studies on earnings forecasts. Our research includes only the firms for which we have satisfaction data. The average number of industries is 4.17. In terms of firm-specific experience, the average analyst has been following a specific company for about fifteen (14.753) quarters. The average general experience is about 82.497 quarters.

In Table 3, we report the different correlations between the variables of interest. As we can see, the correlations between number of firms and number of industries is very high (0.968) and so is the correlation between complexity variables and general experience. To avoid multicollinearity problems, we decided to measure complexity with the average number of industries and firms followed by the analysts and the experience with firm-specific experience.

********* Table 3 about here*********

Testing for Hypothesis 1: ACSI and Actual Earnings Forecasts: In Table 4, we report the results pertaining to H1. Model 1 provides the estimates for the baseline specification with the control variables only. Model 2 accounts for the influence of ACSI. The BIC and AIC, all, show this model is not better than Model 1. Then, we estimated a model that accounts for response heterogeneity. The AIC and BIC show that this specification has a better fit than Models 1-2.

*********** Insert Table 4 about here **************

In Model 3, we can see that larger values of ACSI are associated with a significantly higher level of EPS from the company (0.013, p-value=0.05). This means that 1% change in the ACSI index is associated with a nearly 1.3% increase in EPS in the next quarter. Thus, we find support for H1, i.e. customer satisfaction has a positive association with the company's EPS.

Testing for hypothesis 2: the association between ACSI and EPS Forecasts: The findings pertaining to Hypotheses 2, i.e. customer satisfaction has a positive association with analysts' earnings forecasts, are summarized in Table 5. In Model I, we decompose the variance in analysts' earnings forecasts while accounting for sector dummies. This model shows that most variation is between firms. Then, in Model II, we report the estimates for the model with the control variables. This model has a better fit than Model I. Next, we include ACSI (Model III) and this model has a better fit than the model without ACSI. Further, we estimated the model that controls for the response heterogeneity and the results show that Model IV has a better fit than Model III. In Model IV, we can see that ACSI has a positive association with the earnings forecasts (0.0259, p-value=0.000).

********* **Insert Table 5 about here** ************

Thus, our findings are suggesting that ACSI does influence the analyst's forecasts. The higher the ACSI score the higher the analyst's earnings forecasts. H2 is supported.

Testing for Hypothesis 3: Association between ACSI and Forecast Errors: Table 6 presents the estimate results regarding the analysts' earnings forecasts errors. Model I includes all the control variables. In Model II, we account for the influence of customer satisfaction. The results suggest that the model fit statistics are poorer than in Model I. In Model III, we account for response heterogeneity among firms. The results show that this model has a better fit than Model II. Further, we estimate a model that constrains the non-significant random coefficients to zero and find that this model has an even better fit.

********* **Insert Table 6 about here** ************

In this model (Model IV), we observe that on average analysts make higher forecast errors for companies in financial services (1.346, p-value=0.001), the healthcare sector (1.824, p-value=0.000), information technology (1.195, p-value=0.000) and the utilities (1.157, p-value=0.000) as opposed to the industrial companies (-0.488, p-value=0.000). Similarly, we observe that the forecast errors are higher for companies whose ACSI scores appear in May (1.282, p-value=0.000), probably reflecting a post-earnings announcement drift (i.e. here overreaction) after the first earnings announced in March. The size of the brokerage company reduces the forecast errors (-0.033, p-value=0.05), reflecting the availability of the resources. However, contrary to expectations, we observe a positive association between firm-specific experience and forecast errors (0.012, p-value=0.05). This may reflect overconfidence. Looking at the company-specific variables, we find that the forecast errors are smaller for large companies (-0.405, p-value=0.000), greater for volatile companies (0.756, p-value=0.000), and for companies which made losses in prior periods (1.542, p-value=0.000). However, we find that large analyst coverage may lead to greater forecast errors (0.044, p-value=0.000). Finally, we find that customer satisfaction has a negative association with forecast errors (-0.024, p-value=0.05). Thus, we find support for H3.

Controlling for Differences across Sectors

Industry differences in information asymmetry (e.g. R&D intensity) may influence analysts' forecast errors. Brown et al. (1987) showed the impact of industry on the accuracy of forecasts. Gu and Wang (2005) found that analysts' forecast errors were smaller for biotech/ pharmaceutical and medical equipment firms that are subject to intangibles-related regulation. Furthermore, managers have different latitudes in influencing customers' behaviors through customer satisfaction. Prior research also suggests that the influence of customer satisfaction varies across industries (Anderson et al. 2004; Gruca and Lopo, 2005; Jacobson and Mizik, 2007). Therefore, the influence of customer satisfaction on the analysts' forecast errors should vary across sectors. In Table 7, we report the differential effects of ACSI on actual EPS, forecasted EPS, and Forecast Errors.

**************Insert Table 7 about here**************

We began with the actual EPS. Model I (see Table 7) has poor fit than the main-effects model (see Table 4). However, when we constrain the non-significant interactions to zero, we obtain a model with a better fit. In this model, the main effect of ACSI is not significant anymore. However, we find that ACSI in the current quarter has a positive effect on EPS announced in the subsequent quarter, specifically in the information technology sector (0.116, p-value=0.000).

Then, we estimated a model with the moderating effects of sector dummies with analysts' forecasted EPS as a dependent variable. The goodness fit statistics show that this model has a better fit than the other specifications reported in Table 5. In this model, we can see that the average effect of ACSI is not significant anymore. Nevertheless, the association is greater in information technology sector (0.16, p-value=0.000), the Telecommunication (0.023, p-value=0.000), the utilities (0.047, p-value=0.000), and in the consumer staples (0.024, p-value=0.000).

Next, we examine the differential effects of ACSI across sector regarding the forecast errors. The model that accounts for sector differences has a poorer fit than the last model reported in Table 6. Therefore, we estimated a constrained model, which excludes the non-significant moderators and random coefficients. The results clearly show that this constrained model has a better fit than the other specifications. Focusing on the influence of customer satisfaction, we find that while on average its effect is not significant, the influence of customer satisfaction is positive in the industrial sector (0.073, p-value=0.05) but negative in the information technology sector (-0.316, p-value=0.000).

Does ACSI really have Information Content relevant to Analysts?

Our results suggest that customer satisfaction has a negative effect on earnings forecast errors and these effects differ across sectors. This association occurs because ACSI helps the analysts to make forecasts that are closer to the firm's reality. However, Jacobson and Mizik (2007) have argued that in an efficient market, the metric (e.g. analyst forecast) already reflects the anticipated information and, consequently, the market participants will react primarily to unanticipated information. Results based on levels of variables should be in contradiction to the efficient market theory. As such, to assess the influence of customer satisfaction appropriately, we have to relate the association between earnings forecast errors and the unanticipated component of customer satisfaction. We estimated the following equation:

$$\begin{aligned} y_{hij(t+1)} = {} & \kappa_{000} + \sum_{p=1}^{P} \pi^{Z}_{000,p} \times \Delta Z_{hijt,p} + \sum_{p=2}^{P} \alpha_p \times SEC_{j,p} + \sum_{p=2}^{P} \alpha_p \times QTR_p + \alpha^{CCI} \times \Delta CCI_t \\ & + \pi^{LEPS}_{000} \times \Delta y_{ijt} + \tau^{LEPS}_{00i} \times \Delta y_{ijt} + \sum_{p=1}^{P} \pi^{COV}_{000} \times \Delta COV_{ijt} + \sum_{p=1}^{P} \tau^{COV}_{00i} \times \Delta COV_{ijt} \\ & + \sum_{p=1}^{P} \pi^{SIZE}_{000} \times \Delta SIZE_{ijt} + \sum_{p=1}^{P} \tau^{SIZE}_{00i} \times \Delta SIZE_{ijt} + \sum_{p=1}^{P} \pi^{LOSS}_{000} \times \Delta LOSS_{ijt} + \sum_{p=1}^{P} \tau^{LOSS}_{00i} \times \Delta LOSS_{ijt} \\ & + \pi^{SAT}_{000} \times \Delta ACSI_{ijt} + \tau^{SAT}_{00i} \times \Delta ACSI_{ijt} + \tau_{00i} + \mu_{0hi} + \varepsilon_{(t+1)hij} \end{aligned} \tag{7}$$

Where SIZE refers to the company size, LOSS = 1 if the firm made a loss in prior quarter and 0 otherwise, COV refers to the analyst coverage. In Table 8, we report the results based on Equation (7) for the analysts' forecasts.

**************** **Insert Table 8 about here****************

The results show that on average customer satisfaction has information relevance to financial analysts when preparing their earnings forecasts. A change in ACSI is associated with a small but significant effect on the analyst's EPS forecast (0.003, p-value=0.05). Later, we find that the benefits of customer satisfaction are larger in the telecommunication services sector (0.028, p-value=0.000). In the industrials, there is a marginal but negatively significant association (-0.009, p-value=0.05).

In table 9, we report the results of the same estimation where we changed the dependent variable and used the logarithm of the forecast error.

*************** **Insert Table 9 about here*****************

As can be seen the main-effect model shows that an increase in customer satisfaction reduces the level of the analyst's forecast error (-0.04, p-value=0.05). Furthermore, the results confirm that the relationship is most negative in the information technology sector (-0.219, p-value=0.000). These results confirm the above findings that customer satisfaction has information content that would be relevant to the analysts making earnings forecasts, specifically those who follow companies in the information technology sector.

DISCUSSION AND CONCLUSION

Customer satisfaction has been the focus of marketing studies for some time now. Prior studies show that customer satisfaction has a positive association with many important financial metrics. However, aside from direct analyses of the impacts of customer satisfaction on financial metrics, prior work generally provides little insight into the use of the customer satisfaction information by key market participants such as financial analysts. This study adds to our knowledge about the information content of customer satisfaction by examining its effects on financial analysts' earnings forecasts errors. We find that customer satisfaction is important for the analysts with regard to earnings forecasts. On average, customer satisfaction reduces the analyst's forecast error. The information provided by customer satisfaction is incremental to the traditionally used drivers of forecast errors such as prior earnings, company size (lagged market value), analyst coverage or volatility. Our explanation is that customer satisfaction influences the customer behaviors that stabilize and increase the company's cash flows. Consequently, by increasing the earnings forecasts made by the analyst, customer satisfaction reduces the discrepancy with actual EPS.

Nevertheless, we did find that the benefits of customer satisfaction are larger for some sectors and smaller for others. Additional analyses, using the changes in customer satisfaction, confirm this finding. Specifically, we found that the information technology sector (i.e. the computer, Internet Software & Services) is where customer satisfaction has the largest negative impact on earnings forecast errors. This result is similar to the one reported by Jacobson and Mizik (2007) on the value relevance of customer satisfaction to stock prices. The current research complements previous studies by showing that high customer satisfaction levels are also associated with lower forecast errors in addition to accounting performance (Anderson et al 1994; 1997; Banker et al. 2000), financial performance (Anderson et al. 2004; Fornell et al. 2006), and the firm performance on the bond market (Anderson and Mansi, 2008). This result helps us answer some of the questions raised in the introduction. First, we observe that customer satisfaction increases the accuracy of the analysts' forecasts. Second, we find that analysts do not have access to customer satisfaction through its potential drivers or some of its other correlates such as company size, i.e. the previous market value of the firm. Indeed, our findings show that despite controlling for their influence, the impact of customer satisfaction remains significant. Third, we find that the variables generally used to explain analysts' errors (e.g. the number of companies followed and the firm specific experience) do not proxy for customer satisfaction information. Despite including the firm-specific experience, customer satisfaction still shows incremental value beyond that reflected in those variables when it comes to explain forecast errors. Fourth, the results are clearly indicating that customer satisfaction is important to the financial analysts. The benefits of customer satisfaction are larger for the analysts who follow companies in the information technology sector.

Research Implications

The present study has implications for the study of analysts' performance. We have extended our understanding of the factors that explain the sources of analysts' forecast errors. Prior research has examined the effects of intangible assets (e.g. Barron et al. 2002; Gu and Wang, 2005). To our knowledge, this is the first paper to address the effects of customer satisfaction. In line with Benson et al. (2006) for HR practices, our study suggests that financial analysts should use non-financial information in their earnings forecast efforts and that customer satisfaction data should be part of it. We have taken a step further to examine conditions under which customer satisfaction information would lead to better forecasts. Thus, for managers, our research suggests that, in addition to the effects on customer behaviors and firm profitability, customer satisfaction may also influence the firm's share price movements by allowing analysts to make realistic forecasts (see Figure 1). The negative association between customer satisfaction and forecast errors means that the company value is likely to reflect its true efforts in satisfying customer needs.

The current research contributes to the development of a foundation for a better understanding the relationship between marketing investments and share prices. In the recent years, marketers have voiced concern about the legitimacy of marketing within the firm. More specifically, it appears that marketing's influence has been decreasing at the level of corporate strategy (Anderson, 1982; Day 1992; Webster, Malter and Ganesan 2003; Varadarajan, 1992). This study shows that one way 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 allowing them 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 systematically customer metrics from to explain their followed companies' growth. Our study also shows that one way through which customer metrics may come into share prices is through analysts' earnings forecasts. By influencing the analysts' earnings forecasts, customer satisfaction is likely to influence share prices.

Our study has relevance for corporate disclosure strategy as well. Given the value relevance of customer satisfaction for earnings forecasts, corporate managers should systematically report this data during conference calls and any meeting with financial analysts. Companies increasingly use conference calls to enhance investors' understanding of earnings announcements. They are informative to market participants as they enhance stock price responses and help analysts form more accurate earnings expectations. We suggest that management should provide detailed (key) information such as customer satisfaction improvements to analysts. Similarly, when possible, the management should highlight the role of customer satisfaction in driving the company's earnings.

Limitations and Future Research Questions:

This study also has some limitations, which provide the foundation for additional research. First, we had to limit our sample to firms for which we had data available in the I/B/E/S. We did not study all companies tracked by the ACSI project. Furthermore, we have examined only the short run effects of customer satisfaction. Additional research going beyond the immediate (same-quarter) effects to the long run effects may provide additional insights into the role of non-financial information (such customer satisfaction), 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. For example, do sell-hold-buy recommendations of the high-customer satisfaction firms differ from those for the low-satisfaction companies? Our results suggest that it is important to conduct a fine-grained analysis of the specific customer metrics revealed by firms. For example, we need to examine how customer retention, cross-selling rates do or do not influence the analysts' earnings forecasts. Such analysis would be in line with marketers' concerns regarding the effects of marketing actions on firm value. Such an effort would also show the complementarities between qualitative information and quantitative information, with the potential for enhancing the legitimacy of marketing to the board.

Another question pertains to the reasons why analysts do not use customer satisfaction data as frequently as one might expect. This is a little bit surprising given the publication of the ACSI results in various investor journals such as the *Wall Street Journal*. One possible reason is the analysts' lack of confidence in customer satisfaction data given that they are not trained to use non-financial information such as customer satisfaction data. Therefore, they may not believe in the causality between customer satisfaction and firm performance. Finally, if analysts do not use customer satisfaction information, the question is how does customer satisfaction information comes into stock price, as observed by previous studies (e.g. Fornell et al. 2006). It may be that investors are able to identify the superior performance from high-satisfaction companies independent of the analysts' forecasts. This may happen when the company's actual earnings systematically beat earnings forecasts of these high-satisfaction firms by the analysts. Future research should look at how market valuation leads or lags analysts' forecasts for companies reporting high levels of customer satisfaction. In sum, our findings indicate that if financial analysts neglect customer satisfaction information, they might deprive themselves of an important proxy of non-financial information, specifically those who follow companies in the information technology sector.

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Figure 1: Conceptual Model

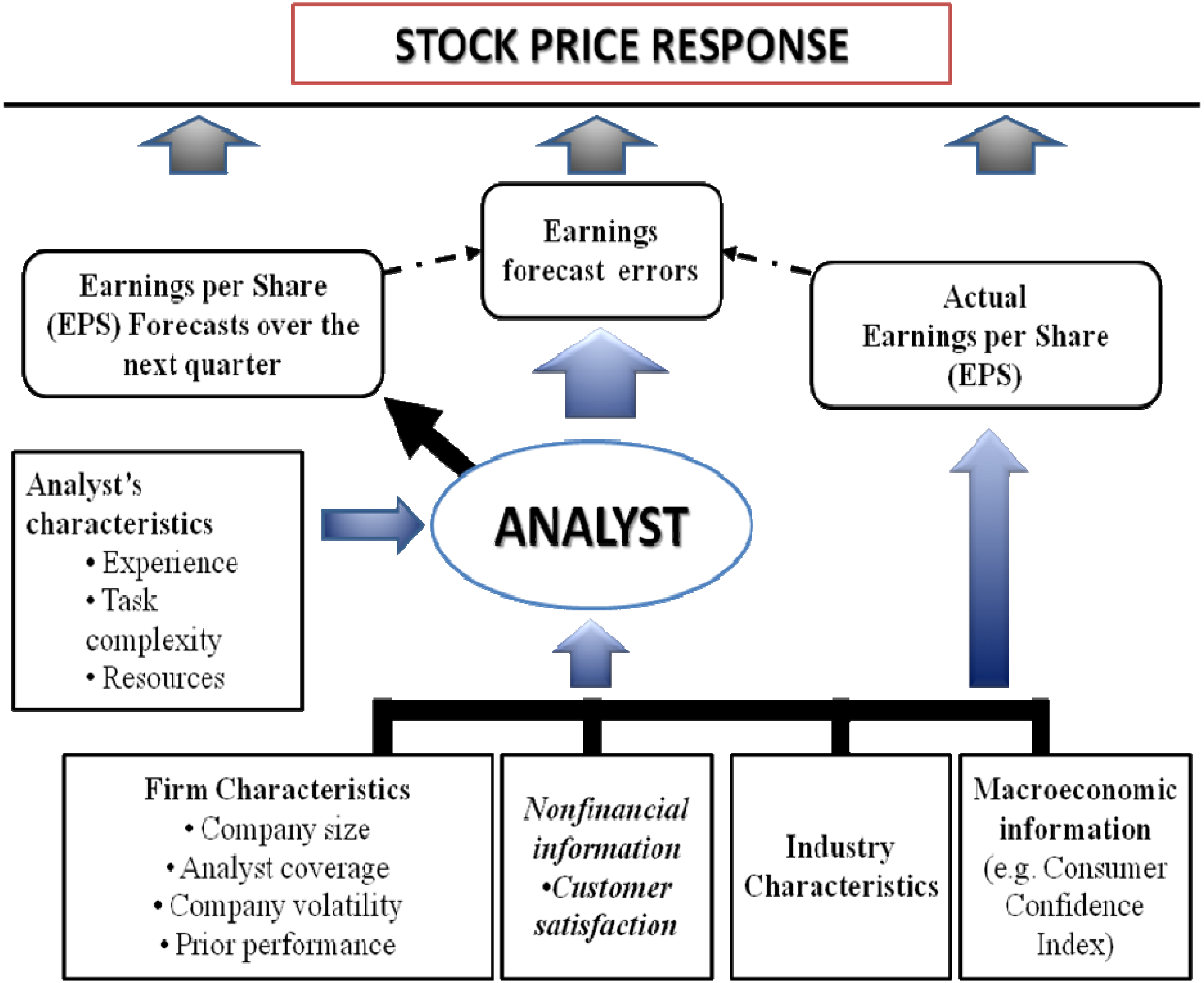

Figure 2: Process of data fusion

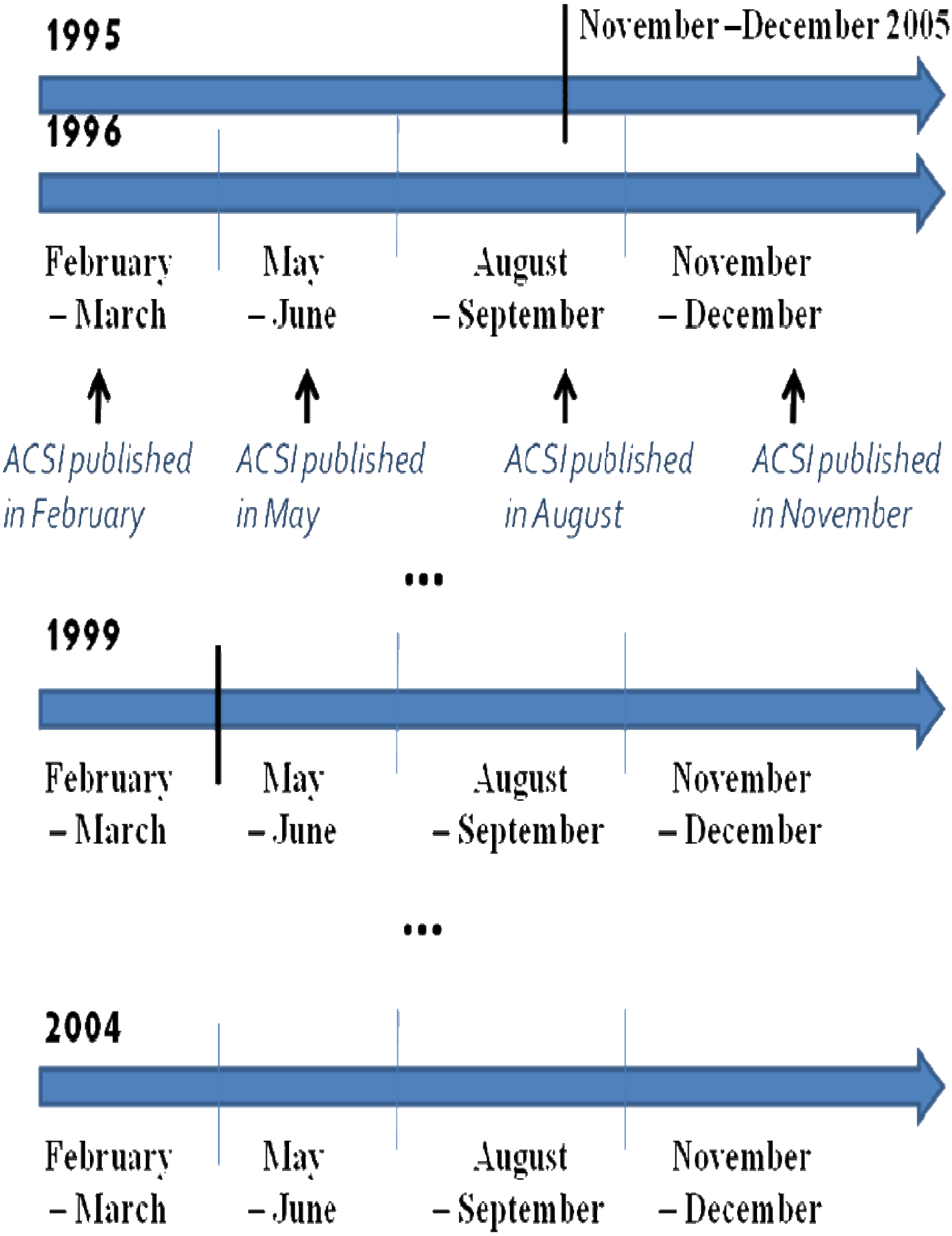

Table 1: List of industries in the data

Industries	**# of firms**	**# of analysts**	**# of observations**
Air Freight & Logistics	1	49	134
Airlines	5	55	597
Apparel, Accessories	2	44	117
Broadcasting & C	4	126	442
Computer Hardware	3	113	529
Computers & Electronics	2	34	106
Department Store	6	145	698
Electric Utilities	10	82	537
Electrical Components	2	101	230
Food Retail	4	60	304
Hotels, Resorts	2	60	184
Household Products	2	45	179
Hypermarkets & Supermarkets	2	108	366
Integrated Telecommunications	4	128	595
Internet Retail	1	38	63
Internet Software	2	94	177
Investment Banking	2	60	125
Life & Health In	1	20	30
Managed Health C	2	50	115
Multi-Utilities	12	104	771
Packaged Foods &	8	94	737
Property & Casualty	2	55	174
Publishing	5	46	244
Restaurants	3	68	298
Soft Drinks	2	65	251
Telecommunications	1	31	31
Total	90	1875	8034

Economic sectors	**Freq.**	**Percent**	**Cum.**
Consumer Discretionary (e.g. Retailers)	2,152	26.79	26.79
Consumer Staples (e.g. Hershey Foods)	1,837	22.87	49.65
Financials (e.g. Wachovia)	329	4.10	53.75
Health Care (e.g. Aetna)	115	1.43	55.18

Industrials (e.g. American Airlines)	961	11.96	67.14
Information Technology (e.g. Dell, HP)	737	9.17	76.31
Telecommunication Services (e.g. BellSouth)	595	7.41	83.72
Utilities (e.g. Duke Energy)	1,308	16.28	100.00
Total	8,034	100.00	

Table 2: Descriptive statistics

variable	Mean	Median	Standard Deviation	Min.	Max.	Skewness	Kurtosis
Company size	9.192	9.168	1.475	2.748	12.424	-0.772	5.511
# of firms	4.106	3.000	3.678	1.000	21.000	2.298	8.628
# of industries	4.175	3.000	3.776	1.000	21.000	2.279	8.472
Firm specific experience	14.753	13.000	10.206	0.000	43.000	0.641	2.614
General experience	82.497	50.000	92.163	0.000	505.000	2.310	9.427
Broker size	6.714	6.000	4.239	1.000	22.000	0.809	3.459
Volatility	0.321	0.183	0.417	0.026	2.078	2.879	10.830
Coverage	15.427	14.000	7.792	1.000	44.000	1.125	4.360
Loss	0.096	0.000	0.294	0.000	1.000	2.746	8.540
ACSI	75.111	75.000	6.274	53.000	90.000	-0.304	2.853
ABS [ERROR]	0.237	0.067	0.985	0.000	51.000	26.181	1065.368

Table 3: Correlation matrix
[Coefficient & p-value]

	1	2	3	4	5	6	7	8	9	10	11
Forecast Error	1.0000										
ACSI	-0.0536	1.0000									
	0.0000										
Company size	-0.0847	0.1411	1.0000								
	0.0000	0.0000									
# of firms	0.0064	0.0685	-0.0850	1.0000							
	0.5651	0.0000	0.0000								
# of industries	0.0047	0.0715	-0.0870	0.9684	1.0000						
	0.6760	0.0000	0.0000	0.0000							
Firm experience	-0.0107	-0.0866	-0.0685	0.0834	0.0695	1.0000					
	0.3394	0.0000	0.0000	0.0000	0.0000						
General experience	0.0072	0.0333	-0.0908	0.6918	0.6881	0.5333	1.0000				
	0.5174	0.0028	0.0000	0.0000	0.0000	0.0000					
Broker size	0.0020	-0.0090	-0.0046	0.1408	0.1518	0.0120	0.0880	1.0000			
	0.8545	0.4175	0.6830	0.0000	0.0000	0.2806	0.0000				
Volatility	0.0820	-0.2497	-0.1645	0.0650	0.0610	0.1472	0.0990	0.0538	1.0000		
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000			
Coverage	0.0184	-0.1355	0.1786	-0.3226	-0.3309	-0.0367	-0.2914	-0.0896	-0.1162	1.0000	
	0.0992	0.0000	0.0000	0.0000	0.0000	0.0010	0.0000	0.0000	0.0000		
Loss	0.2214	-0.1025	-0.2954	-0.0601	-0.0648	0.0046	-0.0672	0.0540	0.2881	0.0338	1.0000
	0.0000	0.0000	0.0000	0.0000	0.0000	0.6825	0.0000	0.0000	0.0000	0.0024	

Table 4: ACSI and Actual Earnings Per Share
(Dependent variable = Actual Earnings Per Share, Mixed effects ML regression - Coefficients and standard errors in parentheses)

Estimated effects	**Model I (Controls)**	**Model II (Model I + ACSI)**	**Model III (Response heterogeneity)**
Intercept	-4,158*** (0.37)	-5,306*** (0.659)	-5,054*** (0.633)
Lagged (EPS)	0,943*** (0,069)	0,927*** (0,069)	0,971*** (0,069)
Consumer Confidence Index	0,000 (0,002)	0,001 (0,002)	0,001 (0,002)
Consumer Staples	-0,445 (0,248)	-0,473 (0,247)	-0,436 (0,233)
Financials	-0,952** (0,319)	-0,973** (0,317)	-1,021*** (0,303)
Health Care	-0,515 (0,463)	-0,441 (0,462)	-0,472 (0,448)
Industrials	0,553 (0,302)	0,570 (0,300)	0,498 (0,281)
Information Technology	-1,232*** (0,299)	-1,22*** (0,298)	-1,260*** (0,287)
Telecommunication Services	-0,920* (0,364)	-0,889* (0,362)	-0,975** (0,360)
Utilities	0,175 (0,230)	0,174 (0,229)	0,030 (0,221)
ACSI 2nd quarter wave	-0,845*** (0,230)	-0,893*** (0,230)	-0,753*** (0,220)
ACSI 3rd quarter wave	-0,808** (0,256)	-0,825*** (0,255)	-0,809*** (0,242)
ACSI 4th quarter wave	-0,311 (0,244)	-0,414 (0,248)	-0,421 (0,235)
Company size	0,348*** (-0,036)	0,348*** (0,036)	0,323*** (0,035)
Volatility	0,837*** (0,221)	0,879*** (0,221)	0,808*** (0,210)
LOSS	0,239* (0,121)	0,230 (0,121)	0,044 (0,290)
Customer satisfaction (ACSI)		0,014* (0,006)	0,013* (0,006)
Sources of variation			
• Between-firm variation	0.566*** (0.05)	0.563*** (0.05)	.458*** (0.09)
○ τ_{00i}^{SAT}			.000 (0.002)
○ $\tau_{00i,LOSS}$			.979*** (0.23)
○ $\tau_{00i,VOLATILITY}$			.000 (0.000)
○ $\tau_{00i,SIZE}$			.030 (0.016)
ll(model)	-441.84	-439.62	-417.96
Df	27	28	31
AIC	937.68	935.25	897.93
BIC	1058.68	1060.74	1036.85

* significant at 5%, ** significant at 1%, *** significant at 0.1%

Table 5: ACSI and Analysts' Earnings Forecasts

(Dependent variable = *Earnings Forecasts*, Mixed effects ML regression - Coefficients and standard errors in parentheses)

LNFORECAST	**Model I** (Industry dummies)	**Model II** (Controls)	**Model III** (Model II + ACSI)	**Model IV** (Response heterogeneity)
Intercept	-.957***	-2.22***	-3.628***	-4.3289
	(0.04)	(0.16)	(0.208)	(0.2725)
Lagged (EPS)	-	1.04***	0.989***	1.088***
		(0.02)	(0.022)	(0.026)
Consumer Confidence Index	-	0.00	0.000	0.001
		(0.00)	(0.001)	(0.002)
Consumer Staples	-.063***	-0.31***	-0.369***	-0.336***
	(.029)	(0.03)	(0.031)	(0.030)
Financials	-.139***	-0.70***	-0.753***	-0.784***
	(0.052)	(0.04)	(0.042)	(0.041)
Health Care	.626***	-0.47***	-0.384***	-0.363***
	(.086)	(0.07)	(0.066)	(0.070)
Industrials	.445***	0.35***	0.384***	0.323***
	(0.03)	(0.03)	(0.033)	(0.032)
Information Technology	-1.301***	-1.06***	-1.040***	-1.008***
	(.039)	(0.04)	(0.037)	(0.036)
Telecommunication Services	.293***	-0.43***	-0.386***	-0.318***
	(0.044)	(0.04)	(0.042)	(0.043)
Utilities	.221***	0.15***	0.180***	0.119**
	(.037)	(0.04)	(0.040)	(0.040)
ACSI 2nd quarter wave	-	-0.61***	-0.742***	-0.7093***
		(0.03)	(0.031)	(0.0318)
ACSI 3rd quarter wave	-	-0.46***	-0.516***	-0.5029***
		(0.04)	(0.035)	(0.0339)
ACSI 4th quarter wave	-	-0.08*	-0.236***	-0.2996***
		(0.03)	(0.033)	(0.0315)
Brocker size	-	0.00	-0.001	-0.0006
		(0.00)	(0.001)	(0.0010)
Firm specific Experience	-	0.01***	0.006***	0.0057***
		(0.00)	(0.001)	(0.0008)
Task complexity	-	0.00	-0.002	-0.0045
		(0.00)	(0.003)	(0.0032)
Company size	-	0.11***	0.114***	0.1207***
		(0.01)	(0.007)	(0.0065)
Volatility	-	0.65***	0.724***	0.8691***
		(0.03)	(0.027)	(0.0357)
Analyst Coverage	-	0.00	-0.001	-0.0006
		(0.00)	(0.001)	(0.0012)
Loss	-	0.19***	0.117**	0.0970*
		(0.04)	(0.042)	(0.0526)
ACSI			0.019***	0.0259***
			(0.002)	(0.0016)
Random-effects Parameters				
Within-analyst	.124***	0.08***	0.08***	0.131***
	(0.02)	(0.02)	(0.020)	(0.041)
Between-analysts	0.33***	0.20***	0.18***	0.218***
	(0.03)	(0.02)	(0.022)	(0.023)
Between-firm variation	.763***	0.59***	0.59***	0.483***
	(0.01)	(0.01)	(0.008)	(0.014)
• $\tau_{00i,EPS}$				0.001
				(0.028)
• $\tau_{00i,SIZE}$				0.011**
				(0.004)

• $\tau_{00i,\mathrm{VOLATILITY}}$				0.514*** (0.068)
• $\tau_{00i,\mathrm{COVERAGE}}$				0.011*** (0.001)
• $\tau_{00i,\mathrm{LOSS}}$				0.476*** (0.058)
• $\tau_{00i}^{\mathrm{SAT}}$				0.000 (0.000)
ll(model)	-8555.43	-6452.178	-6387.087	-6318.865
Df	12	24	25	31
AIC	17134.86	12952.36	12824.17	12699.73
BIC	17218.03	13118.7	12997.45	12914.59

* significant at 5%. ** significant at 1%. *** significant at 0.1%

Table 6: ACSI and Earnings Forecast Errors
(Dependent variable = *ln*(Absolute Value of the Forecast Error))
(Mixed effects ML regression - Coefficients and standard errors in parentheses)

	Model I (Controls)	**Model II (Model I + ACSI)**	**Model III (Response heterogeneity)**	**Model IV (Model III + Constraints)**
Intercept	-1.944**	-0.53	-0.48	-0.411
	(0.759)	(1.19)	(1.13)	(1.137)
Lagged (EPS)	-0.304**	-0.27*	-0.14	-0.148
	(0.118)	(0.12)	(0.11)	(0.111)
Consumer Confidence Index	0.003	0.00	0.00	0.001
	(0.005)	(0.01)	(0.01)	(0.005)
Consumer Staples	-0.489*	-0.43	-0.28	-0.278
	(0.238)	(0.24)	(0.23)	(0.233)
Financials	1.303***	1.35***	1.34***	1.346***
	(0.322)	(0.32)	(0.32)	(0.319)
Health Care	1.800***	1.70***	1.82***	1.824***
	(0.50)	(0.51)	(0.49)	(0.497)
Industrials	-0.503	-0.55*	-0.51*	-0.488*
	(0.259)	(0.26)	(0.24)	(0.241)
Information Technology	1.219***	1.18***	1.17***	1.195***
	(0.28)	(0.29)	(0.28)	(0.282)
Telecommunication Services	-0.288	-0.38	-0.41	-0.387
	(0.29)	(0.30)	(0.30)	(0.303)
Utilities	1.20***	1.17***	1.15***	1.157***
	(0.29)	(0.30)	(0.28)	(0.284)
ACSI 2nd quarter wave	1.137***	1.27***	1.28***	1.282***
	(0.22)	(0.24)	(0.23)	(0.228)
ACSI 3rd quarter wave	-0.112	-0.04	0.07	0.066
	(0.26)	(0.27)	(0.26)	(0.259)
ACSI 4th quarter wave	-0.582*	-0.42	-0.45	-0.434
	(0.22)	(0.25)	(0.25)	(0.249)
Broker size	-0.036**	-0.04**	-0.03**	-0.033*
	(0.013	(0.01)	(0.01)	(0.013)
Firm specific Experience	0.012***	0.01*	0.01*	0.012*
	(0.006)	(0.00)	(0.01)	(0.006)
Task complexity	-0.029	-0.03	-0.02	-0.022
	(0.023)	(0.02)	(0.02)	(0.022)
Company size	-0.433***	-0.43***	-0.40***	-0.405***
	(0.05)	(0.05)	(0.05)	(0.049)
Volatility	0.875***	0.83***	0.76***	0.756***
	(0.181)	(0.18)	(0.18)	(0.177)
Analyst Coverage	0.044***	0.04***	0.04***	0.044***
	(0.009)	(0.01)	(0.01)	(0.009)
Loss	1.392***	1.42***	1.54***	1.542***
	(0.26)	(0.26)	(0.24)	(0.238)
ACSI		-0.02*	-0.02*	-0.024*
		(0.01)	(0.01)	(0.012)
Random-effects Parameters				
Within-analyst	.26***	0.27***	0.25***	0.25***
	(0.08)	(0.09)	(0.08)	(0.08)
Between-analyst/within-firm	.705***	0.71***	0.01*	0.65***
	(0.23)	(0.23)	(0.00)	(0.23)
Between firm	4.84***	4.84***	0.02	0.01
	(0.05)	(0.05)	(0.31)	(0.16)
• $\tau_{00i,EPS}$			0.01	
			(0.09)	
• $\tau_{00i,SIZE}$			0.41***	0.41***
			(0.02)	(0.02)

• $\tau_{00i,VOLATILITY}$			0.04 (0.10)	-
• $\tau_{00i,COVERAGE}$			0.00 (0.00)	-
• $\tau_{00i,LOSS}$			0.08 (0.18)	-
• τ_{00i}^{SAT}			0.04*** (0.00)	0.038*** (0.002)
ll(model)	-23879.27	-23878.04	-23762.82	-23761.68
Df	24	25	30	27
AIC	47806.53	47806.07	47585.64	**47577.37**
BIC	47974.25	47980.79	47795.29	**47766.05**

* significant at 5%, ** significant at 1%, *** significant at 0.1%

Table 7: Effects of ACSI across Sectors
(Mixed effects ML regression - Coefficients and standard errors in parentheses)

Estimated effects	**Model I (Actual EPS)**	**Model II (Actual EPS+ Constrained)**	**Model I Earnings Forecasts**	**Model I Forecast Errors**	**Model I Forecast Errors (constraints)**
Intercept	-3.590***	-4.324***	-2.219***	-2.51	-1.419
	(1.048)	(0.641)	(0.241)	(1.66)	(1.402)
Lagged (EPS)	0.963****	0.976***	1.091***	-0.21	-0.163
	(0.072)	(0.068)	(0.025)	(0.11)	(0.111)
Consumer Confidence Index	0.001	0.001	0.000	0.00	0.002
	(0.002)	(0.002)	(0.001)	(0.01)	(0.005)
Consumer Staples	0.020	-0.423	-2.090***	6.55*	3.846
	(1.368)	(0.228)	(0.341)	(3.02)	(2.903)
Financials	-5.668	-1.021***	-3.407*	-3.09	1.407***
	(4.281)	(0.296)	(1.661)	(13.45)	(0.321)
Health Care	1.847	-0.498	-1.239	-1.11	1.855***
	(3.739)	(0.438)	(1.395)	(10.06)	(0.496)
Industrials	-0.636	0.468	0.119	-5.26*	-5.782**
	(1.497)	(0.274)	(0.341)	(2.48)	(2.259)
Information Technology	-10.352***	-9.665***	-12.598***	26.88***	23.977***
	(1.975)	(1.797)	(0.500)	(4.09)	(4.151)
Telecommunication Services	-2.738	-0.973**	-2.090***	5.14	4.280
	(1.774)	(0.352)	(0.458)	(2.65)	(2.627)
Utilities	-1.269	0.003	-3.474***	2.81	1.257***
	(1.246)	(0.216)	(0.312)	(2.55)	(0.284)
ACSI 2nd quarter wave	-0.700***	-0.713***	-0.664***	1.12***	1.187***
	(0.214)	(0.215)	(0.030)	(0.25)	(0.232)
ACSI 3rd quarter wave	-0.878***	-0.882***	-0.653***	0.32	0.287
	(0.235)	(0.237)	(0.033)	(0.26)	(0.262)
ACSI 4th quarter wave	-0.263	-0.371	-0.264***	-0.03	-0.172
	(0.238)	(0.230)	(0.040)	(0.36)	(0.341)
Broker size			0.000	-0.04***	-0.033*
			(0.001)	(0.01)	(0.013)
Firm specific Experience			0.005***	0.01*	0.014*
			(0.001)	(0.01)	(0.006)
Task complexity			-0.004	-0.03	-0.024
			(0.003)	(0.02)	(0.022)
Company size	0.303***	0.303***	0.113***	-0.43***	-0.429***
	(0.034)	(0.034)	(0.007)	(0.05)	(0.051)
Volatility	0.784***	0.774***	0.788***	1.17***	1.105***
	(0.207)	(0.205)	(0.033)	(0.20)	(0.197)
Analyst Coverage			0.000	0.05***	0.045***
			(0.001)	(0.01)	(0.009)
LOSS	0.029	0.046	0.206***	1.48***	1.478***
	(0.280)	(0.282)	(0.042)	(0.25)	(0.241)
Customer satisfaction (ACSI)	-0.004	0.005	0.000	0.00	-0.011
	(0.013)	(0.006)	(0.002)	(0.02)	(0.016)
ACSI x Consumer Staples	-0.006		0.024***	-0.09*	-0.054
	(0.018)		(0.005)	(0.04)	(0.038)
ACSI x Financials	0.063		0.035	0.06	
	(0.058)		(0.022)	(0.18)	
ACSI x Health Care	-0.036		0.010	0.04	
	(0.055)		(0.021)	(0.15)	
ACSI x Industrials	0.015		0.003	0.06*	0.073*
	(0.020)		(0.005)	(0.03)	(0.030)
ACSI x Information Technology	0.126***	0.116***	0.160***	-0.36***	-0.316***
	(0.027)	(0.025)	(0.007)	(0.06)	(0.058)

ACSI x Telecommunication Services	0.024 (0.023)	-	0.023*** (0.006)	-0.07* (0.04)	-0.062 (0.036)
ACSI x Utilities	0.017 (0.016)	-	0.047*** (0.004)	-0.02 (0.03)	-
Random-effects Parameters					
Within-analyst	-	-	0.076*** (0.016)	0.27*** (0.08)	0.26*** (0.08)
Between-analysts	-	-	0.167*** (0.026)	0.005* (0.002)	0.63** (0.23)
Between-firm variation	.442*** (0.09)	.442*** (0.09)	0.307*** (0.037)	0.07 (0.36)	0.01*** (0.001)
• $\tau_{00i,EPS}$	0.00 (0.00)	-	0.001 (0.024)	0.03 (0.10)	-
• $\tau_{00i,COVERAGE}$	-	-	0.000 (0.001)	0.00 (0.02)	-
• τ_{00i}^{SAT}	.0000 (0.002)	0.00 (0.00)	0.000 (0.000)	0.06*** (0.00)	0.04*** (0.002)
• $\tau_{00i,LOSS}$	0.938*** (0.22)	.949*** (0.22)	0.271*** (0.05)	0.10 (0.18)	-
• $\tau_{00i,VOLATILITY}$	0.000 (0.00)	-	0.375*** (0.070)	0.05 (0.08)	-
• $\tau_{00i,SIZE}$	0.029 (0.016)	-	0.048*** (0.004)	0.17*** (0.02)	0.399*** (0.02)
ll(model)	-404.60	-406.96	-6044.64	-23784.2	-23739.43
df	38	31	37	36	31
AIC	885.20	875.928	12163.28	47640.41	47540.86
BIC	1055.50	1014.85	12419.73	47891.99	47757.5

Table 8: Changes in ACSI and Analysts' Forecasts

(Dependent variable = Earnings Forecasts, i.e. y_{hijt+1})

(Mixed effects ML regression - Coefficients and standard errors in parentheses)

	Model 1 (Main effects)	**Model 2 (Interactions)**	**Model 3 (Constraints)**
Intercept	0.661***	0.660***	0.661***
	(0.02)	(0.020)	(0.020)
ΔCurrent Earnings (Δy_{ijt})	0.277***	0.276***	0.276
	(0.01)	(0.007)	(0.007)
Consumer Staples	-0.297***	-0.297***	-0.297***
	(0.02)	(0.022)	(0.022)
Financials	-0.198***	-0.200***	-0.199***
	(0.04)	(0.037)	(0.037)
Health Care	-0.054	-0.055	-0.057
	(0.06)	(0.062)	(0.062)
Industrials	-0.215***	-0.219***	-0.219***
	(0.03)	(0.027)	(0.027)
Information Technology	-0.231***	-0.229***	-0.229***
	(0.03)	(0.032)	(0.032)
Telecommunication Services	0.365***	0.359***	0.359***
	(0.03)	(0.031)	(0.031)
Utilities	0.117***	0.114***	0.114***
	(0.03)	(0.027)	(0.027)
ACSI 2nd quarter wave	-0.396***	-0.394***	-0.394***
	(0.02)	(0.024)	(0.024)
ACSI 3rd quarter wave	-0.317***	-0.318***	-0.318***
	(0.03)	(0.029)	(0.029)
ACSI 4th quarter wave	-0.065**	-0.065**	-0.065**
	(0.02)	(0.023)	(0.023)
ΔFirm-specific experience	0.001	0.001	0.001
	(0.00)	(0.001)	(0.001)
ΔTask Complexity	-0.004	-0.004	-0.004
	(0.00)	(0.002)	(0.002)
ΔBroker Size	0.000	0.000	0.000
	(0.00)	(0.001)	(0.001)
ΔAnalyst Coverage	0.001	0.001	0.002
	(0.00)	(0.001)	(0.001)
ΔCompany Size	0.032***	0.032***	0.032***
	(0.01)	(0.007)	(0.007)
LOSS	-0.659***	-0.661***	-0.659***
	(0.02)	(0.023)	(0.023)
VOLATILITY	0.582***	0.583***	0.583***
	(0.02)	(0.017)	(0.017)
ΔACSI	0.003*	0.006*	0.001
	(0.00)	(0.003)	(0.002)
ΔACSI x Consumer Staples		-0.006	
		(0.005)	
ΔACSI x Financials		-0.022	
		(0.017)	
ΔACSI x Health Care		0.015	
		(0.018)	
ΔACSI x Industrials		-0.014**	-0.009*
		(0.005)	(0.004)
ΔACSI x Information Technology		-0.009	
		(0.006)	
ΔACSI x Telecommunication Services		0.024***	0.028***
		(0.005)	(0.005)

ΔACSI x Utilities		-0.007 (0.004)	
Within-analyst	0.044** (0.012)	0.041** (0.011)	0.04*** (0.01)
Between-analysts	0.158*** (0.009)	0.154*** (0.009)	0.15*** (0.01)
Between-firm variation	0.350*** (0.007)	0.350*** (0.007)	0.35*** (0.01)
Obs	5602	5602	5602
ll(model)	-2941.46	-2914.261	-2917.349
Df	24.000	31	26
AIC	5930.92	5890.523	5886.698
BIC	6090.061	6096.08	6059.101

Note: Change in consumer confidence index was rejected because of multicollinearity. Furthermore, we do not estimate the response heterogeneity because of model convergence problems.
* significant at 5%, ** significant at 1%, *** significant at 0.1%

Table 9: Changes in ACSI and Forecast Errors
(Dependent variable = *ln*(Absolute Value of the Forecast Error))
(Mixed effects ML regression - Coefficients and standard errors in parentheses)

	Model 1 (Main effects)	**Model 2 (Interactions)**	**Model 3 (Constraints)**
Intercept	-4.63*** (0.20)	-4.62*** (0.20)	-4.627*** (0.195)
ΔCurrent Earnings (Δy_{ijt})	-0.06 (0.08)	-0.07 (0.08)	-0.059 (0.076)
Consumer Staples	-1.25*** (0.26)	-1.26*** (0.26)	-1.256*** (0.258)
Financials	0.78 (0.43)	0.77 (0.43)	0.777 (0.427)
Health Care	1.56* (0.72)	1.56* (0.72)	1.560* (0.715)
Industrials	-0.19 (0.32)	-0.19 (0.32)	-0.189 (0.317)
Information Technology	0.91** (0.37)	0.90** (0.37)	0.909* (0.368)
Telecommunication Services	-1.23*** (0.35)	-1.24*** (0.35)	-1.242*** (0.354)
Utilities	0.36 (0.29)	0.35 (0.29)	0.347 (0.292)
ACSI 2nd quarter wave	0.86*** (0.28)	0.86*** (0.28)	0.866** (0.276)
ACSI 3rd quarter wave	-0.59 (0.34)	-0.59 (0.34)	-0.589 (0.337)
ACSI 4th quarter wave	-0.70** (0.26)	-0.70** (0.26)	-0.703** (0.259)
ΔFirm-specific experience	0.01 (0.01)	0.01 (0.01)	0.009 (0.009)
ΔTask Complexity	-0.02 (0.02)	-0.02 (0.02)	-0.024 (0.024)
ΔBroker Size	-0.03* (0.01)	-0.03* (0.01)	-0.028 (0.014)
ΔAnalyst Coverage	0.04*** (0.01)	0.03*** (0.01)	0.035** (0.011)
ΔCompany Size	-0.20** (0.07)	-0.20** (0.07)	-0.200** (0.075)
Loss	2.20** (0.27)	2.16*** (0.27)	2.158*** (0.270)
Volatility	0.53** (0.21)	0.54** (0.21)	0.537** (0.209)
ΔACSI	-0.04** (0.02)	-0.06 (0.03)	-0.019 (0.016)
ΔACSI x Staples		0.03 (0.05)	
ΔACSI x Health Care		0.11 (0.20)	
ΔACSI x Financials		0.18 (0.20)	
ΔACSI x Industrials		0.09 (0.05)	
ΔACSI x Information Technology		-0.18*** (0.06)	-0.219*** (0.054)
ΔACSI x Telecommunication Services		0.00 (0.06)	
ΔACSI x Utilities		0.07	

		(0.04)	
Within-analyst variation	0.30** (0.10)	0.301** (0.102)	0.297* (0.102)
Between-analyst (within-firm) variation	0.31 (0.61)	0.350 (0.538)	0.368 (0.514)
Between-firm variation	4.85*** (0.06)	4.828*** (0.064)	4.829*** (0.064)
Obs	5614	5614	5614
ll(model)	-16726.17	-16715.1	-16717.93
df	24	31	25
AIC	33500.35	33492.2	33485.87
BIC	33659.54	33697.83	33651.69

Note: Change in consumer confidence index was rejected because of multicollinearity
* significant at 5%, ** significant at 1%, *** significant at 0.1%